DETERMINATION OF SEASONAL ADJUSTMENT FACTORS AND ASSIGNMENT OF SHORT-TERM COUNTS TO FACTOR GROUPINGS

A Dissertation

Presented to

The Graduate Faculty of The University of Akron

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

Ioannis Tsapakis

August, 2009
DETERMINATION OF SEASONAL ADJUSTMENT FACTORS AND ASSIGNMENT OF SHORT-TERM COUNTS TO FACTOR GROUPINGS

Ioannis Tsapakis
Dissertation

Approved:

Advisor
Dr. William H. Schneider IV

Committee Member
Dr. Ping Yi

Committee Member
Dr. Richard Steiner

Committee Member
Dr. Edward Evans

Committee Member
Dr. GunJin Yun

Accepted:

Department Chair
Dr. Wieslaw K. Binienda

Dean of the College
Dr. George K. Haritos

Dean of the Graduate School
Dr. George R. Newkome

Date
ABSTRACT

The traffic volume of a roadway segment is of significant importance for several public and private sections of the industry. This volume is represented by the Annual Average Daily Traffic (AADT). The AADT expresses the average number of vehicles that travel daily on this particular roadway section within a year. The traditional method of estimating AADT is examined along with new methods in order to improve the accuracy of the predictions.

The literature review conducted at the beginning of this study comprises the theoretical background to develop the research methodology. The study data are provided from 2002 to 2007 by the Ohio Department of Transportation (ODOT). The first type of data is obtained from traffic counters that perform continuously throughout a year. The second type of data is generated by portable counters that record traffic volumes for a short-period of time. The prediction of the AADT is based on the combination of both types of data using several mathematical methods and newly developed statistical approaches.

The determination of seasonal adjustment factors (SAF) is the first step of the AADT estimation. Seven SAFs and five approaches of estimating the AADT are examined for thirteen individual vehicle classes and groups of classes. The most effective SAFs are selected based on the mean absolute error (MAE) and the standard deviation (SD) of the predictions. Two analyses are conducted for each step of the study: the first is based on SAFs estimated from the sum of the two directional volumes of a roadway, and; the second on SAFs calculated for each direction of...
the traffic. The continuous counters are grouped together using eight different combinations of traditional grouping techniques and cluster analysis. The k-means algorithm, a non-hierarchical clustering method, is used to group the continuous counters based on their monthly SAFs. Furthermore, a statistical-based method for determining the optimal number of clusters was developed. The results are consistent over time and show a significant improvement in the accuracy of the AADT when clustering is used. Based on the performance, the applicability and the practicality of the examined methods, geographical classification and cluster analysis were selected to generate the final factor groupings.

The assignment of short-term counts to counter groups includes the investigation of three methods: the traditional method; discriminant analysis, and; a new approach based on statistical similarities of traffic and temporal characteristics between a short-period count and factor groups. In total, fifty six assignment models were developed and compared. The analysis based on directional SAFs is more effective than the total volume analysis by 15% to 40%. The final results indicate that the statistical approach developed in this study results in a MAE and SD improvement over the traditional method by 51.75% and 67.73% correspondingly.

In addition to the traditional method, regression and Bayesian negative binomial techniques are examined to predict AADT. In total twelve models are developed with a training data set and the results are compared using a validation data set. Parameters of significance include the HPMS roadway functional classification, population density, spatial location and the average daily traffic. The results show a full Bayesian negative binomial model with a coefficient offset was the most efficient model framework for all four seasons of the year. This model was able to describe between 87% and 92% of the variability within the data set.
DEDICATION

This dissertation is dedicated to my parents, Nickolao and Fereniki Tsapaki for their love, which will always be the main motivation of my work.
ACKNOWLEDGEMENTS

There are many people who have been instrumental in the completion of this dissertation. I would like to take this opportunity to thank them. I would like to express my appreciation to my advisor, Dr. William H. Schneider IV whose constructive advice gave me a great deal of guidance and allowed me to successfully complete the research. I will never forget his encouragement and his helpful suggestions throughout my doctoral studies.

I also thank my committee members, Dr. Ping Yi, Dr. Richard Steiner, Dr. Edward Evans and Dr. GunJin Yun for their assistance. Thanks also go to my research group and specifically to Darren Moore, Srutha Vavilikolanu, Chun Shao, Mike Lupica, Cedric Duah and Yin Ge for their help, as well as for the good times we shared the last three years.

I would also like to express my appreciation to Mr. Evangelo and Ms. Koula Detorakis for the interest they showed me since I came in the USA. I will always be grateful to them for their assistance and their moral support.

Last but not least, I would like to express my hearty gratitude to my parents Nickolao and Fereniki for their countless sacrifices. Also my sisters Evangelia and Vaso as well as my brother Kosta for keeping me focused on my priorities. Their valuable encouragement and advice always accompanied my efforts.
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CHAPTER I
INTRODUCTION

Traffic volume is one of the most important variables used in roadway planning and management. State Departments of Transportation (DOT) devote a significant amount of financial and personnel resources to the improvement of traffic monitoring programs. One of the most important traffic volume parameters reported by monitoring programs is the annual average daily traffic (AADT). AADT is defined as the total vehicle volume at a specific point or section of a roadway during a year, divided by the total number of days of this year and it is expressed in vehicles per day (veh./day). Transportation professionals use AADT for environmental analysis including non-attainment state implementation plans, highway planning, pavement design, work zone plans, and exposure rates for safety analysis. This research focuses on improving such programs by increasing the accuracy of traffic volume data collection and estimation and on improving the coordination of vehicle counts. Several methods for estimating AADT are examined in this study and are subject to suggestions for accuracy improvement.

1.1 Statement of Problem

Transportation agencies devote a large amount of their budget on data collection programs. As a result of financial and manpower limitations, DOTs use a series of continuous Automatic Traffic Recorders (ATR) in association with less expensive more mobile short-term
counts. Substantial traffic data can be produced only by ATRs that perform continuously under perfect conditions. ATRs record traffic volumes continuously, 24 hours every day, 365 days a year. However, their installation, operation, and maintenance are quite costly. Thus, it is economically infeasible for a state or an agency to maintain a large number of ATRs in its transportation network. Due to this limitation, short-term or seasonal counts are conducted in order to cover the whole transportation network of a city, a county or a state. Short-term counts are used to count traffic volume for a short time-period, usually less than 72 hours. Actual values of AADT can be calculated exclusively by using ATR data. The AADT of roadway segments for which there are no ATR sites available, can be estimated by combining data from other ATRs with short-term counts. Once the short-term counts are recorded, a series of adjustment factors, calculated from the ATRs, are applied to the short-term counts. The end result is an estimated AADT for a particular segment of roadway. The traditional method of estimating AADT (Drusch, 1966) or closely related procedures have been used in the past; however there are some unanswered questions on the most effective factors and the most accurate methods to group the ATRs (TMG, 2001). Furthermore, the limited research on applying short-term counts to ATR groupings (Sharma et al., 1999) and the lack of an objective statistical method, highlight the need for further research on this area.

1.2 Purpose and Objectives

The purpose of this research is to help DOT’s, transportation agencies, and public and private companies to improve their traffic monitoring program. This can be achieved by adding new, improved, and innovative elements in the traditional process of estimating AADT, as well as by investigating several parameters associated with data collection programs. Current practice and research are focusing mainly on SAFs estimated for total volume, which includes all types of vehicles, without taking into account the different character of the traffic. The final goal of this
study, derived from this limitation, is to produce more accurate AADT predictions for total volume, cars and trucks. This separation is necessary to account for differences in traffic patterns of each vehicle type (TMG, 2001; Hallenbeck, 1997). The analysis is also conducted using two types of factors: SAFs estimated for two-way traffic; and SAFs calculated for each direction of a roadway. These two types of factors aim at identifying the advantages and disadvantages of directional and total volume analysis. The quantification of the results will assist in the evaluation of the methods. This research investigates new approaches and statistical methods and takes into account new traffic parameters that have not been examined in depth in the past. The following six objectives are examined in this study.

- Objective One - Literature Review:
  The first objective of the study is to review current practice, guidelines and policies on AADT prediction. Chapter II describes traditional methods and more complicated approaches used in the past within each step of the AADT estimation process. The literature review comprises the theoretical background to define the proper analysis methodology.

- Objective Two - Development of Seasonal Adjustment Factors:
  The next objective is to examine the impact of former and new seasonal adjustment factors on AADT. New methods of estimating AADT are employed and compared in order to select the most effective approach. The main part of the analysis includes five formulas to estimate AADT and seven SAFs. The SAFs are 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.
The study also attempts to investigate temporal parameters related with data collection improvements. Sensitivity analyses are conducted to determine what the best months and weekdays are to collect truck data, as well as how the duration of a short-term count impacts the AADT estimates.

- Objective Three - Creation of Factor Groupings:
Several objectives are examined for the grouping of permanent stations, the third step of the analysis. The first objective is the development of eight grouping methods which include current practice, other traditional methods, and new statistical techniques used to cluster data. The second objective is to develop a series of performance measures that are used to assess the overall performance for each method. The determination of the best individual grouping strategy per method is the third task of this analysis. The selection of the most effective method for grouping continuous stations is the final goal within this part of the research.

- Objective Four - Determination of Optimal Number of Clusters:
The factor groupings or clusters are the outcome of cluster analysis. The indetermination of the optimum number of clusters is one of the main disadvantages of clustering (TMG, 2001), and a solution to this problem is one of the objectives of this study. The purpose of this task is the development of a pure statistical approach that takes into account traffic parameters and guidelines; eliminates engineering judgment; and allows the analyst to create and modify simply factor groupings based on a traffic monitoring program’s needs.
Objective Five - Assignment of Short-Term Counts to Factor Groupings:

The main focus of this study is the fourth step of the traditional method of estimating AADT and specifically the assignment of short-term counts to factor groupings. The current research is limited in this research area and little guidance is being offered on how to achieve the assignment accuracy necessary for obtaining reliable AADT forecasts from short-term counts (Sharma et al., 1999). It is important that statistical analysis be employed during the assignment process (Ritchie et al., 1986), because the assignment task is extremely sensitive to error resulting from engineering judgment (Sharma, et al., 1996). 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 a new statistical approach based on the coefficient of variation. These methods are evaluated against each other through ground truth performance, based on the validation of the three techniques. The last objective within this analysis is the determination of the most effective method to assign short-term counts to station groupings.

Objective Six - Alternative Methods in Estimating AADT:

The traditional approach of estimating AADT is the most commonly used method and improvements within each task of the approach are the main goal of the study; however, there are some concerns related with different sources of errors within each step of the process. The last part of the research study is supplementary to the traditional approach and includes three objectives. The first objective is to develop a series of training and validation data sets, one for each season of the year. The second objective is to develop three individual modeling frameworks using the four seasonal training data sets. The three models include: an ordinary least squares regression model, while the second and
third models are full Bayesian negative binomial models. The framework for model two includes a coefficient offset, while model three does not. The third objective is to compare the three models using the validation data sets across all seasonal durations. The end result of this research study will show the effectiveness of the three models for directly predicting heavy-duty annual average daily traffic.

1.3 Benefits

The benefits associated with an improved method for estimating AADT throughout Ohio will provide more information for practitioners, researchers, and consultants. In this study, new methods for determining SAFs will be compared with current methods. New AADTs will help provide better estimates used with environmental analysis in non-attainment areas, in the determination of roadway characteristics, in geometric design (both highway and intersection), in maintenance activities programming (TMG, 2001), or in traffic-congestion and pavement management. More accurate values of SAFs will improve the cost savings at ODOT in the areas described previously, while enhancing efficient travel for motorist across the state.

The AADT is a key component in many transportation areas. It is one of the most important components in pavement design. More accurate pavement design parameters are a critical input to create more cost effective pavements. AADT traffic volume values can also be used in highway planning, the improvement of freeway systems and major arterial street systems, and in the selection of through streets or in the selection of the best route to a new facility (Xia et al., 1999). Not only is this data relevant in highway programming, but also in the determination of driver needs and safety, of countermeasures, and in the prioritization of street improvements. They can contribute to a better assessment of the demand for service by the street or highway or to a better evaluation of the traffic volume regarding a present highway system. This can be achieved through the determination of Level of Service (LOS) and through a comprehensive and
numerical assessment of the general quality of a network. AADT studies can be used before and after highway improvements to determine the effectiveness of road improvement schemes (Lam et al., 2000), or in the identification process of the most hazardous locations within an area, a city, a county or a state. The annual average daily traffic may also serve as a valuable tool in the computation of accident rates (acc./100,000 vehicle-miles), in the evaluation of economic feasibility of potential projects, in the establishment of traffic volume trends, (Xu, 1998; Lam et al., 2000), in the estimation of statewide vehicle miles traveled, or for safety considerations such as determination of exposure rates. The more precise AADT values can assist in the compliance determination with the 1990 clean air act amendments, in the estimation of vehicle use as part of revenue forecasts (TMG, 2001), in the improvement of traffic signal timing and in conducting noise analyses.

The private sectors (business, companies, services) can use them as valuable statistics for different purposes (TMG, 2001). AADT is used to determine the statistic Vehicle Miles Traveled (VMT) which is an important factor used by FHWA for a number of highway funding formulas. More accurate AADTs could result in greater funding for Ohio transportation systems. In addition, the methodology of this study may be adopted by the transportation community and the general public and may be utilized by other DOT’s to update their programs.

1.4 Organization of the Dissertation

This subsection provides the outline of the dissertation, which has been divided into the following sections: literature review; study data; statistical methodology which is described in Chapter IV through Chapter VI; results of the examined methods presented in Chapter VII through Chapter IX; other techniques; and conclusions and recommendations. A brief description of the contents and the layout of each chapter follow.
1.4.1 Chapter II - Literature Review

Chapter II provides an overview of past research and the state of the practice for estimating AADT. Guidelines and findings from previous studies are presented separately for each of the five steps described above.

1.4.2 Chapter III – Study Data

Chapter III includes an analytical description of the study data provided by the Ohio Department of Transportation (ODOT). Information is given about the continuous data, the short-term counts and their locations information. The statistical methodology is described in the following three chapters, with each chapter corresponding to one of the three main steps of the AADT estimation process.

1.4.3 Chapter IV – Seasonal Adjustment Factors

Chapter IV includes the methodology followed to develop seasonal adjustment factors and consists of nine subtasks: the initial importing of the raw data, the data cleaning, the aggregation of the empirical setting, the estimation of average traffic volumes, the development of SAFs, the statistical evaluation, the code used, and the validation of the results.

1.4.4 Chapter V – Factor Groupings

Chapter V provides the description of eight methods used in the development of factor groupings. The methodology used to evaluate the examined models and the innovative method of selecting the optimum number of clusters are presented at the end of this chapter.
1.4.5 Chapter VI – Assignment of Short-Term Counts to Factor Groupings

Chapter VI describes three methods used to assign short-term counts to factor groupings: the traditional method, discriminant analysis, and a method developed based on the coefficient of variation. The process for the statistical evaluation is presented in the last section within Chapter VI. The results produced within each step of the AADT estimation process are presented in the following three chapters.

1.4.6 Chapter VII – Results of Seasonal Adjustment Factors

Chapter VII provides the results obtained from the factoring methods described in Chapter IV. It is divided into eight main subtasks that cover the tasks within the second objective stated in section 1.2.

1.4.7 Chapter VII – Results of Factor Grouping Methods

Chapter VIII includes the results of the grouping process. The results within each method, the comparison of all eight approaches and the selection of the most effective method are the main topics of Chapter VIII.

1.4.8 Chapter VII – Results of the Assignment Methods

Chapter IX presents the results of the application of the assignment models, described in Chapter VI, and the final comparison of the three methods.

1.4.9 Other Techniques

Chapter X includes the methodology and the results of three alternative models used as a supplement to the methods described in the previous chapters. The development of training data
sets, validation data sets, regression and Bayesian models and the assessment of the models are described in Chapter X.

1.4.10 Conclusions and Recommendations

The last chapter of the dissertation, Chapter XI, provides the main conclusions, recommendations of the study and future research areas. The appendices at the end of the dissertation provide additional details of the data used and the results of each method.
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 mathematical practices. As a result of these studies, prior knowledge can 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 stations. In some cases, there may be data imputed in order to estimate any missing values and identify and replace potential incorrect data;

- **Step Two** – Estimation of 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** – Traffic data are grouped together according to their similar traffic patterns and based upon AFs or SAFs;
**Step Four** – Assignment of roads or road segments where short-term counts are recorded and assigned to the above groups; and

**Step Five** – The SAFs developed in Step Two are applied 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. In some cases as described in the “Other Techniques” section, specific methods eliminate Steps Two through Step Four from the procedure.

### 2.2 Task One: Data Cleaning and Data Imputation

The first task in developing AADTs includes the initial cleaning of field data. The initial cleaning removes all unnecessary data. This unnecessary data may be a result of noise within the data or malfunctioning of the data-collection equipment. In this case the researcher/practitioner has two options with the data: To remove this data from the data set; or to use a form of data imputation to create data in place of the missing values. This literature review presents the most common methods used with data cleaning and imputation.

#### 2.2.1 Description of the AASHTO Guidelines

The AASHTO Guidelines for Traffic Data Programs (1992) recommends the identification and exclusion of any missing or suspicious data from the traffic databases. It also discourages users and agencies from employing any kind of data imputation technique. The introduction of errors due to implementation of an imputation method is almost inevitable.

#### 2.2.2 Cambridge Systematics Method

A study in 1994 developed by Cambridge Systematics in partnership with the Washington DOT, applied an implicit method and an explicit imputation technique with two
additional steps (Cambridge Systematics, 1994). It was concluded that the implicit method is more effective when counts of whole days are missing, whereas the basic imputation procedure produces better results in the case of few missing hours during a day (Cambridge Systematics, 1994). The Cambridge Systematics method predicts hourly or daily volumes by using the corresponding hour or day of the preceding year, as shown in Equation 2.1.

\[
C_{it} = \frac{R \times C_{iu}}{n} \sum_{j} \frac{C_{jt}}{C_{ju}}
\]  

(2.1)

where:

\( j = 1 \ldots n, \)

\( C_{it} = \) imputed value,

\( C_{iu} = \) count for day (or hour) \( u \) at station \( i, \)

\( C_{jt} = \) counts for day \( t \) at other stations in the same group,

\( C_{ju} = \) counts at these stations for day \( u, \) and

\( R = \) a growth rate adjustment ratio depending on the amount of missing days.

If only a few days are missing in a data set, then \( R \) is calculated by Equation 2.2.

\[
R = \frac{1}{2} \left( \frac{G_{i,t-}}{n \sum_{j} G_{j,t-}} + \frac{G_{i,t+}}{n \sum_{j} G_{j,t+}} \right)
\]  

(2.2)

where:

\( i = 1 \ldots n, \)

\( t- = \) day of the week as \( t \) but one to three weeks earlier,
\[ t^+ = \text{day of the week as } t \text{ but one to three weeks later,} \]
\[ n = \text{number of ATRs, and} \]
\[ g = \text{growth ratio.} \]

2.2.3 Description of Factor Approaches

Factor approaches use historical data obtained from permanent count stations. These methods include developing factors based on data from neighboring ATRs, previous days, weeks, months or years and then applying the factors to a new data set for traffic parameter predictions (Cambridge Systematics, 2004; Zhong et al., 2004; Chen et al., 2005; Chung et al., 1998).

2.2.4 Description of Time-Series Models

An Autoregressive Integrated Moving Average (ARIMA) model introduced by Box and Jenkins (1976), predicts future values of a time-series by a linear combination of past values and a series of errors. A large number of research efforts have focused on estimating missing values by using the ARIMA model (Kopanezou, 1989; Williams et al., 1998). A general form of the ARIMA model is written as:

\[ \phi(B)(1-B)^d Y_t = \theta(B)\epsilon_t, \]  

where:

\[ B = \text{backshift operator. It shifts subscript of the time series backward in time by one period (e.g. } B_{20}=y_{19}, \]

\[ Y_t = \text{value of the time-series observation at time } t, \]

\[ \epsilon_t = \text{series of random shocks which are assumed to be independently, normally distributed with zero mean and variance,} \]

\[ d = \text{order of difference,} \]
\[ f(B) \text{ polynomial of order } p \text{ in the backshift operator } B, \text{ and} \]
\[ \theta(B) = \text{ polynomial of order } q \text{ in the backshift operator } B. \]

Further Kopanezou (1989) developed an ARIMA multivariate time-series model for daily traffic forecasts (Kopanezou et al., 1989). According to Kopanezou, time-series methods may provide very accurate and efficient short-term forecasts and improve the error results over the traditional model results (Kopanezou et al., 1989).

2.2.5 Artificial Neural Networks

ANNs may be used within any of the five tasks to produce missing values, groupings or in some cases, actual AADTs without any traditional procedures. ANNs are computer based algorithms comprised of units called “neurons” or “processing elements” which together form a “network.” ANNs main characteristic is the adaptive interaction between these elements. ANNs consist of three layers, Figure 2.1, the input, the hidden and the output layer.

![Artificial neural network as a group of interconnected neurons. (Bishop, 1995)](image)

Figure 2.1. Artificial neural network as a group of interconnected neurons. (Bishop, 1995)
The neurons in the input layer receive input signals that are transmitted to the hidden and then the output layer. The information is distributed across complex weighted interconnections (Tang et al., 2003). As the complexity in the relationship between the inputs and the desired output increases, the number of the neurons in the hidden layer should also increase (Resampling Stats - XLMiner User Guide Software, 2008). The disadvantage of an ANN is its “black box” effect. This means the user is not able to follow intermediate steps and the final output may in some cases be hard to explain and interpret.

2.2.6 Regression Analysis

Regression analysis is a method which examines the relation between the predicted variables, response or dependent variable with specified predictor variables independent or explanatory variables. The general linear regression model is shown in Equation 2.4 and contains regression parameters whose values are estimated using the given data (Tang et al., 2003; Zhong et al., 2005).

\[
Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ..... + \beta_{p-1} X_{i,p-1} + \epsilon_i
\]

(2.4)

where:

- \( \beta_0, \beta_1, \ldots, \beta_{p-1} \) = parameters,
- \( X_{i1}, X_{i2}, \ldots, X_{i,p-1} \) = known constants,
- \( \epsilon_i \) = error term, and
- \( i \) = 1,...,n.

Regression analysis is used diversely for prediction, hypothesis testing, inference and modeling of causal relationships.
2.2.7 Comparison of Statistical Techniques used with Data Imputation

The remaining portion of this section provides a comparison of statistical techniques used with data imputation. In general, regression and the spatial models outperformed the historical average and the time-series methods.

