UTILIZATION OF KNOWLEDGE-BASED EXPERT SYSTEMS TO ENHANCE THE DECISION MAKING IN STATES' TRAFFIC MONITORING PROGRAMS – A FOCUS ON TRAFFIC PATTERN GROUP ANALYSIS

by

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ABSTRACT

Traffic monitoring is one of the primary activities of state highway agencies. A reliable estimation of the traffic is vital for the management and future planning of the roadways, and as well as the apportionment of the federal funding. Traffic Monitoring Program in states is responsible for collecting, storing, processing, and disseminating the traffic data. Determination of volume and vehicle classification trends, utilization of appropriate MADT and AADT estimation methods, establishment of Traffic Pattern Groups (TPG) and use of the adjustment factors to expand the short duration counts are some of the primary activities within states' traffic monitoring program.

DelDOT Traffic Monitoring Program has been evaluated and updated to establish the TPGs and derive the adjustment factors to represents the current traffic conditions in Delaware. Analysis of data revealed few problems that should be addressed (i.e. adjustment factors are sometimes not properly used, and TPGs are not regularly evaluated/updated). Additionally, a national level survey conducted to understand the issues and challenges that state highway agencies facing in collecting and processing of state traffic monitoring data, specifically continuous and short-duration data. Both survey responses and DelDOT analysis results have shown that a Knowledge-based Expert System (KBES) application can contribute to states' traffic monitoring program by informing and guiding the user to improve the traffic monitoring related decisions.

The primary objective of this study was to develop a KBES application, called TMDEST, for providing assistance and decision support tool to the transportation

agencies in states' traffic monitoring programs, specifically in TPG analysis. TMDEST asks focused and relevant questions to the user and provide situation-specific advice in six modules. In some modules, the user is asked to provide numerical input such as the number of stations and coefficient of variation value if available.

Class/Weight Trend Module is designed to guide the user to identify the most important vehicle classes and the trucks that exert the most weight by using FHWA's VTRIS W-Tables. MADT/AADT Methods Module and TPG Methods Module are designed to inform the user regarding the major MADT/AADT estimation methods and TPG analysis methods to recommend the most appropriate methods based on the presence and amount of missing data and the inclusion of temporal variations. TPG Groups Module provides an approximate estimation of TPGs based on roadway functional classification and seasonal variation. Sample Size Estimation Module is designed to test the number of continuous count stations in each TPG for statistical significance. Lastly, Adjustment Factors Module incorporates all possible adjustment factors and evaluates the necessity of the use by asking multiple-choice questions to the end user regarding the extent of the collected short duration data.

Overall evaluation of the TMDEST revealed that each module well satisfies the design specifications, and in general, the developed tool (1) informs and guides the user regarding the methods and procedures, (2) provides an approximate method for establishing TPGs. Additionally, verification, validation, and evaluation of the TMDEST showed that the expert system based tool was built right and does the job that it intends to do. Utilization of an expert system development tool (Exsys Corvid® Core) significantly expedited to the verification and validation process. The simple

proof method was used to evaluate each module for completeness, consistency, and correctness. Although the majority of the content in the knowledge base was obtained from FHWA’s traffic monitoring guide, simple true/false test was applied to the modules where the content was partially generated to validate the knowledge base. TMDEST and each module are considered as valid and applicable tool in states traffic monitoring program. Lastly, a discussion of further work is provided to improve the extent of the TMDEST in states’ traffic monitoring program.

Chapter 1

INTRODUCTION

1.1 Background

Traffic monitoring is the process of observing and collecting data that describes the use and performance of the roadway system. Strong and effective traffic monitoring program not only increases the mobility on roadways and the reliability of corresponding decisions, but also makes sure states are receiving appropriate federal funding. Data collection and analysis of the volume, vehicle classification and truck weights on the roadways are the main tasks of the traffic monitoring program in each state. Additionally, many other traffic measures such as travel time, speed, and non-motorized traffic, etc. are used for planning and operational purposes. Federal Highway Administration (FHWA) requires states to report traffic data (volume, vehicle classification, and truck weight) on a regular basis as explained in the Highway Performance Monitoring System (HPMS) *(1, 2)*. Additionally, speed and non-motorized traffic data are becoming more available and expected to be included in federal reporting in the near future. In addition to federal requirements, states also utilize collected traffic data in many operational, planning and decision-making processes.

Guidelines prepared by federal and state level agencies are the primary sources for traffic monitoring programs in states. Although traffic data reporting requirements are clear and straightforward, specifically in the HPMS reporting, obtaining and processing the required data can be difficult. Some of the primary factors affecting the data obtaining and processing can be named as receiving, processing and understanding of huge data sets; quickly evolving traffic detection technologies; rapidly changing computing and communication technologies; and economic, environmental and geographic constraints for data collection. States are required to develop their own traffic monitoring system based on their needs, priorities and limitations in addition to federal requirements.