Tang (2003) compared several models to determine short-term traffic volumes in Hong Kong (Tang et al., 2003). Tang developed a time-series model (ARIMA) and a Gaussian Maximum Likelihood (GML) model. This model uses past and current traffic data and assumes the data follows a normal distribution. Equation 2.5 was used to predict the daily flow as shown below:

\[
\bar{DF}_{w,m} = \frac{[\sigma_{FI,m}^2 (\mu_{FI,m} + DF_{W,M-1}^m) + \sigma_{DF,m}^2 \mu_{DF,m}]}{\sigma_{DF,m}^2 + \sigma_{FI,m}^2}
\]

where:

\[
\begin{align*}
  m & = 1 \ldots n, \\
  \bar{DF}_{w,m} & = \text{predicted daily flow of } w^\text{th} \text{ day of week in month } m, \\
  DF_{w,m} & = \text{observed daily flow of } w^\text{th} \text{ day of week in month } m, \\
  \mu_{DF,m} & = \text{mean of } DF_{w,m}, \\
  \sigma_{DF,m}^2 & = \text{variance of } DF_{w,m}, \\
  \mu_{FI,m} & = \text{mean of } FI_{w,m}, \text{ and} \\
  \sigma_{FI,m}^2 & = \text{variance of } FI_{w,m}.
\end{align*}
\]

The annual average daily traffic for each day of the week is calculated by the following equation.
\[ AADT_w = \frac{\sum_{w=1}^{5} n_{w,m} DF_{w,m}}{n_w} \]  

(2.6)

where:

\[ AADT_W = \text{AADT for } w^{th} \text{ day of the week}, \]

\[ n_{w,m} = \text{total number of } w^{th} \text{ days in } m^{th} \text{ month}, \]

\[ n_w = \text{total number of } w^{th} \text{ days in year}. \]

The AADT estimations are calculated for the days of the week by the following Equations:

\[ AADT_{WKD} = \frac{\sum_{w=1}^{5} n_w AADT_w}{n_{WKD}} \]  

(2.7)

\[ AADT_{All} = \frac{\sum_{w=1}^{7} n_w AADT_w}{n_{ALL}} \]  

(2.8)

where:

\[ AADT_{WKD} = \text{AADT for “weekday”}, \]

\[ AADT_{ALL} = \text{AADT for “all-day”}, \]

\[ n_{WKD} = \text{total number of “weekday” in year}, \]

\[ n_{ALL} = \text{total number of “all-day” in year}. \]

Tang (2003) compared the GML approach with time-series, nonparametric regression and neural network models, and concluded that the GML model had the lowest statistical errors for both predicted short-term volumes and AADT estimates (Tang et al., 2003). Kwon (2004) used three algorithms to impute traffic data: a non-normal Bayesian Imputation algorithm; a non-
normal Bayesian Linear Regression Imputation; and a Bayesian algorithm (Kwon, 2004). The main finding of the study was that missing data may be effectively entered with simulated values that are close to the actual values, by utilizing observable spatial and temporal relations of traffic flow (Kwon, 2004). Zhong (2004) compared four factor models with more genetic, neural and regression imputation techniques (Zhong et al., 2004). The average-history algorithm, Equation 2.9, uses past data of the same hour of a day, whereas the factor-history model, Equation 2.10, accounts for yearly growth by incorporating growth factors.

\[
updateValue = \frac{\sum_{i=1}^{N} HistoricalValue_i}{N} \tag{2.9}
\]

where:

\( N \) = number of years in training set.

\[
UpdateValue = \frac{\sum_{i=1}^{N} (HistoricalValue_i) \times GF_i}{N} \tag{2.10}
\]

where:

\( N \) = number of years in the training set.

\[
GF_i = \frac{AADT_{test}}{AADT_{training}^i} \tag{2.11}
\]

where:

\( AADT_{training}^i \) = AADT of year i and

\( AADT_{test} \) = AADT of the test year (Zhong et al., 2004).
A single-hour monthly factor model was developed and is shown in Equation 2.12.

\[
\text{UpdateValue} = \frac{mf_i \times \text{value}_{i-1} + mf_i \times \text{value}_{i+1}}{2}
\]  

(2.12)

where:

\(mf_i\) = average monthly factor of failure month,

\(mf_{i-1}\) = average monthly factor of the month before the failure month,

\(mf_{i+1}\) = average monthly factor of the month after the failure month,

\(\text{Value}_{i-1}\) = hourly volumes of the same hour in the months before the failure month,

and

\(\text{Value}_{i+1}\) = hourly volumes of the same hour in the months after the failure month.

It is found based on data from before to after the failure that genetically designed regression models produce the most accurate results. Genetic algorithms may be very beneficial to an analyst because they may solve optimization problems (Sakawa, 2002).

Zhong (2005) developed ARIMA models, locally weighted regression and time-delay neural network models (TDNN) (Zhong et al., 2005). The main finding of this study is that regression models outperform neural network models for almost all examined cases and ARIMA models resulted in the lowest errors among the techniques evaluated. Chen (2005) investigated factor approaches that use historical and current data and evaluated them with a hybrid algorithm and artificial neural network models (Chen et al., 2005). The historic average method and an exponential smoothing algorithm in time-series analysis are integrated in a hybrid algorithm. The main equations for a triple exponential smoothing model are the following Equations:
\[ S_t = a \frac{y_t}{I_{t-L}} + (1 - \beta) \times (S_{t-1} + b_{t-1}) \]  
Overall Smoothing (2.13)

\[ b_t = \gamma \times (S_t - S_{t-1}) + (1 - \lambda) \times b_{t-1} \]  
Trend Smoothing (2.14)

\[ I_t = \beta \frac{y_t}{S_t} + (1 - \beta) \times I_{t-L} \]  
Seasoning Smoothing (2.15)

\[ F_{t+m} = (S_t + mb_t) \times I_{t-L+m} \]  
Forecasting (2.16)

where:

- \( y \) = observation,
- \( S \) = smoothed observation,
- \( b \) = trend factor,
- \( I \) = seasonal index,
- \( F \) = forecast at \( m \) period ahead,
- \( L \) = number of periods that a complete season’s data consists of,
- \( t \) = index denoting the time period, and
- \( \alpha, \beta \ and \ \gamma \) = constants obtained through minimizing the error between the estimates and the observations.

Chen found that the missing data percentage do not have a significant impact on the rank order of a particular algorithm contrary to the time-of-day and day-of-week factors that affect it (Chen et al., 2005). The hybrid model is found to be more efficient than the other models and produced relatively accurate estimates and required less input data. Zhong (2006) proposed a new method to estimate missing volume data which is mainly based on the statistic mean squared error (MSE) (Zhong et al., 2006). Zhong compared four traditional factor methods with two time-series analysis models, London exponential smoothing model and Box-Jenkins method. The MSE method outperformed the other techniques. The main advantage of this technique is that it may
estimate large intervals, more than one month, of missing data. The main disadvantage of this method is that it requires accurate data directly around the data point deemed incorrect and thus limiting its use to situations only where this occurs.

2.3 Task Two: Factoring

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 for 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

2.3.1 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 as described in the following Equation:
\[
AADT = \frac{1}{7} \sum_{i=1}^{7} \left[ \frac{1}{12} \sum_{j=1}^{12} \left( \frac{1}{n} \sum_{k=1}^{n} VOL_{ijk} \right) \right]
\]

(2.17)

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.

2.3.2 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, on the other hand, 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. For example it may be equal to a simple average of the ADTs of that month 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 then 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.

2.3.3 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).

2.3.4 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’s method; and
- A weighted average of average of monthly weekday and weekend day averages.

The researchers recommended the use of the “simple average of all days” method, which is the simplest, and produces similar results to the more complex methods. A potential comparison of the above techniques using the study data will show what is the most effective method.

2.4 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.

2.4.1 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 2.18 for the estimated SAFs.

\[
RAF = \frac{1}{AF}
\]  

(2.18)

where:

\[
RAF = \text{reciprocal of the SAF (Sharma et al., 1981).}
\]

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).

2.4.2 Cluster Analysis

Cluster analysis is an exploratory data analysis method used with sorting of 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 statistical analysis program that uses a distance algorithm, Equation 2.19, to determine each group (TMG, 2001).

\[ J = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2 \]  

(2.19)

where:

- \( J \) = intra-cluster variance,
- \( k \) = total number of clusters produced from cluster analysis,
- \( i \) = 1, 2, …, k,
- \( x_j \) = data point,
- \( \mu_i \) = centroid of all the points \( x_j \in S_i \), and
- \( (x_j - \mu_i)^2 \) = is a distance measure (Hartigan et al., 1979).

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 ANN 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 the clusters was determined through Bayesian statistics, Bayesian Information Criterion. The maximum probability of a telemetry traffic monitoring site (TTMS) is calculated and is used as a data-driven criterion to determine the most appropriate group for each ATR. 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. By 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).

2.4.3 Same Road Application of Factors

The same road application factor suggested in Section Two of the TMG applies the same road application of factors to the short-term counts obtained from the same road as the permanent
site (TMG, 2001; Zhao et al., 2004). This method applies the estimated seasonal factors from the ATR to expand the assigned short-period counts for the AADT estimates. These counts exhibit similar traffic patterns with the ATR group because these counts are produced on roads with similar traffic volumes and design characteristics. These similar traffic patterns are the result of socioeconomic and unexpected roadway characteristics, such as vehicle crashes, construction zones, or unexpected roadway geometry, that mainly influence vehicle flow patterns are similar for continuous and short-term counts.

The same road application of factors approach has many advantages and disadvantages. An advantage to this approach is there are no requirements to create vague groups and ambiguously assign road segments to an automatic traffic recorder group (ATRG). The mean factor of an ATRG expresses the traffic patterns of all the ATRs within this group and includes biased errors from ATRs that may not be accurately represented by the average factors of their group. Therefore, the errors associated with the mean factor of each group are avoided. In addition, these errors developed from the assignment of road sections to ATRGs are significantly lower than those of the traditional assignment (TMG, 2001). The lower errors are due to the traffic trend similarities between short-term and continuous counts. Furthermore, less computational efforts are needed. There are several disadvantages to this method. The first disadvantage is the assumption of traditional group factoring. The second disadvantage is the large number of ATRs required in order to cover the whole statewide transportation network. This data requirement prerequisite yields extremely high installation, maintenance and operation cost, and in most cases proves to be cost prohibitive for state DOTs or other agencies. Difficulties in the application of this method may be encountered if the short-period counts are relatively far away from the permanent counter (TMG, 2001).

The same road applications of factors approach may be used as a supplement tool to the cluster analysis or to the geographic/functional assignment of roads to groups’ method (TMG,
2001). In current practice engineering judgment is necessary for a successful determination of seasonal factors and groupings. A combination of the previous approaches and new methods needs to be examined in order to produce better results and minimize human discernment.

2.5 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 high dependent to 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 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:

\[
MSE_i = \frac{1}{12} \sum_{j=1}^{12} (f_{sj} - f_{ij})^2
\]  

(2.20)

where:

\[f_{sj} = \text{monthly factor of seasonal count for month } j \text{ and}\]
Following Equation 2.18, seasonal traffic factors, traffic volumes (AADTs and ADTs) and an index of assignment effectiveness are calculated in Equations 2.21 and 2.22 for each station and group. These equations are shown below:

\[
f_{ij} = \text{average monthly factor of group } i \text{ for month } j.
\]

\[
AE_i = \frac{\max MSE - MSE}{\max MSE - \min MSE}
\]  
Equation 2.21

\[
IAE = \frac{1}{N} \sum_{i=1}^{l} (AE_i)
\]  
Equation 2.22

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 sites 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.
\[ PB95 = |\pm Z_{0.025}| \times S_e \]  \hspace{1cm} (2.23)

where:

\[ Z_{0.025} = \text{standard normal statistic, and} \]

\[ S_e = \text{standard deviation (SD) of errors for an ATR group (ATRG) (Sharma et al., 1996).} \]

Sharma determined the impact of short period count assignments to groups by developing Equation 2.23 as described below:

\[ AE_i = \frac{\max MDE_i - MDE_i}{\max MDE - \min MDE} \times 100 \]  \hspace{1cm} (2.24)

where:

\[ AE_i = \text{assignment effectiveness for ATR}_i, \text{ and} \]

\[ MDE_i = \text{mean squared error for ATR}_i. \]

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 that 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 GIS system 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. The Euclidean distance was used (Equation 2.25) to measure similarities:

\[
D(X, Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}
\]

(2.25)

where:

\[
X = x_1, x_2, \ldots, x_m \quad \text{and} \quad Y = y_1, y_2, \ldots, y_n
\]

represent the attributes value of two sample records (Jin et al., 2008).
The attributes used in the analysis were normalized based on the following equation:

\[ X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \]  

(2.26)

2.5.1 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 to 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 in the application of discriminant analysis in the AADT estimation process. On the other hand, DA has been used extensively in other scientific fields. Gorsevski (2000) presented a method to predict landslides hazard using nearest neighbor discriminant analysis and Geographic Information Systems (GIS). Cross-validation method was used as the basis to estimate the probabilities of misclassification. Olden (2002) predicted species distributions using logistic regression analysis, linear discriminant analysis, classification trees and artificial neural networks to model the presence or absence of 27 fish species and to simulate data sets. The main finding in this study is that neural networks perform better than the other approaches, however all methods predicted species presence and/or absence.
satisfactorily (Olden et al., 2002). Kravchenko (2002) employed discriminant analysis and
geostatistics to create soil drainage maps using topographical and soil electrical conductivity data.
Discriminant analysis and cokriging estimated drainage classes for more than 90% of the sites,
whereas indicator kriging and soil survey data estimated correctly 85 and 63% of the data respectively.

In 2002 Shemyakin used logistic regression techniques and discriminant analysis to estimate the probability of success using the detailed history of communication between a sales agent and a customer. Based on the discriminant analysis, the examined cases were classified in one of the two populations: “success” and “failure”. Prior probabilities were estimated for each customer. The communication history was represented by $X=(X_1,\ldots,X_k)$ and provides information regarding the posterior:

$$P(S = s | X = 1) = \frac{\pi_1 p_1(x)}{\pi_1 p_1(x) + \pi_0 p_0(x)}$$  \hspace{1cm} (2.27)

where:

$$p_r(x) = P(X = x | S = r), r = 0,1$$  \hspace{1cm} (2.28)

The maximum likelihood estimation requires the maximization of the unconditional likelihood as follows:

$$p(s|x)p(x) = \pi_1^{N_1} \prod_{i=1}^{N_1} p_1(x_i) \pi_0^{N_0} \prod_{i=N_1+1}^{N_1+N_0} p_0(x_i)$$  \hspace{1cm} (2.29)

where:

$$N_1 = \text{number of complete success, and}$$

$$N_0 = N - N_1 = \text{number of failure records.}$$
The final comparison revealed that both methods produced similar results (Shemyakin, 2002). Stalinksi (2006) used neural networks, logistic regression and discriminant analysis to predict the firm’s decision to list shares on a foreign stock exchange. It was concluded that neural networks outperform the other two classification techniques. In 2007 Le Jan applied stepwise discriminant analysis and logistic regression on pre-selected variables to identify dyslexia detection. A linear discriminant function was used and under the following assumptions: each group (dyslexics and normal readers) was normally distributed, the covariance matrix was the same for each group, the prior probabilities and the costs of misclassification were assigned to be equal, and the variables were continuous (Le Jan et al., 2007). The following six significant variables were used in the model development: reading speed of near phonological pseudo-words, spoonerism, denomination speed of letters, partial report of letters in position 4, partial report of letters in position 5, and dictation score. The main finding of the study is that the logistic regression is more adaptable to the examined variables that the discriminant model. Walker (2008) developed linear, kth-nearest-neighbor, logistic, and quadratic discriminant models to improve the accuracy of sex determinations, that was tested on a series of 304 skulls of known age and sex. Walker found that logistic regression discriminant analysis produced the best results (Walker, 2008).

2.6 Task Five: Other Techniques

In addition to the traditional methods described in the previous sections of the literature review, there are other techniques that may be used for the estimation of the AADTs. Two of the most common approaches are regression analysis and artificial neural networks. The four different sources of errors associated with each step of the traditional method of estimating AADT may be avoided if alternative methods are used. These methods examined in this section have one source of bias. The following subsections use these two techniques independently from
the traditional methods, thus avoiding each traditional methods respectable disadvantage.

Methodologies, findings and conclusions of past research are described below and are used as the theoretical background in Chapter X to: develop training and test data sets; establish assumptions and criteria; develop predictive models; and develop the methodology for the statistical validation of the results.

2.6.1 Regression

Xia (1999) used multiple regression analyses with a data set obtained from 450 traffic stations to determine the AADT on non-state roads in Florida (Xia et al., 1999). The AADT is selected as the dependent variable and the independent variables are categorized into three groups. The first and the second group contain predictors variables related with roadway and socioeconomic characteristics respectively. The third group describes the accessibility to state and other non-state roads. The final six-variable model is constructed after statistically insignificant variables are eliminated by the coefficient of determination (R²) and other statistics (F-test, VIF, and Cp). When applied, the model estimates 63 percent of traffic conditions accurately. Roadway characteristics, such as number of lanes, functional classification and area type, are the most significant impact on the predicted AADTs (Xia et al., 1999).

Seaver (2000) used principal component analysis, multivariate regression, regression clustering and multiple regression analysis to model ADT on rural local roads in Georgia. The data were obtained from the U.S. census; however they are not always updated and cleaned (Seaver et al., 2000). Zhao (2001) developed four multiple regression models to determine AADT values on expressway roads in a Florida county (Zhao et al., 2001). These models include predictor variables that are grouped into four main categories: roadway, socioeconomic characteristics, expressway accessibility and accessibility to regional employment centers. The four categories contain variables which include the number of lanes, land-use type, functional
classification, employment, population, dwelling units, number of access points and regional accessibility to population centers (Zhao et al., 2001). A preliminary analysis is conducted to select the most significant variables. Outliers are then identified and the models assumptions are checked. The four models are able to reflect 66 to 83 percent of the traffic variability, and the models that include functional-class variables performed better (Zhao et al., 2001).

Lingras (2002) used genetic algorithms to select a set of historical traffic volumes, highly correlated to the next hourly traffic volume, in order to use them as independent variables in regression and time-delay neural networks. Universal models are examined that predict traffic volumes for eight hours and sub-models for hourly volume predictions. Genetically designed regression sub-models for individual hours result in lower errors of less than 1 percent for the training sets and the 95th percentile errors are approximately 2 percent. The average errors for the test set range from 0.5 to 2 percent and the 95th percentile errors are between 2 and 8 percent (Lingras et al., 2002).

Tang (2003) built a nonparametric regression model that uses similar past cases (nearest neighborhoods) to forecast short-term traffic volumes and the AADT for the year 1999 (Tang et al., 2003). Initially, variables are determined including the daily flow of \( w \)th day of week in month \( m \) and month \( m-1 \) and the number of the past cases. Then all the variables are imported into a database. The Euclidean distance is estimated for each variable and outputs are selected based on the nearest neighborhoods. The averages of all the outputs comprise the predicted value (Tang et al., 2003). The predicted volumes are evaluated according to the statistics Mean Absolute Error (MAE) and MSE, whereas the AADT forecasts according to the Absolute Percent Error (APE), less than 1 percent (Tang et al., 2003).

Zhao (2004) conducted multiple linear regression analyses separately for selected rural and urban areas to identify explanatory variables for interpreting seasonal traffic patterns. The estimated monthly seasonal adjustment factors for each TTMS are used as dependent variables.
Roadway and traffic characteristics including the number of lanes and AADT, demographic and socioeconomic features including the number of hotels, motel rooms or retired households, as well as geographic location variables obtained in a previous analysis comprise the independent variables. Then three buffer methods, depending on the TTMSs location and their geographic area of influence are defined and the final variables are selected for the analysis on urban roads. According to the statistical results adjusted R² and significance level, the seasonal patterns of part-time residents/tourists, the number of retired people between age 65 and 75 with high income and the retailed employment are the most significant factors that explain the seasonal traffic patterns (Zhao et al., 2004). On the other hand, different variables and buffer methods are used in order to describe in more detail the traffic patterns in non-urban areas. The first buffer method is related with the functional classification of the ATRs roadway segments and the second method is used with the ATRs area of influence based on the average travel time. The analysis and evaluation process remains the same. Unlike the urban analysis, the regression variables and the buffer methods in the second analysis prove to be inadequate to describe and simulate the real traffic conditions on rural roads in Florida (Zhao et al., 2004).

Zhong (2005) developed a locally weighted regression model, a form of memory based algorithm for learning continuous mapping from real-valued input vectors to real-valued output vectors (Zhong et al., 2005). In this methodology a weight is assigned to each training observation that regulates its influence on the training process. Higher weights are received by observations that are closer to the prediction point. In the study by Zhong, two genetic algorithms are designed: a universal model for 12 hour predictions and a refined model for hourly predictions. The second model is more accurate. The average errors for the refined regression analysis were lower than two and four percent for roads that exhibit stable and unstable traffic patterns respectively (Zhong et al., 2005).
Sliupas (2006) compared AADT values estimates of four methods; an Idaho DOT model, a growth factor approach, linear regression and multiple regression models. The AADT is the response variable and the independent variables are associated with economic and demographic factors that influence the AADT. The gross national product, the number of citizens in the country and the number of vehicles at the end of the year are used as predictors in the regression models. The high $R^2$ of the linear regression model indicates that the predictive power of the model is satisfactory. Five multiple regression models are developed with several transformations that are applied to the independent variables. According to the study, the lowest errors are obtained by the Idaho model, Equations 2.30 and 2.31, which account for the annual growth rate (Sliupas, 2006). Equations 2.30 and 2.31 are described below:

$$E_{t+n} = E_t \times (1 + g)^n$$

(2.30)

where:

$E_{t+n}$ = AADT value of year $t$, forecasted $n$ years in the future,

$E_t$ = base year AADT value in $t$ year,

$n$ = year, and

$g$ = annual growth rate is calculated by the following equation.

$$g = \sqrt[k]{\frac{E_t}{E_{t-k}}} - 1$$

(2.31)

where:

$k$ = number of years between the first and the last AADT value.

Sliupas also concludes that AADT growth should decrease in the future as long as the number of citizens decreases and the economy grows.
2.6.2 Artificial Neural Networks

Various ANNs have been developed for many types of seasonal factor analysis. A study from Faghri (1995) concluded that the Adaptive Resonance Theory neural network model (ART) outperformed the cluster method and the regression models (Faghri et al., 1995). Faghri also recommends that future work should focus on a deep examination of neural network methods. Lingras (1995) used hierarchical grouping and Kohonen unsupervised neural networks to classify highways (Lingras, 1995). The study found that the NNs produce similar results to those of hierarchical grouping approach. In a study by Xu (1998), the results from two traditional factor approach models and two neural network models for the rural roads in Minnesota are compared (Xu et al., 1998). The results show the model developed from unclassified data, without reflecting the seasonal variation, performs better than the other model. By comparing the two models, the results show the estimation errors for the traditional model are lower than those of neural network models, which considers the road classification and the traffic variation. Lingras (2000) conducted an autoregression analysis and developed time-delay neural network models (TDNN) to predict daily traffic volume. The results from Lingras show that TDNN models had lower errors and gave better estimates of the next day’s volume than autoregression models (Lingras et al., 2000). Sharma (1999, 2000) conducted a similar study for the low-volume roads of Alberta, Canada. The supervised learning ANNs are based on a feed-forward and a back-propagation design. The output layer is calculated by using a sigmoid transfer function. Sharma showed that the traditional method may yield better estimates for the AADT than the neural networks, provided that the grouping and the assigning procedures entail small to negligible percent of error. The AADT errors are estimated from the following equation:

\[
PE_i = \frac{EAADT_i - AADT}{AADT}
\]  

(2.32)
where:

\[ PE_i = \text{percentage estimation error for } i^{th} \text{ count, and} \]

\[ EAADT_i = \text{estimated AADT for } i^{th} \text{ count.} \]

The 85th and 95th percentile errors are determined from cumulative frequency distributions of errors. These errors, along with the average errors, compromise the measure of accuracy for the AADT estimates (Sharma et al., 2001). Several ANNs are developed for various months and different durations. Sharma concluded that the 48 hour counts resulted in lower errors than 24 hour counts. However, a potential increase in the counts duration to 72 hour counts does not necessarily provide improvement in estimates accuracy (Sharma et al., 2001).

The most important advantages of ANNs described by Sharma (2000) are the two steps of the traditional method, grouping and assignment, are avoided (Sharma et al., 2000).

Lingras (2002) used genetic algorithms to develop regression and time-delay NN models to predict traffic volumes at rural recreational sites (Lingras et al., 2002). Submodels are built for individual hours, and compared with universal models applicable to all hours. According to the findings of the study, universal NN models perform slightly better than the regression models. The submodels results are almost the same, in terms of percent errors with the universal models (Lingras et al., 2002). The average errors of the subnets are between 5 to 7 percent and the 95th percentile errors range between 11 to 15 percent range. Tang (2003) developed a feed-forward neural network consisting of two inputs, daily flow of current and previous month, one hidden unit and one output unit, predicted daily flow of the next month (Tang et al., 2003). Tang concludes that the accuracy gained by the training back-propagation algorithm is correlated to the ANNs complexity and the actual data (Tang et al., 2003). More details of NNs usage in combination with more advanced statistical techniques can be found in many sources, which are not directly related with the transportation engineering, such as Hecht-Nielsen (1990) and
Lawrence (1993). In 1995, Dougherty describes several applications of NNs in the transportation area.

Regression and neural network analysis are conducted by Lam (2000), to estimate AADT from short-term counts and to determine the most appropriate time length of short-term counts. It is concluded that neural network method performs better than regression models (Lam et al., 2000). Zhong (2005) applied a similar technique used by Lingras (2000) to predict short-term traffic for rural roads (Zhong et al., 2005). In this study the results indicate that the refined Time Delay Neural Network models (TDNN) may limit the average errors, less than 10 percent, whereas the more accurate refined regression models resulted in average errors below 2 percent (Zhong et al., 2005).

In conclusion, regression models and ANNs greatest advantage is their ability to avoid all errors associated with the grouping and assignment procedures required in the traditional methods. These errors are considered negligible even though estimation errors for traditional models are somewhat lower than NN models and may yield better AADT estimates. In general, an extensive dataset is recommended by Smith (1997) in order to train a NN model. These past study-results provide a solid basis for utilizing regression and negative binomial models for the proposed research.
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 Technical Services (OTS), Traffic Monitoring Section and are collected from:

- Continuous count, automatic traffic recorders (ATRs) and weigh-in-motion (WIM);
- Short-term, pneumatic tubes, and 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. This continuous data are used to classify and develop AFs that are later used with the short-term data described in the next session. 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.

<table>
<thead>
<tr>
<th></th>
<th>ATR</th>
<th></th>
<th>WIM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3-Card</td>
<td>C-Card</td>
<td>C-Card</td>
</tr>
<tr>
<td>2002</td>
<td>196</td>
<td>79</td>
<td>75</td>
</tr>
<tr>
<td>2003</td>
<td>202</td>
<td>89</td>
<td>61</td>
</tr>
<tr>
<td>2004</td>
<td>203</td>
<td>114</td>
<td>54</td>
</tr>
<tr>
<td>2005</td>
<td>202</td>
<td>56</td>
<td>51</td>
</tr>
<tr>
<td>2006</td>
<td>206</td>
<td>62</td>
<td>49</td>
</tr>
<tr>
<td>2007</td>
<td>178</td>
<td>-</td>
<td>111</td>
</tr>
</tbody>
</table>

3.1.1 3-Card Format

The 3-Card data vehicle volume data are taken at 60-minute and 15-minute intervals and are formatted with the ODOT Modified 3-Cards as shown in Appendix A, Tables A.1 and A.2. 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, Appendix A, Table A.2, 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 year.
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, shown in Appendix A, Table A.3 contains one record per line per lane for each hour of the day. The 15-minute C-Card file format, shown in Appendix A, Table A.4 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 and are found in Appendix A, Table A.5.

3.1.3 4-Card Format

An older file format, 4-Card is shown in Appendix A, is in the process of being phased-out in the near future and exists for historical records and is included in the data set. Along with the description of the format, a detailed relationship between the 60-minute C-Card and the 4-Card is given for the files 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 dissertation 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), RAMP, 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>
<thead>
<tr>
<th>Table</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permanent Count Locations</td>
<td>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</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Table</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short-Term Count Locations</td>
<td>County, Route, Log_Beg, Station, Location, City_Town, Functional Class, Type_CNT, NLFID</td>
</tr>
<tr>
<td>Short-Term Count Type Description</td>
<td>Type Count, Description</td>
</tr>
</tbody>
</table>
Table 3.4. Short-term count description.

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

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

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. The “clean format” separates the data into the appropriate columns as defined in Appendix A, Tables A.1 through A.4. With the correct numerical format the “clean format” data are considered prepared for future analysis. Appendix A, Tables A.7 and A.8 are examples of the initial raw format and the final clean format. Figure 4.2, below, illustrates the current data structure provided within the SQL platform.
In this structure the data are separated first by the long-term and short-term 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 five 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. Tables 4.1 through 4.3 show the overall results for 3-Card and C-Card ATR and C-Card WIM data.
Table 4.1. Total duplicate records for 3-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>94,813</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2003</td>
<td>102,151</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2004</td>
<td>108,085</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2005</td>
<td>107,163</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2006</td>
<td>254,274</td>
<td>7,626</td>
<td>2.99</td>
</tr>
<tr>
<td>2007</td>
<td>21,382</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Only one of the duplicate rows is deleted. The other row remains in the data set.

Table 4.2. Total duplicate records for C-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,822,980</td>
<td>11,972</td>
<td>0.66</td>
</tr>
<tr>
<td>2003</td>
<td>2,210,612</td>
<td>12,239</td>
<td>0.55</td>
</tr>
<tr>
<td>2004</td>
<td>1,538,010</td>
<td>11,998</td>
<td>0.78</td>
</tr>
<tr>
<td>2005</td>
<td>1,288,639</td>
<td>37,752</td>
<td>2.9</td>
</tr>
<tr>
<td>2006</td>
<td>1,463,040</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2007</td>
<td>No Data</td>
<td>No Data</td>
<td>No Data</td>
</tr>
</tbody>
</table>

Note: Only one of the duplicate rows is deleted. The other row remains in the data set.

Table 4.3. Total duplicate records for C-Card WIM data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,515,125</td>
<td>5,160</td>
<td>0.34</td>
</tr>
<tr>
<td>2003</td>
<td>1,426,964</td>
<td>2,715</td>
<td>0.19</td>
</tr>
<tr>
<td>2004</td>
<td>1,284,865</td>
<td>8,741</td>
<td>0.68</td>
</tr>
<tr>
<td>2005</td>
<td>1,172,301</td>
<td>332</td>
<td>0.03</td>
</tr>
<tr>
<td>2006</td>
<td>953,799</td>
<td>74,238</td>
<td>7.78</td>
</tr>
<tr>
<td>2007</td>
<td>2,751,480</td>
<td>204,431</td>
<td>7.43</td>
</tr>
</tbody>
</table>

Note: Only one of the duplicate rows is deleted. The other row remains in the data set.
In general, the results for the ATR records are satisfactory, producing the lowest percent of data with potential errors. The highest numbers of duplicate rows are $7.43 - 7.78$ percent and occurs with the C-Card WIM data files for the 2006 and 2007.

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. Tables 4.4 through 4.6 show the overall results for 3-Card, C-Card ATR, and C-Card WIM data.

Table 4.4. Partial duplicate records for 3-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>94,813</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2003</td>
<td>102,151</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2004</td>
<td>108,085</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2005</td>
<td>107,162</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2006</td>
<td>246,648</td>
<td>78</td>
<td>0.032</td>
</tr>
<tr>
<td>2007</td>
<td>21,382</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.
Table 4.5. Partial duplicate records for C-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,811,007</td>
<td>16,160</td>
<td>0.89</td>
</tr>
<tr>
<td>2003</td>
<td>2,198,372</td>
<td>22,289</td>
<td>1.013</td>
</tr>
<tr>
<td>2004</td>
<td>1,526,601</td>
<td>2,926</td>
<td>0.19</td>
</tr>
<tr>
<td>2005</td>
<td>1,250,886</td>
<td>4,370</td>
<td>0.35</td>
</tr>
<tr>
<td>2006</td>
<td>1,463,040</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2007</td>
<td>No data</td>
<td>No data</td>
<td>No data</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.

Table 4.6. Partial duplicate records for C-Card WIM data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,509,965</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2003</td>
<td>1,424,249</td>
<td>8,054</td>
<td>0.57</td>
</tr>
<tr>
<td>2004</td>
<td>1,276,124</td>
<td>13,022</td>
<td>1.02</td>
</tr>
<tr>
<td>2005</td>
<td>1,171,969</td>
<td>8,616</td>
<td>0.74</td>
</tr>
<tr>
<td>2006</td>
<td>879,561</td>
<td>56</td>
<td>0.01</td>
</tr>
<tr>
<td>2007</td>
<td>2,547,049</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.

This error does not occur frequently, the highest percent of data with potential errors equals 1.02 percent for the 2004 data, for the ATRs and the WIM data. This inconsistency approaches zero for 2006 and 2007 data.

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. Tables 4.7 and 4.8 show the overall results for C-Card ATR and C-Card WIM data.

Table 4.7. Total volume inconsistencies for C-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,811,007</td>
<td>16,160</td>
<td>0.89</td>
</tr>
<tr>
<td>2003</td>
<td>2,198,372</td>
<td>22,289</td>
<td>1.013</td>
</tr>
<tr>
<td>2004</td>
<td>1,526,601</td>
<td>2,926</td>
<td>0.19</td>
</tr>
<tr>
<td>2005</td>
<td>1,250,886</td>
<td>4,370</td>
<td>0.35</td>
</tr>
<tr>
<td>2006</td>
<td>1,463,040</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2007</td>
<td>No data</td>
<td>No data</td>
<td>No data</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.

Table 4.8. Total volume inconsistencies for C-Card WIM data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,509,965</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2003</td>
<td>1,424,249</td>
<td>8,054</td>
<td>0.57</td>
</tr>
<tr>
<td>2004</td>
<td>1,276,124</td>
<td>13,022</td>
<td>1.02</td>
</tr>
<tr>
<td>2005</td>
<td>1,171,969</td>
<td>8,616</td>
<td>0.74</td>
</tr>
<tr>
<td>2006</td>
<td>879,561</td>
<td>56</td>
<td>0.01</td>
</tr>
<tr>
<td>2007</td>
<td>2,547,049</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.
4.3.4 Incorrect Year

The fourth inconsistency within the data set occurs with an incorrect year. This inconsistency is minor in comparison to others and does not generally affect the overall integrity of the final data set. As a result of the data structure, there is no additional data from the C-Card ATR data. The final values are provided in Table 4.9 and 4.10.

Table 4.9. Incorrect year values for 3-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>94,813</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2003</td>
<td>102,151</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2004</td>
<td>108,085</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2005</td>
<td>107,163</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2006</td>
<td>254,274</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2007</td>
<td>21,382</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.

Table 4.10. Incorrect year values for C-Card WIM data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,509,965</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>2003</td>
<td>1,424,249</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2004</td>
<td>1,276,124</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2005</td>
<td>1,171,969</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>2006</td>
<td>879,561</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2007</td>
<td>2,547,049</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.

4.3.5 Zero Volume Records

The final category within the data cleaning section refers to periods of time in which the ATR or WIM do not register any vehicle volumes. This category, unlike the other four, requires
initial judgment from the user because this category does not necessarily indicate the data are inaccurate. The zero volume counts may suggest that the current location is under construction, the local volumes are very low, or the sensor is inoperable. This research study identified these inconsistencies as when there are no volume counts for all vehicles classifications for 12 or more hours within a 24 hour period. This also includes the total volume column. Tables 4.11 through 4.13 show the overall results for 3-Card and C-Card ATR and C-Card WIM data.

Table 4.11. Zero volume records for 3-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>94,813</td>
<td>514</td>
<td>0.5</td>
</tr>
<tr>
<td>2003</td>
<td>102,151</td>
<td>383</td>
<td>0.37</td>
</tr>
<tr>
<td>2004</td>
<td>108,085</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>2005</td>
<td>107,163</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2006</td>
<td>254,274</td>
<td>473</td>
<td>0.19</td>
</tr>
<tr>
<td>2007</td>
<td>21,382</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.

Table 4.12. Zero volume records for C-Card ATR data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,811,007</td>
<td>31,435</td>
<td>1.7</td>
</tr>
<tr>
<td>2003</td>
<td>2,198,372</td>
<td>37,504</td>
<td>1.7</td>
</tr>
<tr>
<td>2004</td>
<td>1,526,601</td>
<td>36,627</td>
<td>2.39</td>
</tr>
<tr>
<td>2005</td>
<td>1,250,886</td>
<td>10,579</td>
<td>0.85</td>
</tr>
<tr>
<td>2006</td>
<td>1,463,040</td>
<td>336</td>
<td>0.02</td>
</tr>
<tr>
<td>2007</td>
<td>No data</td>
<td>No data</td>
<td>No data</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.
Table 4.13. Zero volume records for C-Card WIM data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total number of records</th>
<th>Total number of potential error values</th>
<th>Percent of data with potential errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>1,509,965</td>
<td>93,567</td>
<td>6.19</td>
</tr>
<tr>
<td>2003</td>
<td>1,424,249</td>
<td>122,905</td>
<td>8.62</td>
</tr>
<tr>
<td>2004</td>
<td>1,276,124</td>
<td>94,669</td>
<td>7.4</td>
</tr>
<tr>
<td>2005</td>
<td>1,171,969</td>
<td>118,724</td>
<td>10.1</td>
</tr>
<tr>
<td>2006</td>
<td>879,561</td>
<td>12,240</td>
<td>1.39</td>
</tr>
<tr>
<td>2007</td>
<td>2,547,049</td>
<td>720</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Note: The total number of records used with this data is developed from the clean data which is defined in error one. No duplicate records are used with these counts.

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

- One Vehicle Groups – 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 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.

Table 4.14. Examined Groups.

<table>
<thead>
<tr>
<th>Groups Examined</th>
<th>Vehicle Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Group</td>
<td>Class 1 - Class 13</td>
</tr>
<tr>
<td>Two Groups</td>
<td>Class 1-Class 3, Class 4-Class 13</td>
</tr>
<tr>
<td>Three Groups</td>
<td>Class 1-Class 3, Class 4-Class 7, Class 8-Class 13</td>
</tr>
<tr>
<td>Four Groups</td>
<td>Class 1-Class 3, Class 4-Class 7, Class 8-Class 10, Class 11-Class 13</td>
</tr>
</tbody>
</table>

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. In addition to the directional analysis, it may be possible to evaluate on a per lane basis creating a SAF per lane. This technique, however, is outside the scope of the current research.

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.

\[
WADT = \frac{\sum_{j=1}^{S} ADT_j}{S}
\]  

(4.1)

where:

\( ADT_j \) = 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:
\[ MAWDT_d = \frac{1}{n} \sum_{g=1}^{n} ADT_{dg} \]  

(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:

\[ MADTa = \frac{\sum_{j=1}^{k} ADT_j}{k} \]  

(4.3)

where:

\( ADT_j \) = 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:

\[ MADT_b = \frac{1}{7} \sum_{d=1}^{7} \left( \frac{1}{n} \sum_{g=1}^{n} ADT_{dg} \right) \]

(4.4)

where:

\( d \) = 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:

\[ WAADT = \frac{1}{7} \sum_{d=1}^{7} \left( \frac{1}{v} \sum_{j=1}^{v} ADT_{j} \right) \]

(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
\[ v = \text{number of available ADTs per year for each day-of-week.} \]

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

The estimation of the average annual 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 describe the five methods used in the estimation of the average annual daily traffic volumes used in this research study in further detail.

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.

$$\text{AADT}_b = \frac{\sum_{j=1}^{w} \text{WADT}_j}{w}$$

where:

- \( \text{AADT}_b \) = the annual average daily traffic (vehicles) using the second method,
- \( \text{WADT} \) = 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 average annual daily traffic is developed for the monthly average daily traffic. In this case, the AADTc is defined in Equation 4.8 as:

$$\text{AADT}_c = \frac{1}{12} \sum_{i=1}^{12} \text{MADT}_{ai} = \frac{1}{12} \sum_{i=1}^{12} \left( \frac{1}{k} \sum_{j=1}^{k} \text{ADT}_{ij} \right)$$

where:

- \( \text{AADT}_c \) = the third estimation of the annual average daily traffic (vehicles),
- \( \text{MADT}_{ai} \) = the monthly average daily traffic (vehicles) for month \( i \) estimated by using a simple average of daily volumes using Method A,
- \( \text{ADT}_{ij} \) = the average daily traffic (vehicles), and
- \( k \) = the number of available daily volumes (ADTs) during month \( i \).
4.6.4 Average of MADT

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

\[
AADTd = \frac{1}{12} \sum_{i=1}^{12} \frac{1}{12} \sum_{i=1}^{7} \left( \frac{1}{g} \sum_{g=1}^{n} ADT_{gdi} \right)
\]  

(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 from first computing average monthly days of the week (12 months by 7 days = 84 values) and then averaging the values to calculate the seven average annual days of the week. Finally, these seven days are averaged to yield the AADT. Equation 4.10 is defined as:
\[
AADTe = \frac{1}{7} \sum_{i=1}^{7} \left[ \frac{1}{12} \sum_{j=1}^{12} \left( \frac{1}{n} \sum_{k=1}^{n} VOL_{ijk} \right) \right]
\]  

(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

Task 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 \((FAHDT)\)

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:

\[
AADT = AAHDT_1 + AAHDT_2
\]  

(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.

\[
F_{AHDT_1} = \frac{AAHDT_1}{AHDT_1}
\]  

(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

\( F_{AHDT_1} \) = 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:

\[
F_{AHDT_2} = \frac{AAHDT_2}{AHDT_2}
\]  

(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
where:

\[ AADT = \text{the annual average daily traffic estimated from continuous data,} \]

all five methods for calculating AADTs are used in this equation,

\[ ADT = \text{the average daily traffic, and} \]

\[ F_{ADT} = \text{the average daily traffic factor.} \]

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:

\[ F_{WADT} = \frac{AADT}{WADT} \]  

where:
\[ AADT = \text{the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,} \]

\[ WADT = \text{the weekly average daily traffic, and} \]

\[ F_{WADT} = \text{the weekly average daily traffic factor.} \]

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 equals 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:

\[ F_{MAWDT} = \frac{AADT}{MAWDT} \]

where:

\[ AADT = \text{the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,} \]

\[ MAWDT = \text{the monthly average weekday daily traffic, and} \]

\[ F_{MAWDT} = \text{the monthly average weekday daily traffic factor.} \]

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

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

\[ F_{MADT_a} = \frac{AADT}{MADT_a} \]

(4.17)
where:

\[ AADT = \text{the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,} \]

\[ MADTa = \text{the average monthly traffic as defined by Equation 4.3, and} \]

\[ FMADTa = \text{the first monthly average traffic factor.} \]

### 4.7.6 Method B: Monthly Average Factor (FMADT2)

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 \( FMADT2 \) as described in Equation 4.18:

\[
FMADT2 = \frac{AADT}{MADTb} \tag{4.18}
\]

where:

\[ AADT = \text{the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,} \]

\[ MADTb = \text{the average monthly traffic as defined by Equation 4.4, and} \]

\[ FMADT2 = \text{the second monthly average traffic factor.} \]

### 4.7.7 Weekday Annual Average Factor (FWAADT)

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.

\[
FWAADT = \frac{AADT}{WAADT} \tag{4.19}
\]
where:

\[ AADT = \text{the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,} \]

\[ WAADT = \text{the weekly average monthly traffic, and} \]

\[ F_{WAADT} = \text{the weekly average monthly traffic factor.} \]

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?
- What are the impacts of grouping years together?

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), Erhunmwansee (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:

\[
MAE = \frac{|AADT_{pred} - AADT_{obs}|}{AADT_{obs}} \times 100
\]  \hspace{1cm} (4.20)

where:

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

There are several sources of errors in the traditional method of estimating AADT (Bodle, 1967). A pure assessment of the examined factors without inserting external sources of bias is possible by following this procedure. Additional errors, produced from the “grouping” process and the assignment of short-term counts to ATR groupings are avoided, since the analysis is conducted only within the “factoring” procedure. Hence, it is ensured that the obtained errors are not affected by other processes. The results from these performance measures are provided in the next section of the methodology section.

4.8.1 Influence of Temporal Selection on the Ground Truth

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 4.15.
Table 4.15. The temporal selection of ground truth examples.

<table>
<thead>
<tr>
<th>Sample Duration</th>
<th>Days of the Week Sampled</th>
</tr>
</thead>
<tbody>
<tr>
<td>24 Hours</td>
<td>Mon, Tue, Wed, Thur, Fri</td>
</tr>
<tr>
<td>48 Hours</td>
<td>Mon-Tue, Tue-Wed, Wed-Thur, Thur-Fri,</td>
</tr>
<tr>
<td>72 Hours</td>
<td>Mon-Wed, Tue-Thur, Wed-Fri</td>
</tr>
<tr>
<td>96 Hours</td>
<td>Mon-Thur, Tue-Fri</td>
</tr>
</tbody>
</table>

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, and 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.](image)

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, 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 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 below 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 the first task, task seven, begins with the three main tables that 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 the 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.
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. As a result of the number of tables and findings, examples of these results are shown in the Appendices B-E.
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 4.5 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. 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.](image)

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.

![Figure 4.6. Temporary table in Microsoft SQL showing the results of the query.](image)
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.

![Figure 4.7. Data after being imported into Microsoft Excel.](image)

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

![Figure 4.9. Table in Microsoft Excel showing results of various “AVERAGEIF” functions.](image)

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.

![Figure 4.10. “SUMIF” function used to calculate total daily traffic.](image)
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, 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.

![Figure 4.11](image)

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 “AVERAGEIFS” and the “SUMIFS” 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.

<table>
<thead>
<tr>
<th>BW</th>
<th>EX</th>
<th>BY</th>
<th>EZ</th>
<th>CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>AADT from MMDT from WAMD</td>
<td>AADT from MMDT s AVG</td>
<td>AADT from WAADT</td>
<td>AADT from WADT</td>
<td>AADT s avg</td>
</tr>
<tr>
<td>21,564</td>
<td>21,568</td>
<td>21,585</td>
<td>21,590</td>
<td>21,587</td>
</tr>
<tr>
<td>2285.806</td>
<td>2288.968</td>
<td>1825.592</td>
<td>2354.870</td>
<td>3203.785</td>
</tr>
<tr>
<td>C.V.</td>
<td>C.V.</td>
<td>C.V.</td>
<td>C.V.</td>
<td>C.V.</td>
</tr>
</tbody>
</table>

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].