The goal of any traffic monitoring program is to obtain complete and continuous data (7/24 in 365 days) on every segment of roadways, which is unrealistic and unaffordable in the current technology and infrastructure settings. At this point, it is extremely important to collect statistically enough and accurate traffic data that represents traffic measures on all roadways in the study area or state. For this reason, grouping of the roadways that have similar traffic patterns, and generating correction factors for each roadway group by using continuous (permanent) count stations will help to expand the short-duration (coverage) counts to yearly averages. In this way, states are able to balance continuous and short-duration count programs to collect reliable and cost-effective traffic data. However, deciding the number and the location of the continuous and short-duration count stations, frequency of data collection, and generating and applying correction factors to short-duration counts need serious consideration *(2)*. Moreover, it is critical to identify and account for the composition of trucks and their travel patterns, truck weights, and seasonal variations for a successful traffic monitoring program.

Variety of traffic measures collected in state's traffic monitoring program is used for planning, design and operational purposes. For instance, temporal (hourly, daily, weekly and monthly) variations are obtained from continuous count stations and used for establishing traffic pattern groups (TPG) and generating adjustment factors. Similarly, K and D factors that are used to represent the hourly design volume and directional volume are utilized for the planning and design of the roadways. Then, these adjustment factors are used to expand the short-duration counts for estimating the Annual Average Daily Traffic (AADT) and Annual Average Daily Truck Traffic (AADTT) for all the remaining roadway sections that do not have continuous count stations. These measures are then used for estimating the Vehicle Miles-Traveled (VMT) and truck traffic statistics for federal reporting and apportionment of federal funding *(2)*.

State highway agencies face ongoing challenges to perform the necessary acts to fulfill their responsibilities. Budgetary pressure, increasing federal requirements/policy changes, and fast changing technologies are some of the main challenges that state agencies are required to consider and manage within their organizational structure *(3)*. Additionally, traffic monitoring program survey that is discussed in detail in Chapter 2 of this dissertation reveals that state highway agencies complain about few common issues such as lack of well-designed programs or well-documented procedures for ensuring the quality of data collection and efficiency of data processing.

At this point, any contribution towards improving the knowledge and decision-making capability of transportation highway agency's responsible personnel greatly impacts the quality of the overall traffic monitoring program in states. In this regard, Knowledge-Based Expert Systems (KBES) is expected to play a critical role both in providing guidance for explaining step-by-step procedure for different tasks and in contributing the decision-making process both in data collection and processing. Evaluating the possible different technologies for a continuous volume/classification data collection, performing or guiding to perform Traffic Pattern Group (TPG) analysis for vehicle classification and weight data programs, determination of optimum locations for short-duration data collection, and evaluating the required minimum number of stations in each TPG can be few examples of KBES involvement in traffic monitoring program. This computer-based interactive platform can provide a guidance for performing the tasks suggested by federal guidelines while incorporating state level constraints and improve the decision making of the state highway agencies.

1.2 Problem Statement

Delaware Center for Transportation at the University of Delaware has performed two studies to establish and update the traffic monitoring program for Delaware Department of Transportation (DelDOT) in 1991 and 1995, and DelDOT again asked for evaluating and updating the traffic monitoring program at DelDOT recently in 2014. This task involved analyzing 2012, 2013 and 2014 volume, vehicle classification and truck weight data from continuous count stations and short-duration data collection. The empirical data set and calculated summary statistics are used for establishing TPGs and deriving necessary correction factors to be used in expanding short-duration counts. The experiences during this project motivated us to carry out a research plan to improve the knowledge and decision making capability of DOT personnel involved in the traffic monitoring program for the following reasons:

- In some cases, mathematical and statistical procedures are difficult for the data analysis personnel to apply to ensure the quality of the data.

For instance, TPG analysis is recommended to be performed regularly (e.g. every three to five years or if there is a significant change in the traffic patterns in the study area or state). However, since this process includes some mathematical and statistical procedures, state personnel may ignore these tasks, which directly affects the accuracy and reliability of the traffic measures estimated for federal reporting and for the apportionment of federal funding.

- State personnel usually rely on software packages either purchased or developed internally for storage and analysis of the traffic monitoring data and they may overlook the procedures, methods and assumptions behind these processes. For instance, a calibration issue is detected in two of the weight-in-motion sensors during the data analysis that are already passed the quality control thresholds of DelDOT *(4)*. However, improving the QC/QA procedures can help identifying the issues and incorporating the necessary measures.
- Traffic monitoring in states involves people from different divisions and backgrounds. In many state DOTs, there are responsible personnel or teams for different data collection types depending on the size of roadway network to be monitored and available resources. In most cases, those personnel are only knowledgeable on the task they are performing and don't have an overall understanding of traffic monitoring program and how the data they are handling is or may be useful. Hence, agencies sometimes collect redundant data (double or even multiple counting for same sites) or are unable to understand the

value of already collected data to improve the data-led decisions. For this reason, National Highway Institute (NHI), FHWA's training and education department, offers Instructor-led and Web-based trainings to inform transportation professionals about the current rules/regulations and practices on many transportation related subjects including traffic monitoring and HPMS *(5)*. Therefore, an interactive web-based tool may initiate and/or improve the communication and coordination between divisions and different governmental bodies. For example, DelDOT Transportation Management Center (TMC) data (primarily used for operational purposes) can be used to supplement and improve the traffic monitoring program.