<table>
<thead>
<tr>
<th>FC</th>
<th>Station Number</th>
<th>Direction</th>
<th>AADT from MADT from MAWDT</th>
<th>Std.Dev</th>
<th>CV</th>
<th>Number_Rows</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12</td>
<td>727</td>
<td>21564</td>
<td>2283.823</td>
<td>10.591</td>
<td>12</td>
</tr>
<tr>
<td>2</td>
<td>12</td>
<td>727</td>
<td>21024</td>
<td>2144.291</td>
<td>10.199</td>
<td>12</td>
</tr>
</tbody>
</table>

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 the Excel produce the AADTb from value of 21,564 which is consistent with the values illustrated in Figure 4.13. These results are slightly different and the error due is a result of the rounding in Excel. Excel displays the numbers as integers (12,467), but in calculations it uses the entire number including any decimals that may be present (12,466.74196). SQL on the other hand, displays the numbers as integers and uses integers in calculations. Any discrepancies between SQL results and Excel results are likely to be due to this 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
DEVELOPMENT OF FACTOR GROUPINGS

5.1 Introduction

Chapter V of this research report describes the methodology used with the grouping/clustering, which is considered the third step associated with the traditional method for estimating AADTs for both the ATR and WIM data. The main objectives within the chapter is the development of eight methods which include current practice, other traditional methods as well as new statistical techniques used to cluster data. A series of performance measures that are used to assess the overall performance for each method is examined in Chapter VIII.

There are several ways of grouping the monthly factors. 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 together. More sophisticated cluster techniques include incorporating geographical or roadway functional class. To account for the various methods for grouping the data, eight methods were developed for the ATR and WIM stations for each year individually. The first four methods are the more traditional ways for grouping data. Methods Five through Eight include cluster analysis and in some cases additional steps for roadway, geographical, or both. 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 / Southwest / Central;
  - Urban / Rural;
- Method Four: Functional and Geographical Classification;
- Method Five: Cluster Analysis;
- Method Six: Functional Classification and Cluster Analysis;
- Method Seven: Geographical Classification and Cluster Analysis; and

5.1.1 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. 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 and vehicle classes 4 through 13. The second division includes total directional volumes and per directional volumes. Based on the recommendations from the TMG the data are grouped annually instead of a rolling average. The division of the data provides a comprehensive data set that will highlight the strengths and weakness associated with each option.
5.2 Method One: Functional Classification

The first method is the most traditional method and the grouping of the data is 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 groupings for example local roads. As a result of these limitations there may be some difficulty in populating some of these groupings.

Groupings 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).

5.3 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;
5.4 Method Three: Geographical Classification

The third method groups the data geographically/spatially. One of the strengths or rationales for dividing the data geographically is 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. 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 5.1 through 5.4.
Figure 5.1. North and south geographical areas.

Figure 5.2. East and west geographical areas.
Figure 5.3. Northeast, northwest, southeast, southwest and central geographical areas.

Figure 5.4. Urban and rural geographical areas.
5.5 Method Four: Functional and Geographical Classification

The fourth method for grouping, shown in Figure 5.5, is the combination of both the roadway functional classification and the geographical locations.

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 separated, 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.

5.6 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 the 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, shown in Equation
5.1. The software program SPSS 16.0 is used with the \( k \)-means cluster algorithm to create groups of permanent stations.

\[
J = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2
\]  

(5.1)

where:

\( J \) = intra-cluster variance,

\( k \) = total number of clusters produced from cluster analysis,

\( S_i \) = \( i = 1, 2, \ldots, k \),

\( x_j \) = data point,

\( \mu_i \) = centroid of all the points \( x_j \in S_i \), and

\( (x_j - \mu_i)^2 \) = 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 variables contribution to the discrimination of the clusters.

5.7 Method Six: Cluster Analysis with Roadway Functional Classification

The sixth method, shown in Figure 5.6, 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 5.6. 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.

5.8 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 5.7, the clustering is based on
one of the five geographical locations that are described in Method Three.

Figure 5.7. 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.

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

Method Eight is the final cluster method. In this method, as shown in Figure 5.8, the clustering is based on dividing the data first by roadway functional class, Method One, and then by geographical/spatial location, Method Three, and then clustering within the subset of the data.

![Flowchart used with Method Eight.](image)

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.

5.10 Evaluation of the Methods

The second objective within this chapter is to determine which technique provides the most accurate and effective method for grouping the data. The final results are compared in respect to the overall statistical performance of the method in association with the level of data manipulation. To determine the most appropriate groupings the final analysis is based on a series of statistical parameters which include the following statistics:
Standard Deviation (SD); Coefficient of Variation (COV); Variance (VAR); 95% Confidence interval; required number of stations so as to achieve a coefficient of variation less than 10%; upper and lower boundaries of 95% confidence interval; and upper and lower boundaries from group factors (±20%).

The statistical parameters presented above are consistent within this research area and are estimated for each group of ATRs. An automated process has been developed in order to update the above statistics when ATRs are moved from one cluster to another, or when new ATRs are added to a cluster. This application allows the analyst to modify the factor groupings easily. Potential changes can be evaluated in two ways as TMG recommends: by comparing the statistics before and after the modifications and by visually examining the traffic patterns of the ATRs within each cluster (TMG, 2001).

5.11 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 one of the most ambiguous tasks related with AADT estimation. There is limited past research in this area where the issues are addressed. The methodology proposed in this study is based upon the following assumptions; derived from recommendations and findings of past research:

1. Each cluster should contain five to eight ATRs, ideally (TMG, 2001);

2. It is desirable to have more than one or two ATRs in each cluster, providing sufficient data to generate the group factors;

3. A maximum precision of 10% with 95% confidence for each individual cluster is recommended (TMG, 2001); and

4. 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).
5. The hierarchy of nonhierarchical clustering may be constructed using the results repeatedly by considering different number of clusters each time (Massart et al., 1989).

Selecting the optimum number of factor groupings 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 presented in Figure 5.9 and includes the following steps.

In the first step the data set is categorized geographically and/or functionally grouped into \( m \) subsets to take into consideration the characteristics associated with this division. The split allows the analyst to conduct the first differentiation of the ATRs prior to applying any statistical methods. The categorization also assists in practical and effective allocation of short-term counts to factor groupings.

In the second step cluster analysis is employed separately for each subset of the data. Initially, all ATRs are put into one group. Two clusters are then created and the number of clusters increases sequentially until a maximum number of clusters is reached. The number is set equal to \( n/5 \) where \( n \) is the number of ATRs in a data set. Five (5) is selected as the denominator based on the first assumption stated above. As a result, \( n/5 \) analyses are conducted for each data set and the jth analysis includes \( j \) clusters. For example if a dataset consists of 40 ATRs, the first cluster analysis \((j=1)\) consists of 1 cluster, the second analysis two clusters, whereas the eighth and last analysis \((j=40/5=8)\) forms eight clusters.

Afterwards, a minimum number \( k \) ATRs within a cluster is established for all analyses, allowing consistency with the first two assumptions of the methodology. Each ATR of the clusters, having fewer stations than the minimum required, is then relocated to other groups of the same analysis-type, based on the three following steps.

The standard deviation (SD) is estimated in the fourth step for each month between the moving ATR and each of the remaining clusters of the analysis, according to Equation 5.2.
\[ SD_{i,m,c,j} = \sqrt{\frac{(F_{i,m,j} - \overline{F}_{m,c,j})^2}{2}} \]  

(5.2)

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.

In the fifth step the Average Standard Deviation (ASD) of all 12 monthly SDs is calculated between the moving ATR and each of the remaining clusters of the analysis. The ASD captures the percent difference of the annual traffic between an ATR and a cluster. All clusters of an analysis, regardless of whether they meet or not the requirement set in step 3, should be compared to the moving ATRs. The main goal behind this methodology is to increase the likelihood of assigning an ATR to a group with similar daily traffic patterns. A cluster that originally had less than \( k \) stations may meet the requirement of step 3 if ATRs from other clusters are grouped with it. Fewer modifications to the original groups are needed as fewer clusters don’t meet the requirement.

The moving ATR is assigned to the cluster with the minimum ASD in the sixth step of the procedure. Steps four through six are then repeated for the other ATRs within this particular cluster. 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. After allocating all 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. The procedure in Step 6 is complete when all analyses are checked and each of their clusters includes at least $k$ ATRs.

In step seven, the overall variation of the clusters included in $j$ analysis is expressed through the weighted coefficient of variation (WCOV), shown in Equation 5.3. The WCOV indicates the level of homogeneity in the groups of a cluster analysis, after the modifications of step 6:

$$WCOV_j = \sum_{c=1}^{I} \left( \frac{\sum_{m=1}^{12} \left( \frac{F_{i,m} - \bar{F}_{m,c}}{\bar{F}_{m,c}} \right)^2 \frac{n_{m,c,j}}{\sum_{m=1}^{12} (n_{m,c,j})} \times 100}{\sum_{c=1}^{I} \left( \sum_{m=1}^{12} (n_{m,c,j}) \right) \times n_{c,j}} \right)$$

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.

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 at this step.
Figure 5.9. Illustration of the process for selecting the optimum number of clusters.
6.1 Introduction

The objective of Chapter VI is to determine the most appropriate methods to use when assigning short-term counts to ATRGs with the goal of creating accurate annual average daily traffic volumes. 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 a new approach based on statistical measures. These methods are evaluated against each other through ground truth validation in Chapter IX.

The short-term counts used within this approach are a 24-hour sample duration period. The seasonal adjustment factors developed from the ATRGs are then applied to the short-term count. The final result is an average annual daily traffic volume for the short-term location. It is important that statistical analysis be employed during the assignment process (Ritchie et al., 1986) because the assignment of short-term traffic counts to a factor group is extremely sensitive to error resulting from engineering judgment (Sharma, et al., 1996). The assignment models developed within each method are described in the following sections.
6.2 Division of the Data Set

The data set developed within the study include over 7.0 million record that are obtained from classification continuous counters throughout the State of Ohio and is developed specifically for total volume on a two-way and a per direction basis. The selection of a per direction basis creates independence between from the direction of traffic flow.

Table 6.1 presents the main characteristics of the data set, per year number of ATRs per geographical region, average ADT, total number of factor groupings estimated from cluster analysis and total number of sample short-term counts used to evaluate the examined methods.

Table 6.1. Characteristics of the Data Set.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of ATRs per Geographical Region</th>
<th>Avg. AADT</th>
<th>Cluster Factor Groupings</th>
<th>Short-Term Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>NE</td>
<td>NW</td>
<td>SE</td>
<td>SW</td>
<td>C</td>
</tr>
<tr>
<td>NW</td>
<td>64</td>
<td>29</td>
<td>12</td>
<td>20</td>
</tr>
<tr>
<td>SE</td>
<td>50</td>
<td>37</td>
<td>18</td>
<td>19</td>
</tr>
<tr>
<td>SW</td>
<td>34</td>
<td>29</td>
<td>9</td>
<td>13</td>
</tr>
<tr>
<td>C</td>
<td>45</td>
<td>23</td>
<td>10</td>
<td>15</td>
</tr>
</tbody>
</table>

Based on the available data presented in Table 6.1 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).

Similarly to the methods examined in the previous chapters, the performance of each assignments approach is quantified. In order to ground truth the final results, the data set described above is divided into a series of short-term counts. These short-term counts originate from all the ATR locations based on 24-hour duration. The reason for the creation of short-term counts from the ATR locations, rather than 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. The
final AADT from the actual short-term counts are estimated and therefore these counts are unable to directly ground truth the different assignment procedures. The most conservative scenario occurs if the longer counts are likely to produce more accurate AADT estimates (Davis et al., 1996; Sharma et al., 2002). In the majority of previous studies (Sharma et al., 1994; Sharma et al., 2001; Sharma et al., 2002; Jin et al., 2008) to evaluate model performance typically only a few ATRs sites are used with a limited number of days as representative short-term counts. In this study, each day of year over the five year duration, from all the available continuous counters, are used as sample short-term counts, totaling 142,177 daily counts. The large sample size allows for a minimization of random errors and the influence of outliers in the final estimates although it requires more computing time.

6.3 Traditional Assignment

The traditional assignment of short-term counts to factor groupings comprises the fourth step of the traditional method of estimating AADT and is described in Chapter II. The allocation of counts to ATRGs is conducted based on their functional/geographical class only. Despite simplicity of computation and the short time needed, the traditional method takes into account only one variable, which cannot represent effectively all the ATRs within a factor grouping. This drawback yields high variability and limited accuracy within each group.

6.4 Discriminant Analysis

The first technique with potential improvement over the traditional method is discriminant analysis. Discriminant analysis is selected for this research 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). That means, to assess the classification
carried out with cluster or principal components analysis, given the resulted groups and provided that the assumptions of linearity and normality are met;

- To classify cases into groups with a 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 for the most appropriate groups (North Carolina State University, 2008).

Discriminant analysis contains two basic steps: 1) An F-test tests if the DA model is significant and 2) If the model is significant, the variables are assessed individually to check which differ significantly in mean by group and then these constitute the base for the classification of the predicted variable (North Carolina State University, 2008). DA includes similar assumptions as in correlation, linear, homoscedastic relationships, and untruncated interval. Therefore, DA may be used either as a descriptive or as a predictive statistic method (ESO, 1999).

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 to 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 is independent, data collected from ATRs has 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 6.1 is used to determine classification score as:

\[
S_i = c_i + w_{i1} * x_1 + w_{i2} * x_2 + \cdots + w_{im} * x_m
\]

(6.1)

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).

The WGCM is utilized during the classification process to describe the relationship between selection variables (SPSS for Windows, 2007). The WGCM is calculated as follows:
\[ w_{jl} = \sum_{j=1}^{g} \sum_{k=1}^{n_j} f_{jk} X_{ijk} X_{ljk} \frac{\sum_{j=1}^{g} \left( \sum_{k=1}^{n_j} f_{jk} X_{ijk} X_{ljk} \right)}{n_j}, \quad i, l = 1, \ldots, p \]  

(6.2)

where:

- \( g \) = number of groups,
- \( p \) = number of variables,
- \( X_{ijk} \) = value of variable \( i \) for case \( k \) in group \( j \),
- \( X_{ljk} \) = value of variable \( l \) for case \( k \) in group \( j \),
- \( f_{jk} \) = case weights for case \( k \) in group \( j \),
- \( n_j \) = sum of case weights in group \( j \), and
- \( M_j \) = number of cases in group \( j \).

Within Groups Covariance Matrix.

\[ C = \frac{W}{(n-g)} , n > g \]  

(6.3)

where:

- \( n \) = total sum of weights,
- \( g \) = number of groups,
- \( W = \begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix} \)

This is useful in determining which variables most affect another variable and which variables provide the most significant discrimination for membership in each factor group. 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 6.1 are described in the following section.
6.4.1 Parameters

Two parameters are implemented 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 represents the daily traffic variability within a 24-hour count and the ADT represents the total volume of traffic per day on a roadway section. The combinations of the two parameters capture both the variability and the magnitude of the daily volumes.

The hourly time-of-day factors include four separate time durations. They are 24 1-hour intervals, shown in Equation 6.4, 12 2-hour intervals, shown in Equation 6.5, 6 4-hour intervals Equation 6.6 and 4 6-hour intervals, and is shown in Equation 6.7. Equations 6.4 through 6.7 are presented below:

\[
F_{1,i} = \frac{ADT}{HV_i} \quad (6.4)
\]

\[
F_{2,j} = \frac{ADT}{HV_j + HV_{j+1}} \quad (6.5)
\]

\[
F_{3,k} = \frac{ADT}{HV_k + HV_{k+1} + HV_{k+2}} \quad (6.6)
\]

\[
F_{4,l} = \frac{ADT}{HV_i + HV_{i+1} + HV_{i+2} + HV_{i+3}} \quad (6.7)
\]

where:

\[
HV = \text{hourly volume that corresponds to the } i, j, k \text{ or } l \text{ hour of a day,}
\]

\[
i = 1, 2, \ldots, 24,
\]

\[
j = 1, 2, \ldots, 12,
\]
The selection of four time aggregations, Equations 6.4 through 6.7, allows for each hourly factor to be examined in capturing changes in daily traffic patterns. A set of 24 separate hourly factors is expected to be more efficient when the traffic volume is high. Although a separate issue is raised during situations where there is low traffic during off-peak periods. The hourly factors, based on the aggregation of consecutive traffic volumes, are then used in order to examine whether they can capture more effectively the traffic patterns of low traffic counts. The comparison of the four factors reveals the overall impact of the aggregation results to the AADT estimates. On the other hand, the ADT is used in order to take into account the amount of the total traffic within a day, which cannot be captured from the hourly factors. The ADT is examined separately and in different combinations with each of the hourly factors.

6.4.2 Model Methodology

Eight discriminant models are developed to determine group membership of the short-term counts. The first four models, DA1 through DA4, take the ADT and daily traffic pattern illustrated by the time-of-day factors into consideration. That means that the first variable \( j \) of Equation 6.4 is the ADT and the 24 hourly factors \( F_{1,i} \) are the remaining variables in model DA1. The variables of each model are presents in Table 6.2. 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 above, Equation 6.4 to Equation 6.7. As it shown in Table 6.2, the last four models (DA5 through DA8) do not include the ADT.
Table 6.2. Models per hourly factor type.

<table>
<thead>
<tr>
<th>Model</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1 (DA1)</td>
<td>ADT+F_{1,1}+F_{1,2}+...+F_{1,24}</td>
</tr>
<tr>
<td>Model 2 (DA2)</td>
<td>ADT+F_{2,1}+F_{2,2}+...+F_{1,12}</td>
</tr>
<tr>
<td>Model 3 (DA3)</td>
<td>ADT+F_{3,1}+F_{3,2}+...+F_{3,8}</td>
</tr>
<tr>
<td>Model 4 (DA4)</td>
<td>ADT+F_{4,1}+F_{4,2}+...+F_{4,6}</td>
</tr>
<tr>
<td>Model 5 (DA5)</td>
<td>F_{1,1}+F_{1,2}+...+F_{1,24}</td>
</tr>
<tr>
<td>Model 6 (DA6)</td>
<td>F_{2,1}+F_{2,2}+...+F_{1,12}</td>
</tr>
<tr>
<td>Model 7 (DA7)</td>
<td>F_{3,1}+F_{3,2}+...+F_{3,8}</td>
</tr>
<tr>
<td>Model 8 (DA8)</td>
<td>F_{4,1}+F_{4,2}+...+F_{4,6}</td>
</tr>
</tbody>
</table>

Based on the above parameters a new assignment procedure was developed and evaluated against the traditional assignment and the DA. This method uses several statistical measures and is described in detail in the following section.

6.5 Coefficient of Variation Approach

A new method was developed to allocate short-term counts to ATRGs. This method is based on the known characteristics of a short-term count, the duration, the time of the year, the hourly volumes, the ADT, and the geographical part of the count. Directional and total volume factors are used separately and the results are compared to those of the other two methods using the same evaluation process.

6.5.1 Parameters

Group membership is established through the use of two parameters: ADT data gathered from the temporary traffic counting equipment and time-of-day factors formulated from the short-term counts. The duration of each short-term count is 24 hours and the time-of-day factors are used to represent the hourly traffic pattern over the count period. Equations 6.4 through 674 are used to determine each set of time-of-day factors.
6.5.2 Model Methodology

The third step in the methodology section is developing the multiple models that are used with the assignment of short-term counts to cluster groups. Figure 6.1 illustrates the process implemented in the development of the models. Within the model development section, step one, there are two data sets. The first data set is the short-term counts collected from the 67 ATR sites. The second data set is comprised of the individual cluster groupings throughout the region and the state and is consistent with traditional cluster analysis. 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.

In the second step, the continuous counts are grouped together based on the traditional cluster analysis algorithm described in Chapter V. In third step of the model process individual hourly factors, calculated by Equations 6.4 through 6.7, are developed for both short-term counts and per cluster group. For example, Equation 6.4 generates 24 1-hour factors per day per short-term count. Equation 6.4 also generates 24 1-hour factors for each individual cluster per day. 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 1, developed by Equation 6.7, corresponds to a time period 12.00 AM to 1.00 AM for each day of the year. This factor is then compared directly to the exact same factor on the same day of the year for each cluster group. Based on this comparison, the hourly COV is calculated between the short-term count and the individual cluster groups.

The COV is dimensionless. In contrast with other statistical measures such as the variance and the SD, the COV does not need to be normalized. That means that COVs of different parameters, such as ADT and hourly factors, may be compared directly. The evaluation of the COV is easier and clearer for the analyst because it is expressed as a percentage. Furthermore, the COV allows the average and the SD of the examined parameters to be
accounted for, useful when the two means are significantly different. 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.
Figure 6.1. Illustration of the model development methodology.
The lowest producing COV between the ATRs and the short-term counts is highly desirable. In step five, since the final assignment is not based on per individual hour COV but the entire duration of the day an average COV (ACOV) based on all the hourly COVs 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.

A final model is developed after all the COV for the time of day factors and the COV for the ADT are calculated. The general model form is based on Equation 6.8 where the two variables are weighted differently and produce a weighted COV (WCOV) as:

\[
WCOV^F_\beta = (1- \beta) \times ACoV_F + \beta \times CoV_{ADT}
\]  

(6.8)

where:

\( \beta \): 0, 0.1, 0.2, ..., 1, and

\( F \): 1, 2, 3, and 4, with each number corresponding to one hourly factor type.

The final results are eleven models for each of the four, time of day factors. Each model produces a WCOV for each factor group. Table 6.3 provides the model structure used in the results section.

| 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} |
In step six, the short-term count is assigned to the factor group with the minimum weighted COV. The WCOV allows for the contribution and assessment of which variable contributes more to the allocation process, will the combination of these variables be more effective, what is their impact on AADT estimates as well as the overall model performance of each model. The rationale behind the estimation of the WCOV is that it allows contribution and assessment of which variable contributes more to the allocation process. Which, in essence determine what combination of these variables is most effective respective impact on AADT estimates, and the overall model performance of each model. In the final step, step seven, the group factor is applied to the short-term count creating an estimated AADT. This estimated AADT will then be directly compared with the actual AADT.

6.6 Statistical Evaluation

The statistical evaluation of the individual models and the traditional method is based on four performance criteria: 1) absolute error (AE) of the AADT estimate, Equation 6.9; 2) the mean absolute error (MAE), Equation 6.10; 3) the SD of the AE, Equation 6.11; and 4) a two sample t-test which is used to evaluate the statistical significance of the final results. Similar statistical performance measures have been used by many studies (Erhumwunsee et al., 1991; Aunet et al., 2000; Faghri et al., 1995; French et al., 2001; Zhao et al., 2004; Jin et al., 2008). The statistical performance measures are presented below.

\[
AE_{v,dd} = \frac{|AADT_{v,Actual} - AADT_{v,dd,Estimated}|}{AADT_{v,Actual}} \times 100
\]  
\( (6.9) \)

\[
MAE = \frac{1}{w} \sum_{s=1}^{w} \left( \frac{|AADT_{v,Actual} - AADT_{v,dd,Estimated}|}{AADT_{v,Actual}} \times 100 \right)
\]  
\( (6.10) \)
\[ SDAE = \sqrt{\frac{\sum_{x=1}^{w} (AE_{v,dd} - MAE)^2}{w-1}} } \]

where:

\[ AADT_{v,actual} = \text{actual annual average daily traffic}, \]

\[ AADT_{v,dd,Estimated} = \text{estimated annual average daily traffic}, \]

\[ w = \text{number of short-term counts}, \]

\[ v = \text{ATR index}, \]

\[ dd = \text{day of year}. \]

The ground-truth of more than 140,000 short-term counts enhances the validity of the results and minimizes the existence 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 VII

ANALYSIS AND FINAL SELECTION OF THE MOST APPROPRIATE FACTORS

7.1 Introduction

The development of the 1,600 SAFs is based on the methodology that is documented in Chapter IV of this report. In Chapter VII 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 nine 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.

7.2 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 7.1 and 7.2. In both figures, the Y-axis is the mean absolute error and the X-axis are the five methods used in calculating AADT for each of the seven SAF calculations.

7.2.1 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.
7.2.2 The AADT analysis of the WIM Data Set

The results for the WIM data, shown in Figure 7.2 are similar to the results shown in Figure 7.1. In Figure 7.2, 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 AADT\(a\) and the AADT\(c\) estimates.
7.2.3 Comparison and Summary of Findings for the AADT methods using the ATR and WIM Data Sets

The results from Figures 7.1 and 7.2 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 AADT\(\text{a}\), Equation 4.6, produces slightly better results. As a result of this finding, the remaining sections of this chapter report results using this method AADT\(\text{a}\) for calculating AADT.

7.3 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 7.3 and 7.4 represent the overall temporal stability for the ATRs, while Figures 7.5 and 7.6 represent the overall temporal stability for the WIMs. For both data sets, Figures 7.3 and 7.5 represent January, a winter month, while Figures 7.5 and 7.6 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. In addition to these results, Appendix B shows the remaining ten months of the year.

7.3.1 ATR Annual Temporal Results

The annual ATR temporal results are shown below in Figures 7.3 and 7.4. The results for the month of January show the overall mean absolute error changes by 5 to 10 percent between 2003 and 2006.
Figure 7.3. Annual temporal sensitivity for the ATR data set for the month of January.

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 2006.
The results for the month of July are shown above in Figure 7.4. In Figure 7.4 the trend remains similar to Figure 7.3 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 7.4 are between 5 and 10 percent lower than the comparable winter month, Figure 7.3, and these findings may be the direct result of adverse conditions associated with the winter months.

7.3.2 WIM Annual Temporal Results

The annual temporal results for the WIM data set are shown in Figures 7.5 and 7.6. 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 2007. In Figure 7.5, the WIM results are displayed 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.
The second set of results for the WIM shown in Figure 7.6 suggest 2003 produces the highest individual mean absolute errors. Other results show on a yearly average that in general 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 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.
7.3.3 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.

7.4 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 7.7 and 7.8 are developed for all roadway classifications for all years of data for MADT. The results for the other six methods are described in Appendix C. In these figures, the Y-axis is the mean absolute error and the X-axis is the number of vehicle groups.
7.4.1 ATR Directional Analysis Results

The results for the ATR directional analysis are shown in Figure 7.7. 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 7.7. ATR directional analysis.](image)

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.
7.4.2 WIM Directional Analysis Results

The WIM analysis is performed in a similar manor as the ATR analysis. In these results, shown in Figure 7.8, 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 7.8. 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.
7.4.3 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.

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

The fourth step of the results section 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 7.9 and 7.10 for the ATR data set, while Figures 7.11 and 7.12 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.

7.5.1 ATR Average Vehicle Classification and all Roadway Functional Classification Results

The results for the ATR data are shown in Figures 7.9 and 7.10. In this 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.
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 7.10.

Figure 7.9. Average SAFs developed for all individual vehicle classes for all roadway functional classes using the ATR data set.
In Figure 7.10, the individual vehicle groupings shown in column one is 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 does 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.
The second set of results is developed for the WIM data. The results from the WIM data are shown in Figures 7.11 and 7.12. In Figure 7.11, the results are developed for the individual vehicle classes. In Figure 7.11, 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.

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 manor to those of the ATRs. The results for the nine vehicle class groupings are found in Figure 7.12. 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 7.12. Average SAFs developed for aggregated vehicle classes for all roadway functional classes using the WIM data set.
7.5.3 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.

7.6 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 individual results are shown in Appendix D. The results highlighted in step five of this chapter are developed for functional class 11 on a per direction basis. Figures 7.13 through 7.16 show the results for the ATRs and the WIMs. Figures 7.13 and 7.15 represent the individual vehicle classes, while Figures 7.14 and 7.16 represent vehicle class groupings and 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.

7.6.1 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 7.9 and 7.10 with higher volume individual vehicle classes produce 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 7.9.

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.

Figure 7.13. The individual SAFs developed for all individual vehicle classes for all roadway functional classes using the ATR data set.
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 7.14 for roadway functional class 11. The other roadway functional classes are shown in Appendix D. In Figure 7.14, 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 7.10.

![Mean Absolute Error (%)](image)

**Figure 7.14.** 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 7.14 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.
7.6.2 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 7.15 and 7.16. These figures are developed in a similar manor as the preceding ATR results section. The results shown in Figure 7.15 are similar to the WIM results shown in Figure 7.11, 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 7.15, the mean absolute errors are lower in Figure 7.15 as compared with Figure 7.11. In the case of the individual heavy-duty vehicle classes, there is significant improvement for vehicle classes 7, 10, 11, and 12.

Figure 7.15. 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 7.16 shows the overall findings for the individual vehicle aggregate groupings for roadway functional class 11.

![Figure 7.16](image-url)

Figure 7.16. The individual SAFs developed for aggregated vehicle classes for all roadway functional classes using the WIM data set.

The results illustrated in Figure 7.16, 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 produce 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 7.16 and Figure 7.12. 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 7.12, the mean absolute error is greater than 100 percent for vehicle classes 11 through 13 and 11 through 15. The results shown in Figure 7.16 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.

7.6.3 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 7.14 and 7.16 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 strongly recommended
to aggregate the vehicle classes together. This recommendation is based on the trends found throughout Appendix D.

7.7 Step Six: Selection of Multiple Factors

The development of multiple factor groupings as seen in Tables 7.1 and 7.2 for the ATR and the WIM data sets are based on the results from Figures 7.13 through 7.16 and Appendix D in combination with the corresponding standard deviations. The suggestions on the most effective SAFs are shown in Tables 7.1 and 7.2. In general the factor groupings are developed based on aggregated vehicle classes have lower mean absolute errors in comparison to the individual vehicle classes.

Table 7.1. SAFs for the ATR data set based on the lowest mean absolute errors and standard deviations per functional class.

<table>
<thead>
<tr>
<th></th>
<th>FC1</th>
<th>FC2</th>
<th>FC7</th>
<th>FC11</th>
<th>FC12</th>
<th>FC14</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Vol</td>
<td>MAWDT MADTa</td>
<td>MAWDT MADTa</td>
<td>MAWDT MADTa</td>
<td>WADT MAWDT MADTa</td>
<td>WAADT</td>
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<tr>
<td>Cars</td>
<td>MAWDT MADTa</td>
<td>MAWDT MADTa</td>
<td>MAWDT MADTa</td>
<td>WADT MAWDT MADTa</td>
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<tr>
<td>Trucks</td>
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Table 7.2. SAFs for the WIM data set based on the lowest mean absolute errors and standard deviations per functional class.

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<th>FC1</th>
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<tbody>
<tr>
<td>Total Vol.</td>
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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 7.3 and 7.4. 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 7.3. Mean absolute error percent improvement for ATRs by using multiple factors instead of individual SAFs.

<table>
<thead>
<tr>
<th></th>
<th>MAE&lt;sub&gt;WADT&lt;/sub&gt; - MAE&lt;sub&gt;M.F.&lt;/sub&gt;</th>
<th>MAE&lt;sub&gt;MAWDT&lt;/sub&gt; - MAE&lt;sub&gt;M.F.&lt;/sub&gt;</th>
<th>MAE&lt;sub&gt;MADT&lt;/sub&gt; - MAE&lt;sub&gt;M.F.&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Group</td>
<td>0.772</td>
<td>0.472</td>
<td>0.341</td>
</tr>
<tr>
<td>Two Groups</td>
<td>2.585</td>
<td>2.211</td>
<td>1.990</td>
</tr>
<tr>
<td>Three Groups</td>
<td>3.927</td>
<td>3.367</td>
<td>3.025</td>
</tr>
<tr>
<td>Four Groups</td>
<td>&gt;100</td>
<td>&gt;100</td>
<td>&lt;100</td>
</tr>
</tbody>
</table>

Notes: 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 7.3. In Table 7.3, 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 7.4. The improvement of the AADT demonstrates 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 7.4. Mean absolute error percent improvement for WIMs by using multiple factors instead of individual SAFs.

<table>
<thead>
<tr>
<th></th>
<th>MAE&lt;sub&gt;WADT&lt;/sub&gt; - MAE&lt;sub&gt;M.F.&lt;/sub&gt;</th>
<th>MAE&lt;sub&gt;MAWDT&lt;/sub&gt; - MAE&lt;sub&gt;M.F.&lt;/sub&gt;</th>
<th>MAE&lt;sub&gt;MAWT&lt;/sub&gt; - MAE&lt;sub&gt;M.F.&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Group</td>
<td>0.125</td>
<td>0.424</td>
<td>0.242</td>
</tr>
<tr>
<td>Two Groups</td>
<td>0.292</td>
<td>0.913</td>
<td>0.928</td>
</tr>
<tr>
<td>Three Groups</td>
<td>0.751</td>
<td>0.455</td>
<td>0.041</td>
</tr>
<tr>
<td>Four Groups</td>
<td>&gt;100</td>
<td>&gt;100</td>
<td>&gt;100</td>
</tr>
</tbody>
</table>

Notes: The column “Average Percent Reduction” is the average MAE percent difference between the examined groups for each scenario separately.

7.7.2 Summary of Results

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<sub>WADT</sub>, F<sub>MAWDT</sub> and F<sub>MAWT</sub>. 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.

7.8 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 7.17 and 7.18, 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 shown in Appendix E. 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.

7.8.1 ATR Temporal Analysis for Monthly Short-Term Data Collection

Figure 7.17, 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 7.17. ATR temporal analysis for the monthly short-term data collection.](image)

**Figure 7.17.** ATR temporal analysis for the monthly short-term data collection.

### 7.8.2 WIM Temporal Analysis for Monthly Short-Term Data Collection

In Figure 7.18, WIM results are the average for years 2003 to 2007. 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 7.18. WIM temporal analysis for the monthly short-term data collection.

7.8.3 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.

7.9 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 7.19 and 7.20. 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.

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

Figure 7.19 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.
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 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 7.19 suggest when using Monday counts the most optimal short-term sampling duration should be 72 hours in length. The final results from Figure 7.19 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.
7.9.2 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 7.20. 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 7.20. WIM temporal analysis for day of the week and sampling duration.
7.9.3 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.
7.10 Summary of Results

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

7.10.1 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.

7.10.2 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 exceptions of two factors, $F_{AIDT}$ and $F_{WADT}$, the remaining mean absolute errors are similar for both the January and July sampling periods.

7.10.3 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.
7.10.4 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 means 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.

7.10.5 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 it is not recommended for directional analysis. These classifications produce errors that are not a precise estimation of AADT.

7.10.6 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.

7.10.7 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.
8.1 Introduction

Chapter VIII describes the final results from the eight methods described in Chapter V. 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 SD, COV, and the variance for each method, on an annual basis. The results provided within this chapter are based on the directional analysis and total direction results are provided in Appendices F and G. 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, cars and trucks 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.

8.2 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 SD, COV and the variance are calculated to compare within 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. Each method’s individual results that perform the best 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. Appendix F provides the results for the 3-Card total volume for both directions. The results from the C-Card data are consistent with the trends provided in the individual results section.

8.2.1 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 outlier and there is no additional way to subdivide the data within this task. The results of the first method are shown in Figure 8.1 through 8.3. The high errors produced within functional class 7 and functional class 9 for the 2006 and the 2005 data set respectively, are due to the small number of continuous stations within the two data sets.
Figure 8.1. Method One standard deviation for 3-Card directional volume.

Figure 8.2. Method One coefficient of variation for 3-Card directional volume.
8.2.3 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 8.4 through 8.6. In general, with the exception of category 7 of local roads, the SD, COV 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 8.3. Method One variance for 3-Card directional volume.
Figure 8.4. Method Two standard deviation for 3-Card directional volume.

Figure 8.5. Method Two coefficient of variation for 3-Card directional volume.
8.2.4 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 8.7 through 8.9. In general the overall SD, COV 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 with 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 is not significantly different between the geographical areas and the urban versus rural at a 95% confidence interval.
Figure 8.7. Method Three standard deviation for 3-Card directional volume.

Figure 8.8. Method Three coefficient of variation for 3-Card directional volume.
8.2.5 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 8.10 through 8.12 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, local roads for example, 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 result shows the SD, COV and the variance remain relatively consistent on a per annual basis.
Figure 8.10. Method Four standard deviation for 3-Card directional volume.

Figure 8.11. Method Four coefficient of variation for 3-Card directional volume.
8.3 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 V. There are many positive aspects to this approach with the two most prominent advantages are; 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 station?

The evaluation of question one is described in detail within the next four sections, Methods Five through Eight. The results of the method analysis are shown in Figures 8.13 through 8.24. 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 straightforward, 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 SD, the COV and the variance of the cluster. The directional analysis results are shown in Figures 8.13 through 8.24 and the total directional results are provided in Appendix G.

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.

8.3.1 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 SD, COV 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 found in Appendix G. 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 G.1 through G.12 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 8.13. Method Five standard deviation for 3-Card directional volume.
Figure 8.14. Method Five coefficient of variation for 3-Card directional volume.

Figure 8.15. Method Five variance for 3-Card directional volume.
8.3.2 Method Six

The results are developed for the combination of clustering based on roadway classification in the sixth method and 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 8.16 through 8.18 and the total directions values are provided in Appendix G. The optimum number of clusters, using Method Six, remains consistent between the five years. The overall trends shown in Figures 8.16 through 8.18 are consistent for 3-card total volumes, vehicle classes 1 through 3 and vehicle classes 4 through 13.
Figure 8.16. Method Six standard deviation for 3-Card directional volume for roadway functional class 11.

Figure 8.17. Method Six coefficient of variation for 3-Card directional volume for roadway functional class 11.
Figure 8.18. Method Six variance for 3-Card directional volume for roadway functional class 11.

8.3.3 Method Seven

The seventh method continues to have the same overall trends as Methods Five and Six and is shown in Figures 8.19 through 8.21. 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 12 clusters. Similar with the other methods the final results are consistent between each year.
Figure 8.19. Method Seven standard deviation 3-Card directional volume for northeast Ohio.

Figure 8.20. Method Seven coefficient of variation 3-Card directional volume for northeast Ohio.
8.3.4 Method Eight

Method Eight, the final method, divides the stations based on both roadway location and the geographical location. The one main advantage in this method is the ability to investigate one area in the state specifically 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 8.22 through 8.24, display the same overall trends in comparison to other Methods. The other findings show the limitations associated with populating all the number of cluster groupings.

Figure 8.21. Method Seven variance 3-Card directional volume for northeast Ohio.
Figure 8.22. Method Eight standard deviation 3-Card directional volume for functional class 11 of northeast Ohio.

Figure 8.23. Method Eight coefficient of variation 3-Card directional volume for functional class 11 of northeast Ohio.
8.3.5 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 of Chapter VIII describes the trade-offs between selecting the number of clusters per method with the overall temporal stability.

8.3.6 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 on 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 increases, 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 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: SD, COV, and variance or they
do not have sufficient stations to meet the minimum suggested number of stations five to ten 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 8.13
through Figure 8.24. Although the number of clusters remains similar from year to year, the
permanent stations that populate each cluster may 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 8.25.

![Graph showing common stations (%) vs. number of clusters](image)

Figure 8.25. Method Five common stations (%) vs. number of clusters 3-Card directional volume.

In Figure 8.25 data from 2002 and 2003 is 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, are station one and two 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 disadvantageous of the cluster analysis is the instability in the cluster especially as a result of the dynamic nature of the roadway network, especially in relation to criterion two and three. More research remains to be completed with regard to criterion three.
8.4 Final Comparison of Results

The final comparison of the individual methods is shown in Figures 8.26 through 8.37. The comparison is based on the overall best individual results per method as described previously in Figures 8.13 to 8.24. The format for this section includes the results for the SD, COV 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 2007. The final results for the total directional volumes are shown in Appendix G.

8.4.1 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 final results will be updated to include 2007 and 2008. The results shown below represent the eight methods described in the previous chapter.

Figure 8.26. Standard deviation 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 SDs when compared with one of the four cluster techniques, Methods Five through Eight. The lowest producing SD 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 COV between the eight methods. The final results remain consistent with the SD. 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 8.27. Coefficient of variation 3-Card directional total volume comparison for all methods.
The final results from the C-Card data set are presented in Figure 8.29 and they remain consistent with the previous findings.

8.4.2 C-Card Directional Total Volume

The first set of results displayed in Figure 8.29 is 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 SDs than more current years. The second results show that generally the non-cluster methods, Method One through Method Four, produce higher SDs within each group. This finding would suggest there is benefit to incorporate a cluster approach with the final selection.
The second statistical method for the assessment of the eight methods is the COV. The comparison of these results is shown in Figure 8.30. In this figure similar to the SD, the higher
the values for the COV 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 COV to less than 15, with Method Five producing the lowest values.

The final figure created by the C-Card directional total volumes is shown below in Figure 8.31. The results are consistent with the previous findings and suggest the implementation of one of the cluster analysis methodologies.

![Figure 8.31. Variance C-Card directional total volume comparison for all methods.](image)

**8.4.3 C-Card Directional Vehicle Classes 1 Through 3**

The results described previously in Chapter VIII 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 8.32 through 8.34, are similar to the previous findings of the cluster techniques that produce
lower SDs, COVs and variances. An important finding when 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 8.32. Standard deviation C-Card directional vehicle classes 1 through 3 comparison for all methods.
Figure 8.33. Coefficient of variation C-Card directional vehicle classes 1 through 3 comparison for all methods.

Figure 8.34. Variance C-Card directional vehicle classes 1 through 3 comparison for all methods.
8.4.4 C-Card Directional Vehicle Classes 4 Through 13

The final set of results is shown in Figures 8.35 through 8.37, developed exclusively for heavy-duty vehicles: vehicle classes 4 through 13. The summary for 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 8.35. Standard deviation C-Card directional vehicle classes 4 through 13 comparison for all methods.
Figure 8.36. Coefficient of variation C-Card directional vehicle classes 4 through 13 comparison for all methods.

Figure 8.37. C-Card directional vehicle classes 4 through 13 variance comparison for all methods.
8.4.5 Summary of Results

In the summary of results there are three research areas of focus. The first is the comparison of the SD, COV and variance for individual techniques utilized within each method. In some cases such as in 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 land-uses, 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 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 SD, COV and the variance. In most cases the overall benefits improve as the number of clusters increase. There is, however, a point in 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 amounts 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 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 are to record how the stations change clusters both annually as well as 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 show cluster methods produce lower SDs, COV, 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 IX
RESULTS AND SELECTION OF THE MOST APPROPRIATE ASSIGNMENT PROCEDURE

9.1 Introduction

The results obtained from the three assignment methods described in Chapter VII 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 SAFs. 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?”

The results produced from discriminant analysis are presented prior to those of the COV method in section 9.2. The comparison of the four hourly factors, estimated from Equations 6.4 to 6.7, precedes the evaluation of the eight discriminant models, described in section 6.5.2. In the comparison that follows, between the DA and the traditional assignment, the effectiveness of both methods is quantified.

Section 9.3 presents the results generated from the COV method. Similar to the organization of section 9.2, the hourly factors are evaluated prior to the assignment models and the most effective model is compared to the traditional approach of assigning short-term counts to factor groupings. The final comparison of the three methods is conducted at the end of this chapter.
9.2 Discriminant Analysis

The selection of the most efficient model includes a first comparison of the four hourly factors (Equation 6.4 to Equation 6.7). Afterwards a second evaluation is conducted for the models that take into consideration the average daily traffic (Model 1 through Model 4) and those that do not include the ADT, (Model 5 through Model 8). At the end of this section, the results from the analysis conducted for two-way volume factors are compared to those of the traditional method and to the results based on directional adjustment factors.

9.2.1 Comparison of Factors

Figure 9.1 displays the examined models on the x-axis and on the y-axis the yearly and the average MAE produced from two-way volume-based SAFs.

![Mean Absolute Error (%)](image)

**Figure 9.1. MAE per year and model for total volume based SAFs.**
A comparison between models 5, 6, 7 and 8, including the factors by themselves, illustrates that the aggregation of factors yields higher predictive errors. When a set of twenty-four hourly factors is used, an average MAE of 13.0% is produced. On the other hand, when twelve, eight or six factors are used the error increases up to 14.5%. A similar trend line is observed for the first four models that take into account both the ADT and the hourly factors. Twenty-four factors result in the lowest error, 13.4% MAE, in contrast with the set of six factors which yields an average 14.8% MAE. Same conclusions can be drawn from Figure 9.2 that shows the results obtained from directional volume-based SAFs.

The MAE is 11.0%, 11.4%, 11.7% and 12.2% for twenty-four, twelve, eight and six factors respectively. The population of each model was tested for statistical difference at a 95% confidence interval with the populations of the other seven models. If the two sample populations are not statistically different then there is no statistical justification for dividing the data set. The
results show that 82% and 89% of the t-tests that were conducted yield different populations at the 95% confidence level for total and directional factor analysis respectively.

Figures 9.3 and 9.4 illustrate the yearly and the average SD of the eight models. The trends between MAE and SDAE for both total and directional volume analysis are obvious. The lowest SDAE is generated for F_{1,i}, followed by F_{2,j}, F_{3,k}, F_{4,l}.

Figure 9.3. Standard deviation per year and model for total volume based SAFs.

Figures 9.3 and 9.4 illustrate the yearly and the average SD of the eight models. The trends between MAE and SDAE for both total and directional volume analysis are obvious. The lowest SDAE is generated for F_{1,i}, followed by F_{2,j}, F_{3,k}, F_{4,l}.
Figure 9.4 Standard deviation per year and model for directional volume based SAFs.

When the ADT is inserted in the models along with the hourly factors, Models One through Four, the SDAE increases slightly but the overall trends remain the same.

9.2.2 Comparison of Models

In this section DA1 is compared against DA5 since the two models are statistically different and they both include the first set of factors $F_{i,j}$, which performs better than the other three types of factors. In Figure 9.1, DA1 results in an average error of 13.40%. Model 5 has slightly lower MAE by 0.37%. The corresponding MAE decrease for the directional volume analysis is 0.29% as it shown in Figure 9.2. In Figures 9.3 and 9.4 the SDAE improvement using Model 5 is 0.56 and 0.29 respectively. Similar MAE and SDAE decreases are observed between the first four models that include the ADT and the last four that do not contain it. Based on the two statistical measurements shown in the above graphs that Model Five, the set of twenty-four hourly factors, results in the lowest errors for all years.
9.2.3 Comparison of Total, Directional and Traditional Methods

The final and one of the most important objectives of this study is to provide a comparison between the traditional allocation of short-term counts and the DA. Prior to the evaluation of the results, tests of statistical significance performed for the three populations per year. The results show that 91% of the compared methods are significant different at a 95% confidence interval. Figures 9.5 and 9.6 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 9.5. MAE for the traditional method and the fifth discriminant model, DA5.