In addition to the experiences from DelDOT traffic monitoring project, a survey was developed and sent out in order to understand the problems and challenges that state DOTs are facing it their traffic monitoring programs. The survey results also pointed out few issues common with our previous experiences such as lack of well-designed software/programs or well-documented procedures for ensuring the quality of data collection and efficiency of data processing, as well as lack of/inefficient QC/QA procedures.

Moreover, state highway agencies are required to increase the amount of data collected, processed and reported as the FHWA revise and improve the regulations on HPMS reporting. Additions of ramp data and currently recommended (expected to be mandatory) non-motorized data are great examples of this constant change. These modifications contribute significantly to the true representation of the traffic on the roadways. However, these changes and lack of available personnel affect the efficiency and quality of the program.

Therefore, there is a need for improving the knowledge and decision making capability of the traffic monitoring personnel in the state highway agencies. In doing so, a simple, easy-to-use, and preferably web-based platform can structure the available knowledge and information in a way that can easily be applied, and explain/guide the different tasks within traffic monitoring program and interact with the user to perform selected suitable steps, if necessary.

1.3 Purpose and Research Objectives

The purpose of this research is to help state highway agencies improve their traffic monitoring program. This can be achieved by a) providing simple and computer-based interactive tool for guiding the state highway agency personnel to conduct the necessary procedures; and b) improving the decision making process in different stages of the traffic monitoring program that affects the overall quality of the data collection, processing and reporting efforts. In this regard, Knowledge-Based Expert Systems (KBES) can be used to integrate the user-specific measurements and constraint with federal requirements to provide customized and case specific decision support.

The primary objective of this research is to develop a methodology for constructing an interactive and user-friendly computer-based decision support tool for states' traffic monitoring program, called TMDEST (**T**raffic **M**onitoring **DE**cision **S**upport **T**ool). The specific objectives for developing the TMDEST include:

- Identifying the current issues and challenges state highway agencies are facing within the traffic monitoring data collection, processing and reporting efforts by conducting a national level survey
- Providing a documented methodology for developing a decision support tool (TMDEST) focusing on states' traffic monitoring programs
- Identifying the potential users and contributors of the proposed tool
- Applying the developed decision support tool for Delaware by using available data and information
- Evaluating the proposed framework
- Provide recommendations for implementing the framework in other states traffic monitoring programs and future research directions

1.4 Scope of the Research

The scope of this research is to perform Traffic Pattern Group (TPG) analysis for the DelDOT traffic monitoring program and to develop the *Traffic Monitoring Decision Support Tool* (TMDEST) framework for state Departments of Transportation in the United States. The proposed TMDEST uses a Knowledge Based Expert System (KBES) approach to improve collecting, processing and summarizing the traffic monitoring data. A general methodology is developed for incorporating the TMDEST framework into states' traffic monitoring programs and a case study is conducted on Delaware Department of Transportation traffic monitoring program with a focus on the establishment of TPGs. The proposed framework can be applied to all state highway agencies' traffic monitoring programs with slight adjustments to meet the geographical differences, traffic characteristics, and highway agency's priorities.

The primary focuses in this research are volume, vehicle classification and truck weight data in states' traffic monitoring programs. Speed and non-motorized (bicycle and pedestrian) traffic measures are not included due to the fact that these measures are still in the development phase and not required to be reported in the HPMS. Additionally, the proposed framework intends to contribute to the traffic monitoring program more in the planning perspective rather than the operational perspective. Planning aspect deals more with historical and near-time data for the future planning of the roadways and meeting the federal requirements. On the other hand, operational aspect deals with real-time data to provide/improve the mobility on the roads.

This dissertation utilizes the continuous and short-duration data provided by Delaware Department of Transportation (DelDOT) covering the vast majority of the roadways in the State of Delaware.

The target audience of this research is state Departments of Transportation, specifically divisions that are responsible for traffic monitoring program. The primary target audience of the TMDEST is the state DOT personnel who are responsible for collecting, analyzing and reporting traffic monitoring data. However, the proposed tool can be utilized by any state of federal agencies, private companies and/or research community that are interested in traffic monitoring data, spatial and temporal patterns of traffic monitoring data, establishment of TPGs, and data collection and analysis methods.