The directional volume based DA yields a 5.74 average decrease of the MAE, corresponding to a 30.7% improvement in the accuracy of the final estimates. The corresponding improvement in 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. On the other hand, the directional factors perform better than the total volume based SAFs. The corresponding average MAE and SDAE decrease is 15.8% and 13.2%.

Furthermore, a comparison between Figures 9.1 and 9.2 verifies that lower MAEs are produced for all eight models that use directional-based adjustment factors. The same conclusion can be reached for the SDAE by visually examining Figures 9.3 and 9.4.

9.3 Coefficient of Variation Approach

The results produced from the COV method are divided into three sections: 1) the comparison of the hourly factor groupings, 2) the comparison of the models and the third section compares the total, and 3) directional and traditional methods for assigning short-term counts. The results from the analysis are shown in Figures 9.7 through 9.11. The MAE and the SDAE for
each model are presented for two-way volume and directional volume-based factors. In Figure 9.7 and Figure 9.8, the x-axis represents one of the eleven models described in Table 9.1. Model 1 (M1) does not include the COV of the ADT while the final model on the right model 11 (M11) does not include the average COV for the temporal factors. The y-axis is the mean absolute error or the SD of the absolute error.

![Graph showing mean absolute errors for four hourly time of day factors](image)

Figure 9.7. Mean absolute errors for the four hourly time of day factors.

### 9.3.1 Comparison of Factors

The initial results are based on the comparison between dividing the day into 24 1-hour factors versus 4 6-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 9.2 are consistent across the four methods with lower errors associated with the models with less weight on the average COV of the ADT. In some cases, models 1 through 4, there is a statistical difference at the 95% confidence level between the best case 1-hour factors versus the worst case...
4-hour factors. The total direction versus the directional based analysis, the directional based analysis produces lower mean absolute assignment errors across all models.

There is a slight statistical benefit, in the performance of models M1 through M4, with the 24 1-hr factors in comparison to the other factors. As a result of this benefit, the remaining results are based on the models developed specifically with the 24 1-hour time of day factors.

9.3.2 Comparison of Models

The comparison of the model performance using the 24 1-hr factors is shown below in Figures 9.8 and 9.9. The general errors tend to increase in all cases as the weight of the COVADT increases. Furthermore, they are significantly improved over other studies that produce average errors of 20% (Davis et al., 1996).

Figure 9.8. Mean absolute errors for all models based on hourly factors.
Similar conclusions to the MAE are reached for the SDAE is shown in Figure 9.9. M1 and M2 are the most accurate models while M11 is the least accurate. The directional volumes produce lower SDs of the absolute errors when compared with the total volumes, similar to the results shown in Figure 9.7.

There are two outcomes from Figures 9.8 and 9.9. First the models with less weight on the COV, from the AADT, produce lower mean absolute errors and a tighter distribution about the mean.

9.3.3 Comparison of Total, Directional and Traditional Methods

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

The most efficient method is the development of directional specific assignments. The directional specific assignments improve the mean absolute error from 6% to 8% which is approximately half the error of the traditional method. The SD of the mean absolute error also improves to 6%-10%. This is one third the SD of the traditional method. Two potential explanations for this finding is the statistical difference between the two populations between the directions and the sample size is almost double, which in turn yields more factor groupings. The greater the possibility to assign a short-term count to a group with similar traffic pattern and ADT as the number of groups increases.
Figure 9.11. SDAE over time for total and directional volume-based factors.

The statistical difference between the two populations is the primary reason behind this finding. Another possible explanation is the difference in sample size. When directional factors are used, the sample size is almost doubled, which yields additional factor groupings. The greater the possibility to assign a short-term count to a group with similar traffic pattern and ADT as the number of groups increases.

9.4 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, estimated using directional SAFs too. Figures 9.12 and 9.13 illustrate the MAE and the SDAE respectively of each method over time, respectively. It is apparent from both figures 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 in average by 8.01% and the SDAE by 14.21%. The equivalent MAE and SDAE percentage improvement is 51.75% and 67.73%, respectively. On the other hand, the fifth discriminant model improves the MAE, produced from the traditional method, by 30.74%. The associated improvement in the SDAE is 58.03%.

9.5 Summary of Results

The two methods, discriminant analysis and the COV approach, used in the assignment of roadway segments to ATR groupings proved to be more effective than the traditional method, which is only based on the functional and/or the geographical class of traffic counts. The new method, which is based on traffic counts’ characteristics, statistical measures and past findings, reduces significantly the AADT errors. It is also found that the AADT estimation using directional factors is more accurate than an analysis of total volume factors.

To conclude, the overall improvement of AADT predictions is a result of the combined application of several methods. These approaches not only use statistical measurements, but they take into account traffic parameters derived from guidelines and past research findings. This study contributes to the research community by giving alternative solutions to ambiguous issues and by adding new elements to the current practice. Improvements in data collection programs, calculation of seasonal adjustment factors, determining the optimal number of clusters, grouping continuous sites and assigning short-term counts to station groupings are the main achievements of this research. DOTs, transportation agencies, public and private companies may adopt and apply to their programs part or the whole estimation process recommended in this research.
CHAPTER X
OTHER TECHNIQUES FOR ESTIMATING AADT

10.1 Introduction

The development of accurate AADT estimates plays a vital role for day to day operations within a department of transportation. As a result of this need for accurate AADT estimates, there have been many research studies over the last few decades focused on developing more efficient methods to estimate AADTs. The traditional approach of estimating AADT is the most commonly used method. There are some concerns with this traditional approach which include the development of errors and uncertainties throughout each step of the process.

As a result of these concerns some research has focused on developing new methods for directly estimating AADTs based on local conditions. Some of the more common approach includes artificial neural networks and ordinary least squares regression (Faghri et al., 1995; Lam et al., 2000; Lingras et al., 2000, Sharma et al., 2000; Sharma et al., 2001). The data requirements from these methods vary from simple regression models based on roadway functional classification to increased data needs such as socioeconomic and land use parameters. Some examples of these research studies include work from Neveu, Mohamad, Fricker, Xia and Zhao. Neveu developed regression models to predict AADT for roads of each functional class (Neveu, 1983). Mohamad et al. developed a multiple regression model to estimate AADT on county roads (Mohamad et al., 1998). Fricker and Saha used population, vehicle registration and employment as predictors in their models (Fricker et al., 1987). Xia (1999) developed multiple regression models based on roadway characteristics, such as number of lanes, functional classification for
non-state roads in Florida (Xia et al., 1999). Zhao (2001) used roadway data, socioeconomic characteristics, expressway accessibility and accessibility to regional employment centers to develop four multiple regression models for expressway roads in a Florida county (Zhao et al., 2001). In 2004, Zhao used weighted regression models to estimate AADT (Zhao et al., 2004). He conducted multiple linear regression analyses separately for selected rural and urban areas to identify explanatory variables for interpreting seasonal traffic patterns (Zhao et al., 2004).

In addition to more traditional regression models researchers have added innovative statistical modeling to improve the overall performance of the predictions. Lingras (2002) used genetically designed regression models for individual hours while Tang (2003) built a nonparametric regression model to forecast short-term traffic volumes for the year 1999 (Lingras et al., 2002; Tang et al., 2003). Zhong (2005) developed a locally weighted regression model, a form of memory based algorithm for learning continuous mapping from real-valued input vectors to real-valued output vectors (Zhong et al., 2005). In most cases the more advanced models improve the findings by a few percent.

One area for potential development is the altering of the model framework to include negative binomial models into a full Bayesian framework. The potential benefits of the Bayesian framework include the implementation of prior knowledge into the prediction model as well as developing a posterior distribution of the beta coefficients.

10.2 Objectives

This research study has three objectives. The first objective is to develop a series of training and validation data sets, one for each season of the year. The second objective is to develop three individual modeling frameworks using the four seasonal training data sets. The three models include an ordinary least squares regression model, while the second and third models are full Bayesian negative binomial models, the framework for model two includes a
coefficient offset, while model three does not. The third objective is to compare the three models using the validation data sets across all seasonal durations. The end result of this research study will show the effectiveness of the three models for directly predicting heavy-duty seasonal average annual daily traffic (AADT).

10.3 Description of the Empirical Setting

There are 67 continuous count stations that are located across the State of Ohio from 2002 through 2007 that collect volume counts for heavy-duty vehicles, vehicle classes 4 through 13. Based on these continuous count stations, the final development of the data sets used in this study are based on three criteria which include site specific daily hourly minimum collection durations, the temporal annual aggregation of the data and the development of the training and validation data sets. Additional land-use, socio-economic, and population data are provided at the county level by the US census.

10.4 Site Specific Requirements

The first criterion is site specific. In this case, each site used in the development of the final data sets requires a continuous 24 hour collection period to calculate the Average Daily Traffic (ADT), as well as a minimum of 280 complete days to estimate the AADT per station. This 24-hour count may include hourly volumes with no recorded/zero hourly heavy-duty volumes. The second site specific constraint is based on suggestions from AASHTO (AASHTO Guidelines, 1992).
10.5 Temporal Aggregation of the Data Sets

The temporal aggregation of the data is based both annually as well as seasonally. The initial data set is comprised of data for the years 2002 through 2007 for the State of Ohio. The data before 2005 are used as prior knowledge for the full Bayes models, while the data collected from 2005 through 2007 are development for the comparison of the three model frameworks. The second temporal aggregation is based on seasonality of the data. The winter months are December through February, spring months are March through May, summer is June through August and fall is September through November. Table 10.1, shown below is a summary of the parameters populated in the final data sets. In the final data set as shown in Table 10.1 represent urban and rural countries, spatial distribution, and multiple roadway functional classes creating a representative statewide empirical setting.

Table 10.1. Summary statistics in the final data set.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Entire Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional Class</td>
<td>N/A</td>
</tr>
<tr>
<td>Percent Interstate</td>
<td>0.439</td>
</tr>
<tr>
<td>Percent Freeway</td>
<td>0.175</td>
</tr>
<tr>
<td>Percent Principal Arterial</td>
<td>0.326</td>
</tr>
<tr>
<td>Lanes</td>
<td>4.3</td>
</tr>
<tr>
<td>ADT Classes 4 through 13</td>
<td>3608.2</td>
</tr>
<tr>
<td>AADT Classes 4 through 13</td>
<td>3609.7</td>
</tr>
<tr>
<td>Population Density</td>
<td>993.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional Class</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>Percent Interstate</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Percent Freeway</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Percent Principal Arterial</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Lanes</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>ADT Classes 4 through 13</td>
<td>0</td>
<td>24234</td>
</tr>
<tr>
<td>AADT Classes 4 through 13</td>
<td>15</td>
<td>14050</td>
</tr>
<tr>
<td>Population Density (population/mi²)</td>
<td>33.1</td>
<td>3035.7</td>
</tr>
</tbody>
</table>

Notes: The roadway functional classification is based on the guidance provided by the HPMS. Percent refers to the total number of observations for each roadway functional class for the entire data set.
10.6 Development of a Training and Validation Data Set

The final step in the description of the empirical setting is separating the data sets into seasonal training and validation data sets. The first data set is used to develop the final prediction models, while the second data set, the validation data set, is used to verify the model’s ability to predict future AADTs. This selection process ensures that the data used to create the model parameters are randomly selected, consistent, and completely separate from the validation data set.

10.7 Statistical Methodology

There are three model methodologies developed in this study. Model one is an ordinary least squares regression model and models two and three are full Bayesian negative binomial models.

10.7.1 Model One: Ordinary Least Squares Regression

There are some potential limitations associated when using an ordinary least squares method with predicting AADT. AADT is considered count data and should not be modeled as a continuous variable. As a result of modeling AADT as a continuous variable there is potential for predicting negative values which is impossible with AADT predictions.

10.7.2 Model Two and Three: Negative Binomial

As a result of the limitation with the regression model there are two common ways for modeling count data. These two methods are Poisson and negative binomial models. One criterion for the correct use of the Poisson model is the mean and variance of the prediction should be equivalent. If this criterion is not satisfied the negative binomial model should be used. As a result of non-equivalent mean and variance the negative binomial model is selected over the
Poisson model. In this study, there are two negative binomial model frameworks, shown in Equations 10.1 and 10.2. Equation 10.1, includes a coefficient offset, while Equation 10.2 does not include a coefficient offset:

\[
\lambda_i = \beta_1 x_i e^{(\beta_0 + \beta_1 x_2 + \ldots + \beta_n x_n)}  
\]

(10.1)

\[
\lambda_i = e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}  
\]

(10.2)

where:

\[
\beta_0 = \text{constant term}, \\
\beta_1, ..., \beta_n = \text{estimated parameters in vector form, and} \\
x_1, ..., x_n = \text{explanatory variables developed for the individual models.}
\]

In this study the models require all variables to have a p-value less than 0.05 which corresponds to a 95% confidence level. Once the key parameters are identified, the next phase is to develop eight predictive models, one model for each season using both Equations 10.1 and 10.2 implementing a full Bayesian methodology.

**10.7.3 Full Bayes Methodology**

Once the initial models are developed a Bayesian methodology with Gibbs sampling is adopted in order to obtain the predictive posterior simulation of the AADTs. In a fully Bayesian framework for modeling and inference of estimated parameters, the Bayesian model specification requires a likelihood function and prior distribution to obtain the posterior density of the
estimated parameters from the given data. The Bayes methodology is developed from the following equation:

\[
p(\Theta | \chi) = \frac{p(\Theta)p(\chi | \Theta)}{\int p(\Theta)p(\chi | \Theta) d\Theta} \propto p(\Theta)p(\chi | \Theta)
\]  

(10.3)

where:

\[
p(\theta) = \text{the prior distribution that expresses the uncertainty before, and}
\]

\[
p(\Theta | \chi) = \text{the posterior distribution that describes the uncertainty after seeing the data.}
\]

In order to obtain the predictive posterior simulation associated with the AADTs three Monte Carlo Markov Chains are developed with Gibbs sampling. In the Monte Carlo simulation, informative priors with some precision are assigned to the parameter coefficients. These informative priors are based on the model results using data provided from 2002 through 2004. In addition of the prior knowledge, a three chain approach is used in the simulation. In each of the chains, different initial values are selected for each chain and after enough simulation iterations, the three chains are evaluated for convergence. In this study the convergence of the three chains is based on Gelman-Rubin statistics, Kernel density, autocorrelation, trace plots and times series plots (Spiegelhalter et al., 2004; Gelman et al., 2003). Once the model is converged the posterior distributions are summarized (shown later in Tables 10.3 through 10.10).

10.8 Results

The AADT predictions developed in this study are based on the initial results for the three models for each season of the year. The initial results are based solely on the model
training data set which randomly samples 75% of the data. The second set of results is based on the estimated model performance. The model performance is evaluated with the validation data set. As described previously it is important to note that no data from the validation data set is used in the initial model development. The model performance is based on the model prediction values versus the actual validation data set AADTs. The overall model structure includes average daily traffic volumes for vehicle classes 4 through 13, HPMS roadway functional classes which include interstate, freeway and principal arterial, spatial locations which includes northeast, northwest, central, southeast and southwest locations within Ohio and temporal, Mondays, Midweek and Fridays.

10.8.1 Initial Results Ordinary Least Squares Regression Models

The results from the regression models for the four seasons are shown in Table 10.2. The variables with a statistical significance at the 95% confidence level include heavy-duty truck ADTs, HPMS interstate, freeway, and principal arterial roadway functional classifications. Other variables of significance include the population density, as well as the spatial location within the state. The final sets of variables are temporal based on the day of week, Monday, Midweek and Friday. In addition to these variables, other variables including number of lanes, socio-economic and additional land-use categories are also tried. Unfortunately these parameters are not considered statistically significant or in the case of lanes create multicolinearity problems with other variables.

The results show the AADT predictions are higher with an increase in heavy-duty ADT. The roadway classification for interstates produces higher prediction AADTs than do freeway and principal arterials. Other findings of interest show the northwest and central areas predict higher AADTs than southern Ohio. The final overall results are developed for the day of the week. In general the average ADT are lower for Monday followed by Friday with the highest during the
midweek, Tuesday through Thursday. As a result of the higher prediction values associated with
the ADT and the other variables remaining constant, the net effect of the day of the week is
similar to a daily adjustment factor which results in a larger subtraction of values with the
midweek followed by Friday and lastly Monday. The temporal factor would in-turn create a
relatively similar AADT estimate for one particular section of roadway for all weekday samples.

Table 10.2. Regression model coefficients.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Spring Model</th>
<th>Summer Model</th>
<th>Fall Model</th>
<th>Winter Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>700.036</td>
<td>563.920</td>
<td>977.529</td>
<td>982.359</td>
</tr>
<tr>
<td>Truck ADT Classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 through 13</td>
<td>0.638</td>
<td>0.634</td>
<td>0.597</td>
<td>0.573</td>
</tr>
<tr>
<td>Interstate</td>
<td>3199.530</td>
<td>2941.930</td>
<td>2665.136</td>
<td>3756.312</td>
</tr>
<tr>
<td>Freeway</td>
<td>1105.856</td>
<td>1121.471</td>
<td>998.724</td>
<td>1295.978</td>
</tr>
<tr>
<td>Principal Arterial</td>
<td>335.872</td>
<td>254.929</td>
<td>258.363</td>
<td>392.389</td>
</tr>
<tr>
<td>Population Density (population/mi²)</td>
<td>-1.63E-01</td>
<td>-1.74E-01</td>
<td>-1.97E-01</td>
<td>-3.71E-01</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>845.400</td>
<td>933.432</td>
<td>462.919</td>
<td>466.904</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>842.494</td>
<td>702.819</td>
<td>476.775</td>
<td>375.207</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>226.096</td>
<td>565.635</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>464.130</td>
<td>565.500</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Monday</td>
<td>-1566.896</td>
<td>-1495.514</td>
<td>-1313.483</td>
<td>-1136.265</td>
</tr>
<tr>
<td>Midweek (Tuesday through Thursday)</td>
<td>-2044.769</td>
<td>-1889.574</td>
<td>-1664.600</td>
<td>-1593.948</td>
</tr>
<tr>
<td>Friday</td>
<td>-1604.455</td>
<td>-1619.532</td>
<td>-1306.301</td>
<td>-1308.538</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>3,546</td>
<td>3,363</td>
<td>4,315</td>
<td>3,119</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>7915.67</td>
<td>7799.64</td>
<td>9039.98</td>
<td>6249.31</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.89</td>
<td>0.90</td>
<td>0.88</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 0.05 level.
N/A the variable is not statistically significant and was not included in the final model.
10.8.2 Initial Results Full Bayesian Negative Binomial Model

The second set of results are developed for models two and three using a full Bayesian model framework. The results for the offset, model two are shown in Tables 10.3 through 10.6 and the results with no offset, model three, are shown in Tables 10.7 and 10.10.

10.8.3 Initial Results Full Bayesian Negative Binomial Model, With Coefficient Offset

The results for model two with the offset show as the heavy-duty ADT increases, the predicted AADT also increases. In terms of the HPMS roadway classification, the interstate has the greatest influence on AADT followed by freeway and principal arterials. Field data estimates developed in the northwest increase the AADT prediction, while southwest and southeast lower AADT estimates and the central geographic location is no longer significant. Similar to the regression findings, the highest ADT volumes on average occur during the midweek followed by Friday and Monday. In order to predict relatively similar AADT for an individual segment independent of the day of the week, the temporal results show the requirement to lower AADT predictions for the midweek followed by Friday and Monday. The highest inverse dispersion which results in the lowest overall dispersion, a measurement of model performance, (the variance divided by the mean) shows the spring is the most efficient model followed by summer, winter and finally the fall.
Table 10.3. Full Bayesian framework with coefficient offsets for spring.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.937</td>
<td>0.035</td>
<td>0.002</td>
<td>1.870</td>
<td>1.936</td>
<td>2.010</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>0.754</td>
<td>0.006</td>
<td>0.000</td>
<td>0.741</td>
<td>0.754</td>
<td>0.765</td>
</tr>
<tr>
<td>Interstate</td>
<td>1.005</td>
<td>0.038</td>
<td>0.002</td>
<td>0.931</td>
<td>1.005</td>
<td>1.079</td>
</tr>
<tr>
<td>Freeway</td>
<td>0.687</td>
<td>0.033</td>
<td>0.002</td>
<td>0.623</td>
<td>0.687</td>
<td>0.753</td>
</tr>
<tr>
<td>Principal Arterial Population Density (population/mi²)</td>
<td>0.414</td>
<td>0.028</td>
<td>0.001</td>
<td>0.359</td>
<td>0.414</td>
<td>0.467</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>0.068</td>
<td>0.015</td>
<td>0.000</td>
<td>0.040</td>
<td>0.068</td>
<td>0.098</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>-0.101</td>
<td>0.022</td>
<td>0.001</td>
<td>-0.143</td>
<td>-0.102</td>
<td>-0.058</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>-0.133</td>
<td>0.030</td>
<td>0.001</td>
<td>-0.192</td>
<td>-0.133</td>
<td>-0.073</td>
</tr>
<tr>
<td>Monday</td>
<td>-0.805</td>
<td>0.017</td>
<td>0.000</td>
<td>-0.839</td>
<td>-0.805</td>
<td>-0.771</td>
</tr>
<tr>
<td>Midweek (Tuesday through Thursday)</td>
<td>-0.967</td>
<td>0.015</td>
<td>0.001</td>
<td>-0.996</td>
<td>-0.967</td>
<td>-0.938</td>
</tr>
<tr>
<td>Friday</td>
<td>-0.880</td>
<td>0.018</td>
<td>0.001</td>
<td>-0.916</td>
<td>-0.880</td>
<td>-0.845</td>
</tr>
<tr>
<td>Inverse Dispersion</td>
<td>11.810</td>
<td>0.287</td>
<td>0.002</td>
<td>11.250</td>
<td>11.810</td>
<td>12.380</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.
Table 10.4. Full Bayesian framework with coefficient offsets for summer.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.161</td>
<td>0.042</td>
<td>0.002</td>
<td>2.073</td>
<td>2.162</td>
<td>2.240</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>0.570</td>
<td>0.006</td>
<td>0.000</td>
<td>0.558</td>
<td>0.571</td>
<td>0.582</td>
</tr>
<tr>
<td>Interstate</td>
<td>2.035</td>
<td>0.047</td>
<td>0.002</td>
<td>1.947</td>
<td>2.035</td>
<td>2.128</td>
</tr>
<tr>
<td>Freeway</td>
<td>1.583</td>
<td>0.041</td>
<td>0.002</td>
<td>1.505</td>
<td>1.583</td>
<td>1.663</td>
</tr>
<tr>
<td>Principal Arterial Pop. Density (population/mi²)</td>
<td>1.02E-05</td>
<td>8.73E-06</td>
<td>2.94E-07</td>
<td>-6.67E-06</td>
<td>1.02E-05</td>
<td>2.74E-05</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>0.174</td>
<td>0.020</td>
<td>0.001</td>
<td>0.135</td>
<td>0.174</td>
<td>0.214</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>-0.053</td>
<td>0.027</td>
<td>0.001</td>
<td>-0.106</td>
<td>-0.053</td>
<td>-0.002</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>-0.541</td>
<td>0.022</td>
<td>0.001</td>
<td>-0.584</td>
<td>-0.541</td>
<td>-0.497</td>
</tr>
<tr>
<td>Monday Midweek (Tuesday through Thursday)</td>
<td>-0.603</td>
<td>0.017</td>
<td>0.001</td>
<td>-0.637</td>
<td>-0.602</td>
<td>-0.570</td>
</tr>
<tr>
<td>Friday Inverse Dispersion</td>
<td>-0.568</td>
<td>0.023</td>
<td>0.001</td>
<td>-0.613</td>
<td>-0.567</td>
<td>-0.523</td>
</tr>
<tr>
<td>Inverse Dispersion</td>
<td>6.786</td>
<td>0.168</td>
<td>0.001</td>
<td>6.464</td>
<td>6.784</td>
<td>7.122</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.
Table 10.5. Full Bayesian Framework with Coefficient Offsets for fall.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>3.311</td>
<td>0.039</td>
<td>0.002</td>
<td>3.234</td>
<td>3.312</td>
<td>3.384</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>0.389</td>
<td>0.005</td>
<td>0.000</td>
<td>0.380</td>
<td>0.389</td>
<td>0.399</td>
</tr>
<tr>
<td>Interstate</td>
<td>2.512</td>
<td>0.038</td>
<td>0.002</td>
<td>2.437</td>
<td>2.513</td>
<td>2.585</td>
</tr>
<tr>
<td>Freeway</td>
<td>1.763</td>
<td>0.039</td>
<td>0.002</td>
<td>1.687</td>
<td>1.764</td>
<td>1.840</td>
</tr>
<tr>
<td>Principal Arterial</td>
<td>1.000</td>
<td>0.035</td>
<td>0.002</td>
<td>0.929</td>
<td>1.000</td>
<td>1.069</td>
</tr>
<tr>
<td>Population Density (population/mi²)</td>
<td>-8.38E-05</td>
<td>9.13E-06</td>
<td>2.17E-07</td>
<td>-1.02E-04</td>
<td>-8.36E-05</td>
<td>-6.63E-05</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>0.211</td>
<td>0.022</td>
<td>0.001</td>
<td>0.167</td>
<td>0.211</td>
<td>0.254</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Monday</td>
<td>-0.436</td>
<td>0.025</td>
<td>0.001</td>
<td>-0.486</td>
<td>-0.436</td>
<td>-0.386</td>
</tr>
<tr>
<td>Midweek (Tuesday through Thursday)</td>
<td>-0.451</td>
<td>0.020</td>
<td>0.001</td>
<td>-0.489</td>
<td>-0.451</td>
<td>-0.412</td>
</tr>
<tr>
<td>Friday</td>
<td>-0.378</td>
<td>0.025</td>
<td>0.001</td>
<td>-0.427</td>
<td>-0.378</td>
<td>-0.329</td>
</tr>
<tr>
<td>Inverse Dispersion</td>
<td>4.036</td>
<td>0.085</td>
<td>0.001</td>
<td>3.871</td>
<td>4.035</td>
<td>4.205</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.
Table 10.6. Full Bayesian framework with coefficient offsets for winter.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>3.141</td>
<td>0.041</td>
<td>0.002</td>
<td>3.062</td>
<td>3.142</td>
<td>3.218</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>0.593</td>
<td>0.007</td>
<td>0.000</td>
<td>0.580</td>
<td>0.593</td>
<td>0.606</td>
</tr>
<tr>
<td>Interstate</td>
<td>1.294</td>
<td>0.047</td>
<td>0.002</td>
<td>1.200</td>
<td>1.294</td>
<td>1.382</td>
</tr>
<tr>
<td>Freeway</td>
<td>0.839</td>
<td>0.042</td>
<td>0.002</td>
<td>0.754</td>
<td>0.840</td>
<td>0.917</td>
</tr>
<tr>
<td>Principal Arterial</td>
<td>0.403</td>
<td>0.035</td>
<td>0.002</td>
<td>0.332</td>
<td>0.404</td>
<td>0.473</td>
</tr>
<tr>
<td>Population Density</td>
<td>-6.97E-05</td>
<td>8.86E-06</td>
<td>2.40E-07</td>
<td>-8.72E-05</td>
<td>-6.94E-05</td>
<td>-5.28E-05</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>0.069</td>
<td>0.023</td>
<td>0.001</td>
<td>0.022</td>
<td>0.069</td>
<td>0.115</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>-0.320</td>
<td>0.029</td>
<td>0.001</td>
<td>-0.379</td>
<td>-0.319</td>
<td>-0.263</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>-0.287</td>
<td>0.046</td>
<td>0.001</td>
<td>-0.377</td>
<td>-0.286</td>
<td>-0.198</td>
</tr>
<tr>
<td>Monday Midweek (Tuesday through Thursday)</td>
<td>-0.874</td>
<td>0.020</td>
<td>0.001</td>
<td>-0.914</td>
<td>-0.873</td>
<td>-0.835</td>
</tr>
<tr>
<td>Friday Inverse Dispersion</td>
<td>-0.806</td>
<td>0.025</td>
<td>0.001</td>
<td>-0.854</td>
<td>-0.806</td>
<td>-0.757</td>
</tr>
<tr>
<td>Inverse Dispersion</td>
<td>6.005</td>
<td>0.152</td>
<td>0.001</td>
<td>5.713</td>
<td>6.002</td>
<td>6.307</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.

10.8.4 Initial Results Full Bayesian Negative Binomial Model, No Coefficient Offset

The results for model three with no offset in general have similar trends in terms of sign and magnitude when directly compared with model two, as the ADT values increase so do the predicted AADT predictions. The HPMS interstate roadway classification still has the greatest influence on AADT followed by freeway and principal arterials. ADT estimates developed in the northwest increase the AADT prediction, while southwest and southeast lower AADT estimates. The central geographic location is not significant in the spring and summer, while the northwest is not significant in the fall. The results remain consistent with the other models with the highest ADT volumes occurring during the midweek followed by Friday and Monday, which in-turn requires temporal adjustment as seen with the midweek followed by Friday and then Monday to
remains relatively similar AADT final predictions for individual segments. The lowest overall
dispersion remains the spring followed by summer, fall and winter. In comparison to model two
the inverse dispersion values are smaller and therefore these models are not as efficient as model
two.

Table 10.7. Full Bayesian framework with no coefficient offsets for spring.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.927</td>
<td>0.056</td>
<td>0.003</td>
<td>4.821</td>
<td>4.923</td>
<td>5.040</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>1.44E-04</td>
<td>4.24E-06</td>
<td>1.57E-07</td>
<td>1.36E-04</td>
<td>1.44E-04</td>
<td>1.53E-04</td>
</tr>
<tr>
<td>Interstate</td>
<td>3.250</td>
<td>0.063</td>
<td>0.003</td>
<td>3.121</td>
<td>3.253</td>
<td>3.374</td>
</tr>
<tr>
<td>Freeway</td>
<td>2.647</td>
<td>0.056</td>
<td>0.003</td>
<td>2.535</td>
<td>2.648</td>
<td>2.754</td>
</tr>
<tr>
<td>Principal Arterial Population Density (population/mi²)</td>
<td>1.913</td>
<td>0.048</td>
<td>0.002</td>
<td>1.816</td>
<td>1.914</td>
<td>2.005</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>-4.84E-05</td>
<td>1.18E-05</td>
<td>3.47E-07</td>
<td>-7.12E-05</td>
<td>-4.86E-05</td>
<td>-2.51E-05</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>0.196</td>
<td>0.030</td>
<td>0.001</td>
<td>0.136</td>
<td>0.196</td>
<td>0.254</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>-0.643</td>
<td>0.057</td>
<td>0.001</td>
<td>-0.753</td>
<td>-0.643</td>
<td>-0.531</td>
</tr>
<tr>
<td>Monday</td>
<td>-0.384</td>
<td>0.031</td>
<td>0.001</td>
<td>-0.446</td>
<td>-0.385</td>
<td>-0.322</td>
</tr>
<tr>
<td>Midweek (Tuesday through Thursday)</td>
<td>-0.498</td>
<td>0.026</td>
<td>0.001</td>
<td>-0.549</td>
<td>-0.498</td>
<td>-0.446</td>
</tr>
<tr>
<td>Friday</td>
<td>-0.423</td>
<td>0.031</td>
<td>0.001</td>
<td>-0.484</td>
<td>-0.423</td>
<td>-0.362</td>
</tr>
<tr>
<td>Inverse Dispersion</td>
<td>3.454</td>
<td>0.079</td>
<td>0.000</td>
<td>3.300</td>
<td>3.453</td>
<td>3.610</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.
Table 10.8. Full Bayesian framework with no coefficient offsets for summer.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.721</td>
<td>0.049</td>
<td>0.002</td>
<td>4.633</td>
<td>4.729</td>
<td>4.829</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>1.35E-04</td>
<td>4.07E-06</td>
<td>1.37E-07</td>
<td>1.27E-04</td>
<td>1.35E-04</td>
<td>1.43E-04</td>
</tr>
<tr>
<td>Interstate</td>
<td>3.456</td>
<td>0.057</td>
<td>0.003</td>
<td>3.341</td>
<td>3.450</td>
<td>3.563</td>
</tr>
<tr>
<td>Freeway</td>
<td>2.794</td>
<td>0.050</td>
<td>0.002</td>
<td>2.695</td>
<td>2.794</td>
<td>2.893</td>
</tr>
<tr>
<td>Principal Arterial</td>
<td>2.002</td>
<td>0.042</td>
<td>0.002</td>
<td>1.919</td>
<td>2.003</td>
<td>2.082</td>
</tr>
<tr>
<td>Population Density (population/mi²)</td>
<td>-8.98E-05</td>
<td>1.30E-05</td>
<td>3.67E-07</td>
<td>-1.15E-04</td>
<td>-8.96E-05</td>
<td>-6.46E-05</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>0.186</td>
<td>0.034</td>
<td>0.001</td>
<td>0.120</td>
<td>0.186</td>
<td>0.250</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>-0.358</td>
<td>0.039</td>
<td>0.001</td>
<td>-0.435</td>
<td>-0.357</td>
<td>-0.280</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>-0.585</td>
<td>0.062</td>
<td>0.002</td>
<td>-0.706</td>
<td>-0.585</td>
<td>-0.461</td>
</tr>
<tr>
<td>Monday</td>
<td>-0.348</td>
<td>0.033</td>
<td>0.001</td>
<td>-0.412</td>
<td>-0.348</td>
<td>-0.283</td>
</tr>
<tr>
<td>Midweek (Tuesday through Thursday)</td>
<td>-0.427</td>
<td>0.027</td>
<td>0.001</td>
<td>-0.478</td>
<td>-0.428</td>
<td>-0.375</td>
</tr>
<tr>
<td>Friday</td>
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<td>0.035</td>
<td>0.001</td>
<td>-0.438</td>
<td>-0.372</td>
<td>-0.304</td>
</tr>
<tr>
<td>Inverse Dispersion</td>
<td>3.061</td>
<td>0.071</td>
<td>0.000</td>
<td>2.922</td>
<td>3.060</td>
<td>3.203</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>5.439</td>
<td>0.040</td>
<td>0.002</td>
<td>5.361</td>
<td>5.440</td>
<td>5.518</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>1.36E-04</td>
<td>3.70E-06</td>
<td>1.20E-07</td>
<td>1.29E-04</td>
<td>1.36E-04</td>
<td>1.43E-04</td>
</tr>
<tr>
<td>Interstate</td>
<td>2.744</td>
<td>0.046</td>
<td>0.002</td>
<td>2.657</td>
<td>2.743</td>
<td>2.836</td>
</tr>
<tr>
<td>Freeway</td>
<td>2.235</td>
<td>0.045</td>
<td>0.002</td>
<td>2.150</td>
<td>2.235</td>
<td>2.322</td>
</tr>
<tr>
<td>Principal Arterial Population Density (population/mi²)</td>
<td>1.494</td>
<td>0.040</td>
<td>0.002</td>
<td>1.416</td>
<td>1.494</td>
<td>1.572</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>-8.07E-05</td>
<td>1.09E-05</td>
<td>2.53E-07</td>
<td>-1.02E-04</td>
<td>-8.07E-05</td>
<td>-5.99E-05</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>0.091</td>
<td>0.031</td>
<td>0.001</td>
<td>0.031</td>
<td>0.091</td>
<td>0.150</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>-0.431</td>
<td>0.031</td>
<td>0.000</td>
<td>-0.493</td>
<td>-0.431</td>
<td>-0.370</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>-0.439</td>
<td>0.048</td>
<td>0.001</td>
<td>-0.533</td>
<td>-0.439</td>
<td>-0.346</td>
</tr>
<tr>
<td>Monday Midweek (Tuesday through Thursday)</td>
<td>-0.339</td>
<td>0.029</td>
<td>0.001</td>
<td>-0.396</td>
<td>-0.339</td>
<td>-0.283</td>
</tr>
<tr>
<td>Friday Inverse Dispersion</td>
<td>3.055</td>
<td>0.063</td>
<td>0.000</td>
<td>2.932</td>
<td>3.055</td>
<td>3.179</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.
Table 10.10. Full Bayesian framework with no coefficient offsets for winter.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>MC Error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>5.396</td>
<td>0.064</td>
<td>0.003</td>
<td>5.270</td>
<td>5.399</td>
<td>5.517</td>
</tr>
<tr>
<td>Truck ADT Classes 4 through 13</td>
<td>1.36E-04</td>
<td>5.09E-06</td>
<td>1.68E-07</td>
<td>1.26E-04</td>
<td>1.36E-04</td>
<td>1.46E-04</td>
</tr>
<tr>
<td>Interstate</td>
<td>2.965</td>
<td>0.070</td>
<td>0.004</td>
<td>2.830</td>
<td>2.964</td>
<td>3.106</td>
</tr>
<tr>
<td>Freeway</td>
<td>2.292</td>
<td>0.064</td>
<td>0.003</td>
<td>2.166</td>
<td>2.291</td>
<td>2.417</td>
</tr>
<tr>
<td>Principal Arterial</td>
<td>1.510</td>
<td>0.059</td>
<td>0.003</td>
<td>1.395</td>
<td>1.512</td>
<td>1.623</td>
</tr>
<tr>
<td>Population Density</td>
<td>-1.33E-04</td>
<td>1.36E-05</td>
<td>3.79E-07</td>
<td>-1.59E-04</td>
<td>-1.33E-04</td>
<td>-1.06E-04</td>
</tr>
<tr>
<td>Northwest Ohio</td>
<td>0.136</td>
<td>0.037</td>
<td>0.001</td>
<td>0.062</td>
<td>0.136</td>
<td>0.207</td>
</tr>
<tr>
<td>Central Ohio</td>
<td>0.179</td>
<td>0.042</td>
<td>0.001</td>
<td>0.098</td>
<td>0.178</td>
<td>0.261</td>
</tr>
<tr>
<td>Southwest Ohio</td>
<td>-0.558</td>
<td>0.043</td>
<td>0.001</td>
<td>-0.644</td>
<td>-0.557</td>
<td>-0.473</td>
</tr>
<tr>
<td>Southeast Ohio</td>
<td>-0.579</td>
<td>0.069</td>
<td>0.002</td>
<td>-0.713</td>
<td>-0.581</td>
<td>-0.442</td>
</tr>
<tr>
<td>Monday</td>
<td>-0.271</td>
<td>0.037</td>
<td>0.001</td>
<td>-0.343</td>
<td>-0.271</td>
<td>-0.199</td>
</tr>
<tr>
<td>Midweek (Tuesday through Thursday)</td>
<td>-0.412</td>
<td>0.030</td>
<td>0.001</td>
<td>-0.470</td>
<td>-0.412</td>
<td>-0.353</td>
</tr>
<tr>
<td>Friday</td>
<td>-0.332</td>
<td>0.037</td>
<td>0.001</td>
<td>-0.405</td>
<td>-0.333</td>
<td>-0.260</td>
</tr>
<tr>
<td>Inverse Dispersion</td>
<td>2.612</td>
<td>0.063</td>
<td>0.000</td>
<td>2.490</td>
<td>2.612</td>
<td>2.738</td>
</tr>
</tbody>
</table>

Notes: All variables are statistically significant at the 95% confidence level, N/A suggests that this variable is not statistically significant in the final model.

10.9 Comparison of Results

The final comparison of the model performance for each of the three model frameworks are shown in Figures 10.1 through 10.4. In each case the models developed with the training data sets are then compared with the AADTs provided by the validation data set. As described previously the training and the validation data sets for each season are both developed randomly and no data are used in both data sets. In each of the four figures the x-axis is the validation data set AADTs for vehicle classes 4 through 13 and the y-axis is the predicted AADTs from each of the three models.
10.9.1 Spring Results

The results for the three models developed for spring 2005 through 2007 are shown in Figure 10.1. The results show model one under predicts the AADT by 4%, while model three over predicts by 20%. The overall explanation of the variability within the validation data set by the prediction models ranges from 70% to 91%. When comparing the negative binomial models, model two with the ADT offset performs better than model three. Model three does not have an ADT offset and the predicted AADTs are significantly over estimated when the AADTs are greater than 10,000 veh/day. In terms of model selection, the impact of the ADT offset is diminished as the predicted AADTs are lowered.

Figure 10.1. Comparison of the spring model results.
10.9.2 Summer Results

The results for the summer are shown below in Figure 10.2. Models one and two slightly under predict by 4% and 9% respectively, while model three on average over predicts by 26%. This over prediction is influenced by the ADT values. The model ability to describe the variability within the validation data set range from 70%, model three to 92% for models one and two.

![Figure 10.2. Comparison of the summer model results.](image)

10.9.3 Fall Results

The results from the fall, Figure 10.3, show models one and two both under predict the AADTs by 7% and 5%. In both cases the $R^2$ values are 0.93 and 0.95. The results for model three explains 70% of the variability and on average are closer in prediction over predict by 6% with
the validation data set AADTs. The overall results show less variability between the three models as well as the three other seasons.

Figure 10.3. Comparison of the fall model results.

10.9.4 Winter Results

The final seasonal comparison of the data is shown below in Figure 10.4 for the winter. The overall findings remain consistent with the spring and summer seasons. Models one and two predict similar values with model one under estimating the AADT by 4% and model two over predicting the AADT value by 1%. In both cases the average prediction values are a good fit with the validation data set. Model three still over predicts on average by 23%, and the ability to explain 72% of the variability within the validation data set.
The final summary of the three model performance evaluations are provided within Table 10.11. There are two sets of results from this table. The first set of results show the percentage of predicted heavy-duty AADTs that are within 10% of the validation data set AADTs per season. The overall result shows model two has the highest percentage of values within 10% of the actual value for all seasons. The results when comparing models one and three are mixed. Model three performs slightly better for the spring and summer months while model one is more efficient in prediction for the fall and winter. In general there are less variables required in model three than model one. All three models have the overall highest accuracy rating for the spring season, while the lowest predicting accuracy varies per model across the other three seasons.

Other results stem from the inclusion of the offset as shown in model two. Model two with the offset has less variation with an overall improvement of 5% to 10% over the non-offset model,
model three. The inverse dispersion term is higher, better performance, for all negative binomial models with coefficient offsets, model two, than model three with no coefficient offsets. Other findings include higher inverse dispersion parameters for the spring followed by the summer for both models two and three while the fall and winter provide lower inverse dispersion values.

Table 10.11. Summary of the model performance.

<table>
<thead>
<tr>
<th></th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model One</td>
<td>20.1%</td>
<td>19.7%</td>
<td>18.6%</td>
<td>19.1%</td>
</tr>
<tr>
<td>Model Two</td>
<td>33.9%</td>
<td>20.7%</td>
<td>21.1%</td>
<td>22.7%</td>
</tr>
<tr>
<td>Model Three</td>
<td>22.4%</td>
<td>21.7%</td>
<td>16.7%</td>
<td>15.0%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model One</td>
<td>9.8%</td>
<td>12.9%</td>
<td>8.3%</td>
<td>8.7%</td>
</tr>
<tr>
<td>Model Two</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Model Three</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: The predicted values may be +/- 10%.

Additional findings show the influence of the model framework between the ordinary least squares regression model and the two negative binomial models. In the case of model one for each season the individual models predict negative heavy-duty truck AADTs for approximately 8% to 13% of the total number of observations, while the negative binomial models on the other hand predict no AADTs less than zero. The negative predictions show the potential limitations when using ordinary least squares regression.

10.10 Final Comparison of All Methods - Summary of Results

This section provides the final comparison of the following six methods examined in this research study to estimate AADT: 1) Traditional Method based on functional classification; 2) Discriminant Analysis; 3) “COV approach”; 4) Ordinary least square regression; 5) Bayesian negative binomial with offset; and 6) Bayesian negative binomial without offset. The DA and the “COV approach” are based on factor groupings determined applying geographical classification.
and cluster analysis. The last three statistical models produce AADT predictions directly from the input data, avoiding the “factoring” and the “grouping” process of the first three techniques.

Seasonal adjustment factors calculated for total volume, both directions of a road, are used in each method. The data set described in section 10.2 was used for all methods to generate two performance measurements: the MAE (Equation 6.10), and the standard deviation of the MAE (Equation 6.11). The results are presented in Table 10.12.

Table 10.12. MAE and SDAE for all methods.

<table>
<thead>
<tr>
<th></th>
<th>Traditional Method</th>
<th>COV Approach</th>
<th>Discriminant Analysis</th>
<th>Ordinary Least Square Regression</th>
<th>Bayesian Neg. Bin. with Offset</th>
<th>Bayesian Neg. Bin. without Offset</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE (%)</td>
<td>25.01</td>
<td>17.50</td>
<td>19.82</td>
<td>106.71</td>
<td>34.02</td>
<td>73.27</td>
</tr>
<tr>
<td>SDAE</td>
<td>27.81</td>
<td>18.42</td>
<td>22.42</td>
<td>423.04</td>
<td>43.55</td>
<td>133.64</td>
</tr>
</tbody>
</table>

It is obvious from the above table that the first three methods result in lower errors than the three models described in Chapter X. The lowest MAE (17.50%) and SDAE (18.42) are produced from the “COV approach”, followed by the DA and the traditional method. On the other hand, the regression model yields the highest MAE (106.71%) and SDAE (423.04). It can be concluded that the two non-traditional methods described in the previous chapters produce more accurate estimates of heavy-duty traffic than the traditional approach and outperform the three predictive models examined within this chapter. Chapter XI provides conclusions and recommendations derived from the analyses conducted in this study.
CHAPTER XI
CONCLUSIONS AND RECOMMENDATIONS

11.1 Introduction

Chapter XI provides the main findings of this research study. An extensive data set, collected continuously from sites in the state of Ohio, is used to investigate new methods in order to improve the AADT predictions. Accurate seasonal adjustment factors and improvements in the traditional process of estimating AADT are the main objectives of this study and are important issues for researchers and practitioners in traffic studies. Conclusions are presented with regards to the following subject matters: 1) improving the estimation of seasonal adjustment factors; 2) recommendations for the development of factor groupings; 3) alternatives for the assignment of short-term counts to factor groupings; 4) other techniques for estimating AADT; and 5) areas for future research. A brief description of each task along with recommendations, derived from the assessment of the results and current practice, are provided in the following sections.