1.5 Organization of Dissertation

This dissertation presents the research involved in performing the TPG analysis for DelDOT traffic monitoring program and proposed TMDEST framework that is applicable to all states' traffic monitoring programs. The content of this dissertation is as follows:

Chapter 2 focuses on providing the relevant literature on traffic monitoring program in the states. A comprehensive evaluation of traffic measures such as volume, vehicle classification and truck weights that are crucial for state traffic monitoring programs is given within this chapter. Data collection, processing and reporting procedures and requirements are also presented. Issues and challenges are highlighted for defining the basis for proposed decision support tool. These problems and challenges are also supported with a national level survey that is conducted to investigate the current issues and challenges encountered in states' traffic monitoring programs.

Chapter 3 provides a review of relevant literature on Knowledge-Based Expert Systems (KBES) and its potential use in the transportation decision support systems. It provides a background on expert systems and its primary components such as knowledge base, inference engine and user interface. Additionally, it explains the relevant expert systems concepts such as forward and backward chaining, and end-used developers to provide the necessary background for the development of the TMDEST. In this chapter, an evaluation of the appropriate validation and verification processes that are applicable for the proposed framework is proposed as well.

Chapter 4 presents the study to review and update the DelDOT traffic monitoring program. This chapter evaluates the DelDOT's current traffic monitoring program, specifically volume, vehicle classification and truck weight measures for updating the Traffic Pattern Groups (TPG) and Vehicle Classification Groups (VCG). Seasonal variation was the primary focus for establishing TPGs/VCGs and generating appropriate correction factors to expand the short-duration counts. Number of continuous count stations in each TPG/VCG was evaluated based on statistical significance and geographic coverage. A new set of TPGs and VCGs are recommended to represent the current traffic characteristics in Delaware.

Chapter 5 presents proposed TMDEST framework and respective TMDEST Modules. It starts with presenting the methodology for developing the TMDEST framework and providing the details for establishing knowledge base and necessary rules in each module. Total of six modules are developed to represent the different but related tasks for the establishment/control of the TPG analysis. These modules evaluate the volume, vehicle classification, and truck weight characteristics; evaluate variety of MADT/AADT estimation and TPG analysis methods; provide an approximate method to establish the TPGs by considering the roadway functional classification and seasonal variation; perform the necessary calculations to check the number of stations in each TPG for statistical significance; and recommend the necessary adjustment factors to be used in expanding short duration counts. Each module clearly explains the necessary rules and logic behind the decisions while requiring minimum possible amount of input from the user. Chapter 5 also presents the Verification, Validation and Evaluation (VV&E) of each module as well as whole concept.

Chapter 6 summarizes the study and results, and discusses the contribution of the research as well as the directions for the future research in the area.

Chapter 2

LITERATURE REVIEW ON TRAFFIC MONITORING

2.1 Introduction

Traffic data plays a vital role in the decision making process of all responsible transportation agencies for the continuous mobility of people and goods. Data and information on traffic volume, vehicle classification, truck weights and many other measures such as speed and average travel time are fundamental to all transportation related decisions. Federal Regulations 23 CFR 500.202 states, *"Traffic monitoring system means a systematic process for the collection, analysis, summary, and retention of highway and transit related person and vehicular traffic data."* Moreover, Federal Regulations 23 CFR 500.203 mandates, *"Each state shall develop, establish, and implement, on a continuing basis, a Traffic Monitoring System to be used for obtaining highway traffic data…."* Strong and effective traffic monitoring program not only improves the accuracy and reliability of decisions based on collected data, but also makes sure states are receiving appropriate federal funding.

The fundamental elements of the traffic monitoring program in states are the collection and analysis of volume, vehicle classification, vehicle speed, and truck weight data among others. In this regard, the hypothetical goal of any traffic monitoring program is to obtain complete continuous data (7/24 in 365 days) on every segment of the roadways, which is unrealistic and unaffordable in the current technology and infrastructure settings. At this point, it is extremely important to collect statistically enough and accurate traffic data that represents traffic attributes on all roadways in the study area or state. For this reason, small amount of continuous count stations are combined with comprehensive short-duration counts help states to balance the data collection for a reliable and cost-effective traffic monitoring program *(2)*. However, deciding the number and location of the continuous and short-duration count stations, frequency of data collection, and generating and applying correction factors to short-duration counts need detailed consideration.

2.2 Concept of Traffic Monitoring

Traffic monitoring is the collection of data and information on variety of traffic measures to understand the use and performance of the roadway system. Traffic monitoring is used by various federal, state, and local governmental agencies to assess travel patterns in their responsible regions. Collected data is primarily used for providing necessary input for traffic operations, pavement and bridge design, highway planning, land use planning, research, etc., as well as providing information to the public.

Traffic monitoring is also used to provide necessary data to federal agencies. The FHWA requires every state to submit an annual Highway Performance Monitoring System (HPMS) report containing traffic count data, roadway physical characteristics, estimated vehicle miles traveled (VMT), and other pertinent road data. The HPMS reports are then used for legislation and the determination of the federal transportation funding apportionment allocated to the states. FHWA also utilize monthly traffic volume data for generating Traffic Volume Trends Report on national level *(1)*.

Traffic monitoring is measured at various spatial and temporal settings to collect the necessary data. The choice of location and time period can vary depending on the intended use and expected outcome of the collected traffic information. For example, continuous counts are primarily used for monitoring the volume variation in time (e.g. hourly, weekly and monthly), and short-duration counts are used for increasing the spatial coverage. Moreover, level of detail in the data helps producing different traffic measures used in variety of applications. For instance, hourly traffic data is used to identify the peak hours; combined hourly data within a 24-hour period is used for generating Average Daily Traffic (ADT), and the estimation of monthly average daily traffic (MADT) and annual average daily traffic (AADT). Additionally, day-of-week and monthly aggregation of data is used for observing weekly, weekday/weekend, and seasonal variation of the traffic.

There are variety of factors effecting the efficiency and reliability of traffic monitoring program. Available and potential vehicle detection technologies and associated cost values, availability of work force for data collection and processing, geographic limitations, technical and communication infrastructure, budgetary constraints, etc. are some of the primary factors shaping the traffic monitoring program in states. However, the focus in this dissertation will be on the evaluation of temporal variations of volume, vehicle classification and truck weights, and establishing TPGs for the generation of adjustment factors for DelDOT. The procedure of TPG analysis and generated adjustment factors significantly affect the accuracy and reliability of AADT estimations and other measures that are generated based on collected traffic data. Then, more emphasize will be placed on developing an expert system based framework for facilitating the data collection and processing and improving the overall quality of the traffic monitoring program.

In many state DOTs, there are responsible personnel or team for the collection and analysis of different data types depending on the size of roadway network to be monitored and available resources. Both collection and analysis of each data types are sometimes fully or partially performed by contractors. Nevertheless, state DOTs are responsible for the accuracy and reliability of data collection, analysis and reporting, and should perform quality control (QC) and quality assurance (QA) procedures to ensure the quality of the data *(6)*.

Traffic monitoring is performed by using variety of methods and technologies depending on the location and duration of the collected data. Continuous and short-duration data programs are the two primary programs in states traffic monitoring program.

2.2.1 Continuous Data Programs

Continuous data program forms the basis for traffic monitoring program in states. Continuous data program helps monitoring the volume, vehicle classification, and weight attributes on the roadways by using continuous count stations that provide data 24 hours each day over 365 days. These continuous data helps with monitoring the temporal and spatial variation in traffic, and generating appropriate correction factors. Determination of peak hours, K-factor, D-factor (directional distribution), and monthly adjustment factors are some of the measures derived by using data from continuous count stations. Since the monitoring of each roadway segment with continuous count stations is unrealistic and unaffordable with the current technology and infrastructure settings, states balance the overall traffic monitoring with both continuous and short-duration data programs. With this perspective, states are recommended to establish at least statistically significant number of continuous count stations to be used for determining the traffic patterns and developing the necessary adjustment factors for short-duration counts.

2.2.2 Volume Data Program

Traffic volume is one of the essential parts of the traffic monitoring programs in all states. Volume data program includes the collection, processing and reporting of the traffic volume data from continuous and short-duration counts. Continuous counts are used for the evaluation of the spatial and temporal variations, while developing appropriate adjustment factors to expand the short-duration counts. These variations which are classified as daily, weekly, monthly, and seasonal variations are then used for planning and operation of the existing and future roadways. On the other hand, short-duration counts provide extensive spatial coverage where continuous counts are not available. Therefore, states balance limited number of continuous count stations with wide-coverage short-duration data for the estimation of traffic volume on all roadways within study area or state.

The objectives of volume data program are but not limited to:

- Providing a basis for statewide estimation of Vehicle-Miles Traveled (VMT)
- Annual reporting of VMT and AADT estimations to the FHWA

- Developing adjustment factors such as hour of day (HOD), day of week (DOW), month of year (MOY) and growth factors
- Determination Peak Hour Factor (PHF), K-Factor and D-factor for roadway planning and design
- Understanding travel trends between different regions, cities, attraction locations, etc.
- Informing the general public

There are different approaches for estimating the MADTs and AADTs for each continuous count station. These approaches range from simple average of available days to more complicated specific day, week and month factors. Much research has been done on increasing the accuracy of the AADT estimations, specifically if the data set contains missing days, weeks, etc.