11.2 Estimation of Seasonal Adjustment Factors

This section includes the main conclusions drawn from the following analyses conducted within the “factoring” step: 1) estimation of AADT using five approaches; 2) impact on AADT by developing different vehicle groupings; 3) comparison between multiple SAFs and individual SAFs; 4) determination of best months to collect truck data; and 5) impact on AADT of the length and the timing of a short-term count.
11.2.1 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. According to the findings of the analysis which 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 only 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).

11.2.2 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 have higher values of the mean absolute errors in comparison to aggregate vehicle classes. Comparatively more accurate AADT predictions are obtained by applying SAFs to 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; classes with low truck traffic. In cases where vehicle classes carry less traffic than the heavy traffic classes, the individual vehicle volumes are low. The small sample size results in an increased mean absolute error, especially when compared with more common vehicle types with larger sample sizes. 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. In general, the more groups of vehicle classes examined, the higher the predicted errors.

11.2.3 Multiple Factors

The analysis includes two scenarios: 1) application of one seasonal adjustment factor to all functional classes and; 2) use of multiple factors. In the first scenario the three best performing factors \(F_{WADT}, F_{MAWDT} \) and \(F_{MADT}\) are examined. 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.

11.2.4 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 error. 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 can be drawn from the final comparison that the ATR data set generally produces less error than the corresponding WIM data set. This difference in the performance may be due to the different operating systems of the two recorders.
11.2.5 Day of the Week and Sampling Duration for the Short-Term Data Collection

Two objectives are examined within this part of the study: 1) how the length of a short-term count affects the AADT; 2) what is the impact on the AADT when a short-term count is conducted on different weekdays within a week. The results from the day of the week and duration of the short-term data collection analysis are that 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. 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 that Mondays produce the highest mean absolute errors, followed by Tuesdays and Thursdays. Wednesdays have the lowest errors of the week. A careful selection of the length and the beginning weekday of the short-term count is recommended.

11.3 Development of Factor Groupings

There is a significant amount of disagreement 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 6, 7 and 8), the variation within each cluster and the required computational time increases. The advantage of the combined grouping techniques is the
identification of specific characteristics such as functional class, geographical region, and seasonal traffic patterns. These characteristics allow for a simple and efficient assignment of short-term counts to factor groupings. Finally, the combination of a geographical classification and clustering is recommended to produce factor groupings for the state of Ohio.

The second set of results is developed to address 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. In this research, many of the cluster groupings have less than three stations per cluster. In some cases a cluster is populated with only one station, violating suggestions provided within the TMG. The second main disadvantage of clustering is temporal instability within each cluster. Stations have different cluster membership from year to year. The reason for this is the overall dynamic nature of the roadway network. Record must be taken for how the stations change clusters both annually and as the number of cluster groupings increases. In essence, 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 by the practitioner. As a result, stations with similar characteristics are only required to have one of the stations to remain in function. New factor groupings are recommended to be created every year.

11.3.1 Determination of the optimal number of clusters

An important contribution of the study to this particular research area is the innovative method for determining the optimal number of clusters. Based on recommendations and findings
of past research, a mathematical process is deployed in order to determine the most effective factor groupings. The recommended approach is data-driven and statistically based. It minimizes the engineering judgment and eliminates the human factor; the main disadvantages of non-hierarchical cluster analysis. The recommended approach allows the analyst to add potential elements to it and adjust it to his needs.

11.4 Assignment of Short-Term Counts to Factor Groupings

The assignment of short-period counts to factor groupings is the last and most critical step of the AADT estimation process. The following two subsections include the findings from the two assignment methods examined, the discriminant analysis and the COV approach, against the traditional method.

11.4.1 Discriminant Analysis

Discriminant analysis is the third method examined to assign short-period counts to factor groups. Eight models are developed using two parameters: hourly factors and the average daily traffic volume. The results from the comparison of the four sets of factors show that a set of twenty-four hourly factors produces better results than a set of twelve, eight or six factors. The evaluation of the two parameters shows that the hourly factors improve the accuracy of the assignment models and reduces the variation of the results. The lowest errors are produced by Model Five, which includes the 24 hourly factors.

The comparison between total two-way and the directional volume-based factors reveals that the latter produces more accurate estimates. The SD of the estimated AADTs is also improved at the same extent.

It can also be concluded from the final comparison of the discriminant analysis against the traditional assignment, that DA improves the accuracy of the estimates. The temporal analysis
conducted within this task verifies the validity of the results over time for both total and directional volume factors.

11.4.2 COV Method

A statistically-based method, consisting of seven steps, was developed assigning short-term counts to factor groupings. This innovative method is data-driven and eliminates engineering judgment. Forty-four models are developed that take into account two parameters: hourly factors and average daily volumes. The first objective includes the comparison of the most effective set of factors. From this research four factor methodologies are developed which include twenty-four 1-hour, twelve 2-hour, eight 3-hour, and six 4-hour time of day factors. The results show that twenty-four hourly factors are more effective than a set of twelve, eight or six aggregate factors. The second conclusion is developed based on the model development. The most effective models place more weight on the average COV of the time of day factors than the COV of the ADT. This finding is plausible because the time of day factors provide a more exact account of the variability within the traffic stream than the single ADT value.

The comparison between the total and the directional factor analyses show that the directional-based models may assign short-term counts to groups approximately 40% more accurately than those of the total volume analysis. Two potential explanations for this finding are: 1) the statistical difference between the two directions; and 2) the doubling sample size, which in turn yields more factor groupings. As a result, when the number of groups increases, the possibility to assign a short-term count to a group that has similar traffic patterns and ADT increases.

From the last comparison between the traditional method against the DA and the recommended approach, it can be concluded that the most efficient model is the COV approach, (directional model one using 24 1-hour factors). It improves dramatically the accuracy in
comparison to the other two methods. When the COV is used instead of the traditional method, the equivalent MAE and SDAE percentage improvement is 51.75% and 67.73%, respectively. These are the most important findings of the study. More accurate AADT predictions are obtained using the above assumptions and combinations of techniques.

Figure 11.1 shows the range and the percentage of the absolute difference of the AADT estimates obtained from the COV approach and the traditional method. It is obvious that 65% of the short-term counts predictions differ by 250 vehicles between the two methods. Fifteen percent of the predictions fall within a range of 250-500 vehicles, whereas the remaining 20% of the short-term counts give a difference of 500 or more vehicles. These results express the real absolute difference of the outcomes produced from the traditional and the proposed method.

Figure 11.1. Range and percentage of the absolute AADT difference between the COV approach and the traditional method for total volume using directional factors.
In Figure 11.2 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.

![Graph showing percentage of AADT difference between COV approach and traditional method.]

**Figure 11.2.** Percentage of the AADT difference between the COV approach and the traditional method for total volume using directional factors.

It can be concluded from Figure 11.1 and Figure 11.2 that a small amount of the final estimates differs 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 corresponding graphs for light duty vehicles, heavy-duty vehicles and two-way volume factors are presented in Appendix H. The more accurate AADTs improve current practice and may impact transportation agencies that use it in their programs. The better predictions may also affect positively other scientific areas, since the AADT is being used diversely by practitioners, researchers, consultants, companies, and many non-transportation related industries.
11.5 Other Techniques for Estimating AADT

Three modeling frameworks were developed to predict the annual average daily traffic for a segment of highway: 1) ordinary least squares regression, 2) full Bayesian negative binomial model without coefficient offset, and 3) full Bayesian negative binomial model with coefficient offset. The random separation of the training and validation data sets for each season of the year allows for a non-biased assessment of the prediction capabilities developed per season for each of the models. Parameters of significance were found to be the HPMS roadway functional classification, the population density, the spatial location and the average daily traffic. The three models show that the increase in ADT yields an increase in the predicted AADTs. The HPMS roadway classifications show the interstate indicator variable has the greatest influence followed by freeway and principal arterial on AADTs. Northern samples over southern areas increase AADT estimates. The negative binomial model with an offset performed the best, while the other two models had mixed results. The offset limits the variation as seen in model three with the higher ADTs and therefore produces more accurate results. The final conclusion is that the limitations with model one is the prediction of negative AADTs. In this study, model one predicted negative values approximately 10% of the time for each season, while the negative binomial by nature does not predict negative values. The comparison of the models shows that the negative binomial model with the offset is more efficient that the other two models; however the final comparison of all methods of the study reveals that the COV approach and the discriminant analysis outperform the traditional method and the three predictive models examined in Chapter X.
11.6 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: 1) the cleaning and organization of the data obtained from the continuous recorders located within this particular geographical part; 2) the estimation of seasonal adjustment factors for each station; 3) 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; 4) the application of the “COV Approach”, developed in this study, to assign the short-term count to one of the groups defined in the previous step; 5) 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.

11.7 Future Research

The traditional method of estimating AADT has been used for many years but there are several areas that have yet to be further examined. One potential subject that needs to be addressed is the determination of the minimum required number of days or hours with available data, in order to estimate the AADT and other average traffic volumes such as the ADT, the WADT, the MADT and the MAWDT. Sensitivity analyses need to be conducted to investigate how the minimum required number of days/hours affects the final predictions. In past research and current practice there are not any available efforts or guidelines to clarify this subject. DOTs or other transportation agencies need to establish their own criteria in order to determine the above volumes, which impact the values and the accuracy of the seasonal adjustment factors.

Another potential research field that needs to be investigated is how statistical measurements of determining the optimal number of clusters may incorporate traffic parameters.
The Bayesian Information Criterion (BIC) and the Cubic Clustering Criterion (CCC), included in SAS software, may be used for this purpose (SAS, 1999). The use of genetic algorithms or the development of a fuzzy logic decision tree may be another possible solution to this subject. The use of logistic regression, more discriminant algorithms and parameters to assign short-term counts to factor groupings is another future topic for consideration. The quantification of the performance of different statistical methods and a potential comparison with other assignments’ approaches will reveal the magnitude of their effectiveness.

The above recommendations including the future topics of 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 dissertation. Guidelines and new specifications may also be defined based on the previous results.


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

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

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

<table>
<thead>
<tr>
<th>Class One</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Motorcycles. All two-wheeled or three-wheeled motorized vehicles. Typical</td>
</tr>
<tr>
<td></td>
<td>vehicles in this category have saddle type seats and are steered by handle</td>
</tr>
<tr>
<td></td>
<td>bars rather than wheels. This category includes motorcycles, motor scooters,</td>
</tr>
<tr>
<td></td>
<td>mopeds, motor-powered bicycles, and three-wheeled motorcycles.</td>
</tr>
<tr>
<td>2.</td>
<td>Passenger Cars. All sedans, coupes, and station wagons manufactured</td>
</tr>
<tr>
<td></td>
<td>primarily for the purpose of carrying passengers and including those</td>
</tr>
<tr>
<td></td>
<td>passenger cars pulling recreational or other light trailers.</td>
</tr>
</tbody>
</table>

Class Two

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passenger Cars. All sedans, coupes, and station wagons manufactured</td>
</tr>
<tr>
<td>primarily for the purpose of carrying passengers and including those</td>
</tr>
<tr>
<td>passenger cars pulling recreational or other light trailers.</td>
</tr>
</tbody>
</table>
Table A.5. FHWA vehicle classification scheme (continued).

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class Three</td>
<td>Other Two-Axle, Four-Tire, Single Unit Vehicles. all two-axle, four-tire,</td>
</tr>
<tr>
<td></td>
<td>vehicles other than passenger cars. Included in this classification are</td>
</tr>
<tr>
<td></td>
<td>pickups, panels, vans, and other vehicles such as campers, motor homes,</td>
</tr>
<tr>
<td></td>
<td>ambulances, hearses, carryalls, and minibuses. Other two-axle, four-tire</td>
</tr>
<tr>
<td></td>
<td>single unit vehicles pulling recreational or other light trailers are</td>
</tr>
<tr>
<td></td>
<td>included in this classification.</td>
</tr>
<tr>
<td>Class Four</td>
<td>Buses. all vehicles manufactured as traditional passenger-carrying buses</td>
</tr>
<tr>
<td></td>
<td>with two axles and six tires or three or more axles. This category includes</td>
</tr>
<tr>
<td></td>
<td>only traditional buses (including school buses) functioning as passenger-</td>
</tr>
<tr>
<td></td>
<td>carrying vehicles. Modified buses should be considered to be trucks and be</td>
</tr>
<tr>
<td></td>
<td>appropriately classified.</td>
</tr>
<tr>
<td>Class Five</td>
<td>Trucks. all vehicles on a single frame including trucks, camping and</td>
</tr>
<tr>
<td></td>
<td>recreational vehicles, motor homes, etc., having three axles.</td>
</tr>
<tr>
<td>Class Six</td>
<td>Three Axle Single Unit Trucks. all trucks on a single frame with three</td>
</tr>
<tr>
<td></td>
<td>axles.</td>
</tr>
<tr>
<td>Class Seven</td>
<td>Four or More Axle Single Unit Trucks. all trucks on a single frame with four</td>
</tr>
<tr>
<td></td>
<td>or more axles.</td>
</tr>
<tr>
<td>Class Eight</td>
<td>Four or Less Axle Single Trailer Trucks. all vehicles with four or less</td>
</tr>
<tr>
<td></td>
<td>axles consisting of two units, one of which is a tractor or straight truck</td>
</tr>
<tr>
<td></td>
<td>power unit.</td>
</tr>
<tr>
<td>Class Nine</td>
<td>Five-Axle Single Trailer Trucks. all five-axle vehicles consisting of two</td>
</tr>
<tr>
<td></td>
<td>units, one of which is a tractor or straight truck power unit.</td>
</tr>
<tr>
<td>Class Ten</td>
<td>Six or More Axle Single Trailer Trucks. All vehicles with six or more</td>
</tr>
<tr>
<td></td>
<td>axles consisting of two units, one of which is a tractor or straight truck</td>
</tr>
<tr>
<td></td>
<td>power unit.</td>
</tr>
<tr>
<td>Class Eleven</td>
<td>Five or Less Axle Multi-TRailer Trucks. all vehicles with five or less</td>
</tr>
<tr>
<td></td>
<td>axles consisting of three or more units, one of which is a tractor or</td>
</tr>
<tr>
<td></td>
<td>straight truck power unit.</td>
</tr>
<tr>
<td>Class Twelve</td>
<td>Six-Axle Multi-TRailer Trucks. all six-axle vehicles consisting of three or</td>
</tr>
<tr>
<td></td>
<td>more units, one of which is a tractor or straight truck power unit.</td>
</tr>
<tr>
<td>Class Thirteen</td>
<td>Seven or More Axle Multi-TRailer Trucks. all vehicles with seven or more</td>
</tr>
<tr>
<td></td>
<td>axles consisting of three or more units, one of which is a tractor or</td>
</tr>
<tr>
<td></td>
<td>straight truck power unit.</td>
</tr>
<tr>
<td>Class Fourteen</td>
<td>Class fourteen is defined by ODOT personnel for special studies.</td>
</tr>
<tr>
<td>Class Fifteen</td>
<td>Class fifteen will, by default, identify any vehicle which does not</td>
</tr>
<tr>
<td></td>
<td>conform to the classification criteria for Class 1 through Class 14.</td>
</tr>
</tbody>
</table>

Note. The data provided in this table is based on the FHWA vehicle classification descriptions. (FHWA, 2001, TMG Section 4).
Table A.6. 60-minute 4-card sample of the format provided by the TKO.

<table>
<thead>
<tr>
<th>Item</th>
<th>Columns</th>
<th>Width</th>
<th>Alpha/Numeric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
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<td>1–1</td>
<td>1</td>
<td>A</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
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<td>39</td>
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<td>N</td>
<td>FC</td>
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<td>Station Number</td>
</tr>
<tr>
<td>5</td>
<td>9–9</td>
<td>1</td>
<td>N</td>
<td>Dir.</td>
</tr>
<tr>
<td>6</td>
<td>10–11</td>
<td>2</td>
<td>N</td>
<td>YY</td>
</tr>
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<td>12–13</td>
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<td>N</td>
<td>MM</td>
</tr>
<tr>
<td>8</td>
<td>14–15</td>
<td>2</td>
<td>N</td>
<td>DD</td>
</tr>
<tr>
<td>9</td>
<td>16–17</td>
<td>2</td>
<td>N</td>
<td>HH</td>
</tr>
<tr>
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<td>18–19</td>
<td>2</td>
<td>N</td>
<td>Class 1</td>
</tr>
<tr>
<td>11</td>
<td>20–23</td>
<td>4</td>
<td>N</td>
<td>Class 2</td>
</tr>
<tr>
<td>12</td>
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<td>Class 4</td>
</tr>
<tr>
<td>14</td>
<td>29–31</td>
<td>3</td>
<td>N</td>
<td>Class 5</td>
</tr>
<tr>
<td>15</td>
<td>32–33</td>
<td>2</td>
<td>N</td>
<td>Class 6</td>
</tr>
<tr>
<td>16</td>
<td>34–35</td>
<td>2</td>
<td>N</td>
<td>Class 7</td>
</tr>
<tr>
<td>17</td>
<td>36–37</td>
<td>2</td>
<td>N</td>
<td>Class 8</td>
</tr>
<tr>
<td>18</td>
<td>38–40</td>
<td>3</td>
<td>N</td>
<td>Class 9</td>
</tr>
<tr>
<td>19</td>
<td>41–42</td>
<td>2</td>
<td>N</td>
<td>Class 10</td>
</tr>
<tr>
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<td>43–44</td>
<td>2</td>
<td>N</td>
<td>Class 11</td>
</tr>
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<td>21</td>
<td>45–46</td>
<td>2</td>
<td>N</td>
<td>Class 12</td>
</tr>
<tr>
<td>22</td>
<td>47–48</td>
<td>2</td>
<td>N</td>
<td>Class 13</td>
</tr>
<tr>
<td>23</td>
<td>49–49</td>
<td>1</td>
<td>N</td>
<td>Motorcycle indicator</td>
</tr>
<tr>
<td>24</td>
<td>50–50</td>
<td>1</td>
<td>N</td>
<td>V-class combo</td>
</tr>
<tr>
<td>25</td>
<td>51–51</td>
<td>1</td>
<td>N</td>
<td>Lane</td>
</tr>
<tr>
<td>26</td>
<td>52–80</td>
<td>31</td>
<td>A</td>
<td>Optional State data</td>
</tr>
</tbody>
</table>
Table A.7. C-card “Raw data” file example in Microsoft SQL.

| C390001531105042212013110000000897002120000400028001600010001001500124000100002000000002 0600112011300 6 |
| C390001531105042212011020000000811001760001000200000004000200001000072000200020000100001 0600112011300 6 |
| C39000153110504221201005111000000024000084000000000000000100000000000000100000000000000000001 0600112011300 6 |
| C39000153110504221201279000000094100163000000032000210001000100000000100000000000000000000 0600112011300 6 |
| C390001531105042212011020000000811001760001000200000004000200001000072000200020000100001 0600112011300 6 |
| C390001531105042212010051110000000024000084000000000000000100000000000000100000000000000000001 0600112011300 6 |
| C39000153110504221201279000000094100163000000032000210001000100000000100000000000000000000 0600112011300 6 |
| C390001531105042212011020000000811001760001000200000004000200001000072000200020000100001 0600112011300 6 |
| C390001531105042212010051110000000024000084000000000000000100000000000000100000000000000000001 0600112011300 6 |
| C39000153110504221201279000000094100163000000032000210001000100000000100000000000000000000 0600112011300 6 |
| C390001531105042212011020000000811001760001000200000004000200001000072000200020000100001 0600112011300 6 |
| C390001531105042212010051110000000024000084000000000000000100000000000000100000000000000000001 0600112011300 6 |
| C39000153110504221201279000000094100163000000032000210001000100000000100000000000000000000 0600112011300 6 |
| C390001531105042212011020000000811001760001000200000004000200001000072000200020000100001 0600112011300 6 |
| C390001531105042212010051110000000024000084000000000000000100000000000000100000000000000000001 0600112011300 6 |
| C39000153110504221201279000000094100163000000032000210001000100000000100000000000000000000 0600112011300 6 |
| C390001531105042212011020000000811001760001000200000004000200001000072000200020000100001 0600112011300 6 |
| C390001531105042212010051110000000024000084000000000000000100000000000000100000000000000000001 0600112011300 6 |
| C39000153110504221201279000000094100163000000032000210001000100000000100000000000000000000 0600112011300 6 |
| C390001531105042212011020000000811001760001000200000004000200001000072000200020000100001 0600112011300 6 |
| C390001531105042212010051110000000024000084000000000000000100000000000000100000000000000000001 0600112011300 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
C  39 153 5 4 5 4 22 19 666 0 549 56 1 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
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
```
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

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).
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.

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.

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SAF PER MONTH AND FUNCTIONAL CLASS

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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
ANN  Artificial Neural Network
APE  Absolute Percent Error
ARIMA Autoregressive Integrated Moving Average
ART  Adaptive Resonance Theory
ATR  Automatic Traffic Recorder
ATRG  Automatic Traffic Recorder Group
CNT  Coordinated Network Test
COV  Coefficient of Variation
DA  Discriminant Analysis
DF  Daily Flow
<table>
<thead>
<tr>
<th>Abbreviation</th>
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<tr>
<td>DOT</td>
<td>Department of Transportation</td>
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<tr>
<td>EA</td>
<td>Effectiveness of Assignment</td>
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<tr>
<td>EAADT</td>
<td>Effective Annual Average Daily Traffic</td>
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<tr>
<td>FHWA</td>
<td>Federal Highway Administration</td>
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<tr>
<td>FC</td>
<td>Functional Class</td>
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<tr>
<td>FI</td>
<td>Flow Increments</td>
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<tr>
<td>GA</td>
<td>Genetic Algorithms</td>
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<td>GIS</td>
<td>Geographic Information Systems</td>
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<tr>
<td>GML</td>
<td>Gaussian Maximum Likelihood</td>
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<tr>
<td>HPMS</td>
<td>Highway Performance Monitoring System</td>
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<td>HSM</td>
<td>Highway Safety Manual</td>
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<td>IAE</td>
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<tr>
<td>ITS</td>
<td>Intelligent Transportation Systems</td>
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<tr>
<td>LOS</td>
<td>Level of Service</td>
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<td>MAE</td>
<td>Mean Absolute Error</td>
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<td>MAWDT</td>
<td>Monthly Average Weekday Daily Traffic</td>
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<td>MDT</td>
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<td>MPO</td>
<td>Metropolitan Planning Organization</td>
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<td>MS</td>
<td>Microsoft</td>
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<td>MSE</td>
<td>Mean Squared Error</td>
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<td>Description</td>
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<tr>
<td>NLFID</td>
<td>Network Linear Feature Identification</td>
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<td>NN</td>
<td>Neural Network</td>
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<td>QA/QC</td>
<td>Quality Assurance Quality Control</td>
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<td>ODOT</td>
<td>Ohio Department of Transportation</td>
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<td>PTC</td>
<td>Permanent Traffic Counters</td>
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<td>RAF</td>
<td>Reciprocal of the Adjustment Factors</td>
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<td>RAMP</td>
<td>Responsible Alcohol Management Program</td>
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<td>RI</td>
<td>Roadway Inventory</td>
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<td>SAF</td>
<td>Seasonal Adjustment Factor</td>
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<td>Standard Deviation</td>
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<td>Structured Query Language</td>
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<td>Time Delay Neural Network</td>
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<td>VIF</td>
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<tr>
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<td>Weighted Coefficient of Variation</td>
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<tr>
<td>WIM</td>
<td>Weigh in Motion</td>
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