The American Association of State Highway and Transportation Officials (AASHTO) method, which is also recommended by TMG, calculates the average of day-of-week (DOW) values and computes an annual average daily traffic. For instance, average of Mondays in January, average on Mondays in February, …, average of Sundays in December (total of 7*12=84 values) yields the calculation of yearly average (AADT). Similarly, monthly average daily traffic (MADT) is calculated in a similar way, considering the day-of-week averages to reach the average daily volume in a month. This approach eliminates the bias resulting from missing days specifically if missing days are not equally distributed *(2)*. Following formulas present the calculation of MADTs and AADTs for each continuous count stations:

$$MADT = \frac{1}{7}\left[\sum_{i=1}^{7}\left(\frac{1}{n}\sum_{j=1}^{n} VOL_{ij}\right)\right]$$

Where:

VOL = daily traffic for day *j*, of DOW *i*

i = day of the week

j = 1 when the day is the first occurrence of that day of the week in a month, 3 when it is the third day of the week

n = the number of days of that day of the week during that month (for which you have data)

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

Where:

VOL = daily traffic for day *k* of DOW *i*, and month *j*

i = day of the week

j = month of the year

k = 1 when the day is the first occurrence of that day of the week in a month, 3 when it is the third day of the week

n = the number of days of that day of the week during that month (for which you have data)

One of the early studies on evaluating different AADT estimation methods is concocted by Cambridge Systematics and Science Application International Cooperation in 1994 *(7)*. This research evaluated seven different procedures from simple average of all days to specific day, week and month factors for developing adjustment factors and concluded that all seven approaches produce unbiased results *(7)*. A similar study conducted by Wright at al. *(8)* compared five different approaches including AASHTO method, and found that all methods are within at most 5% of each other. Although researchers have not observed significant differences between different methods, they recommended monitoring missing data and selecting an appropriate method for agencies current data analysis settings. Moreover, Jessberger et al. *(9)* proposed a new method for improving the AADT estimations specifically for the days where 24-hour data is not available. This new approach utilizes hourly volume data, and improves the MADT and AADT estimations specifically if the missing data are prevalent within 24-hour daily data.

In our study, MADTs and AADTs are calculated by using the AASHTO method recommended by TMG due to the empirical data set was available only in daily volume format. Additionally, this method helps eliminating the bias caused by missing data where the missing data is not equally or randomly distributed.

After selecting the proper approach for estimating MADTs and AADTs for each continuous count station, it is required to select an appropriate method to develop TPGs incorporating the seasonal variation. There are several approaches for determination of TPGs and grouping the seasonal adjustment factors such as geographical assignment *(10-12)*, cluster analysis (*(13-15)*), regression analysis *(16, 17)*, neural networks *(18, 19)*, same road factor *(13, 20)*, etc. Tsapakis *(21)* successfully presented different approaches for establishing TPGs as well as other developed methods for AADT estimation and data imputation for missing data. Hall et al. *(22)* emphasized that clustering-based factor groups provide more precise AADT estimations from short-duration counts than using roadway functional classification and volume range associated groupings. Among all, three statistically valid and relatively easy to apply approaches that are also recommended by TMG are presented below *(2)*:

Geographical/Functional Assignment is a traditional approach uses functional classification of the roadways to establish roadway groups and to derive adjustment factors. Although this traditional approach provides easy and quick assignment of the roadways into respective groups, it is also highly subjective and open to errors.

Cluster Analysis is a highly used statistical approach incorporates Coefficient of Variation (CV) values at the continuous count stations in addition to volume measures for grouping the roadways. CV represents the seasonal variation by calculating the ratio of standard deviation of MADTs to AADT (or using monthly adjustment factors instead of monthly volumes), where high CV represents high seasonal variation and low CV represents low seasonal variation. Therefore, continuous count stations can be grouped based on their similarities on monthly variations in addition to AADTs, and other factors such as geographical regions. Two main advantages of cluster analysis are that it provides an objective evaluation of similarities between groups, and it can detect similarities or differences that may not be clearly obvious by graphical examination. However, it is difficult to determine the optimum number of clusters with this statistical approach and requires further evaluation. Another major drawback of cluster analysis is that formed groups cannot be clearly defined. For example, a cluster group can include combination of principal arterials and major collectors that have similar monthly variations, which makes it difficult for assigning short-duration counts into proper groups.

Volume Factor Groups approach uses the volume characteristics of the roadways for determination of the traffic pattern groups. Therefore, determination of the groups and assignment of short-duration counts become much easier compared to other methods. However, monthly variations and functional classification characteristics may not be truly accounted for while grouping the roadways. TMG recommends at least 5 traffic pattern groups for volume based factoring which are Interstate Urban, Other Urban, Interstate Rural, Other Rural and Recreational *(2)*.

TMG summarizes the advantages and disadvantages of the three common methods in the following table.

Table 1. Advantages and Disadvantages of Traffic Pattern Group Analysis Methods *(2)*

Type	Advantages	Disadvantages
Traditional	1 – Creation of groups is easier 2 – Application for factoring can be explained 3 – Easier to assign short-term count to a group	1 – May not stand statistical scrutiny
Cluster Analysis	1 – Independent determination of similarity of groups without bias 2 – Traffic pattern can be found which may not be intuitively obvious 3 – Efficient and accurate factor groups	1 – Lack of guidelines for establishing optimal number of groups 2 – Groups that are formed often cannot be adequately defined 3 – Difficult to assign short-term count to a group
Volume Factor Group	1 – Consistent national framework for comparison among the states 2 – The precision of the seasonal factors can be calculated 3 – Easier to assign short-term count to a group	1 – Functional or road classification may not be based on travel characteristics 2 – May not stand statistical scrutiny

Although these three applications are widely used by state highway agencies, there are some other approaches implemented. For instance, Virginia DOT has been using same road approach by simply controlling the temporal variation with a continuous count station placed on each roadway. Surely, this approach requires significant number of continuous count stations, and VDOT has been operating over 300 vehicle classification stations in this program.

Calculating the mean and standard deviation of coefficient of variation for all continuous count stations in a group reflects the representation of the seasonal factors in that group. TMG states that typical coefficient of variation in urban areas is below 10 percent, in rural areas between 10 and 25 percent and recreational areas higher than 25 percent.

In this study, hierarchical cluster analysis method is used for evaluation of similarities for continuous count stations and determination of traffic pattern groups as suggested by TMG. To overcome the limitations of clustering method for creating identifiable groups, DelDOT's current traffic pattern groups and graphical evaluation of the monthly changes are also incorporated. Initial number of clusters is selected from cluster analysis results, and each group is individually evaluated based on urban/rural and functional classification as well as graphical examination.

The hierarchical clustering technique groups the continuous count stations whose traffic characteristics and/or measurement values are similar to each other. There are two approaches to hierarchical clustering: one goes "from the bottom up", grouping small clusters into larger ones, called agglomerative clustering, and other the one "from the top down", splitting big clusters into small ones, divisive clustering. The procedure in this study uses agglomerative clustering approach for determining the traffic pattern groups. The procedure starts with each station in its own cluster and continues with combining the closest values in a cluster until all data is merged into one single cluster.

Scree plot and Cubic Clustering Criterion (CCC) are commonly used for considering the optimal number of clusters in hierarchical clustering in addition to dendogram observations. Scree plot presents the trend of actual joining distance between points in a graphical way and breaking points are generally considered for deciding the optimum number of clusters in addition to other factors such as graphical examination and judgement of the expert. Similarly, CCC is a measure of *"homogeneity relative to between-cluster heterogeneity"* and used for determining the optimum number of clusters *(23)*. The cluster analysis helps with the determination of intuitively rational and identifiable groups.

2.2.3 Vehicle Classification Data

Vehicle classification counts are used to determine the type of vehicle at a count location and are useful in evaluating the composition of vehicles on roadways. Composition of vehicles, specifically the percentage of different truck types (single-unit, multi-unit, etc.), has a significant impact on planning and operation of the roadways in states. Therefore, understanding the spatial and temporal variation of truck traffic, determining the number and location of continuous vehicle classification stations, and developing necessary adjustment factors are crucial for a successful vehicle classification and truck weight data program.

Vehicle classification counts can be performed manually or by automatic counters that measure the number of axles on a vehicle or the length of a vehicle depending on the type of sensor used. FHWA's 13 vehicle classification categories (Figure 1) are primarily used for classifying vehicles and reporting to federal agencies through HPMS. However, different vehicle classification categories can be used to accommodate other data and reporting needs, such as monitoring a special facility generating substantial truck traffic, monitoring a roadway or corridor where conventional vehicle classification technologies cannot be used, etc. Traffic monitoring guide *(2)* recommends investigating the composition of vehicles in at least 6 aggregate classes of vehicles; motorcycles (MC), passenger cars (PV), light duty trucks (LT), buses (BS), single unit trucks (SU) and multi-unit combination trucks (CU). These classes can also be merged into fewer groups if they show similar travel patterns while deriving the adjustment factors *(2)*. Evaluating traffic patters of these classes can help establish Vehicle Classification Groups (VCG), which are then used for developing and applying adjustment factors to expand the short-duration classification counts for estimating the annual average volumes by vehicle types.

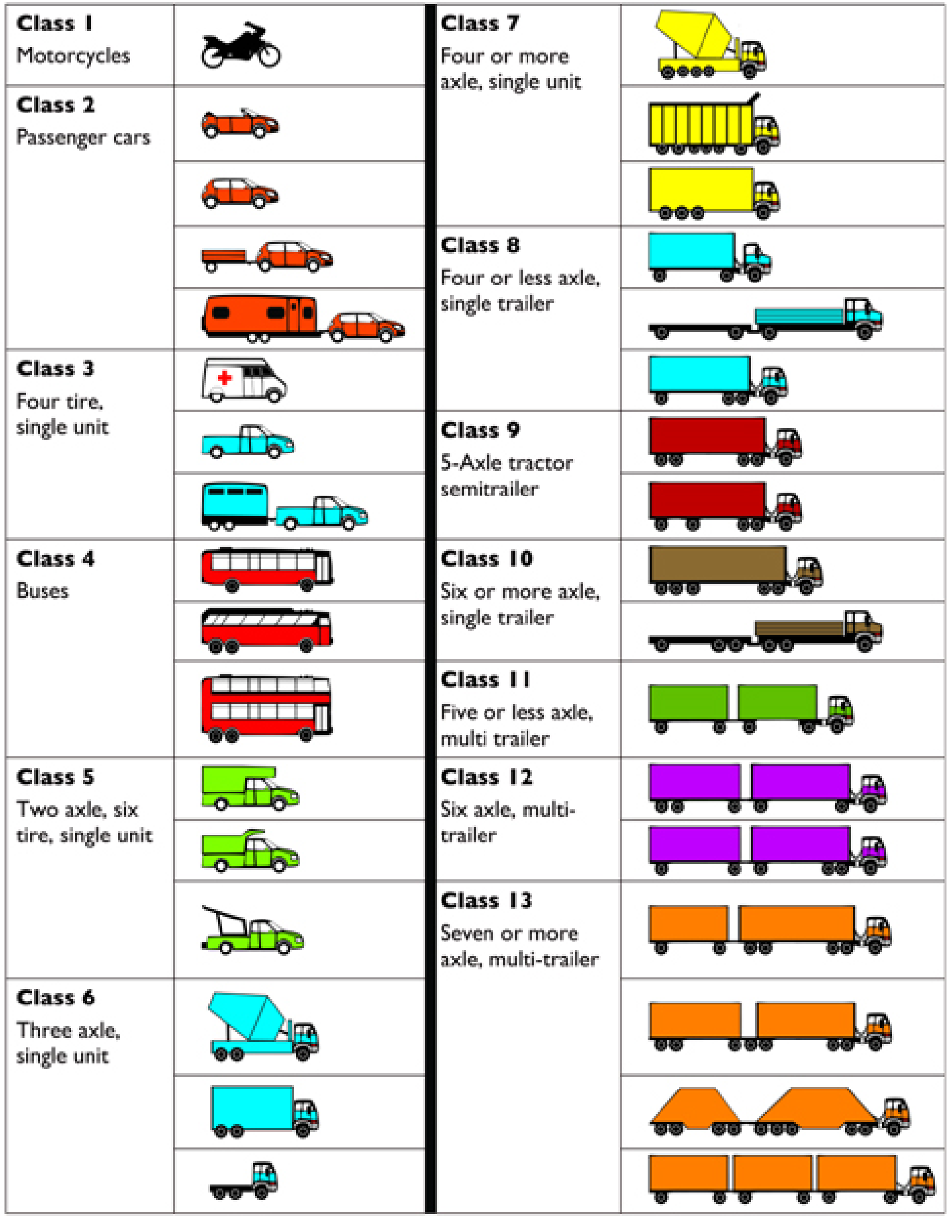


Figure 1. FHWA's 13 Vehicle Category Classification *(2)*

Research has shown that different vehicle types may have different time-of-day, day-of-week and seasonal patterns as proportion of the total volume *(24, 25)*.

For instance, Hallenbeck et al. *(25)* investigated the vehicle volume distribution by classification from 99 sites in 19 states and concluded that cars and combination trucks have much lower seasonal variations compared to single unit trucks (Figure 2). In the same study, it was also discovered that much of the high variability in single-unit and multi-trailer truck volumes are located in low volume roads where even little changes can have a large impact on the adjustment factors. Additionally, Hallenbeck et al. *(25)*also reported that using adjustment factors for all 13 FHWA vehicle classes will create unstable and unreliable representation of seasonal variations. Similarly, TMG indicates that computing adjustment factors for 13 vehicle class category increases the complexity of data processing without providing much gain *(2)*.

Among these different temporal variations, seasonal patterns are primarily used for monitoring the change in truck traffic volume and loads. Evaluation of the seasonal patterns can be accomplished by using statistical procedures such as cluster analysis and/or graphical examination of the seasonal patterns of individual sites in addition to prior knowledge of state's truck traffic facts. This procedure helps understanding the seasonal variation of composition of vehicles and establishing VCGs that accurately represents this variation for developing adjustment factors. Although mathematical and statistical procedures can help establish the optimum number of vehicle classification groups, it is also critical to create practical and identifiable groups. Therefore, it is not strictly necessary to use VCGs to be identical to the clustering groups generated by statistical procedures. VCGs can be adjusted to maximize the seasonal variation similarities within a group while facilitating the easy assignment of short-duration classification counts into proper groups by creating identifiable groups *(2)*.

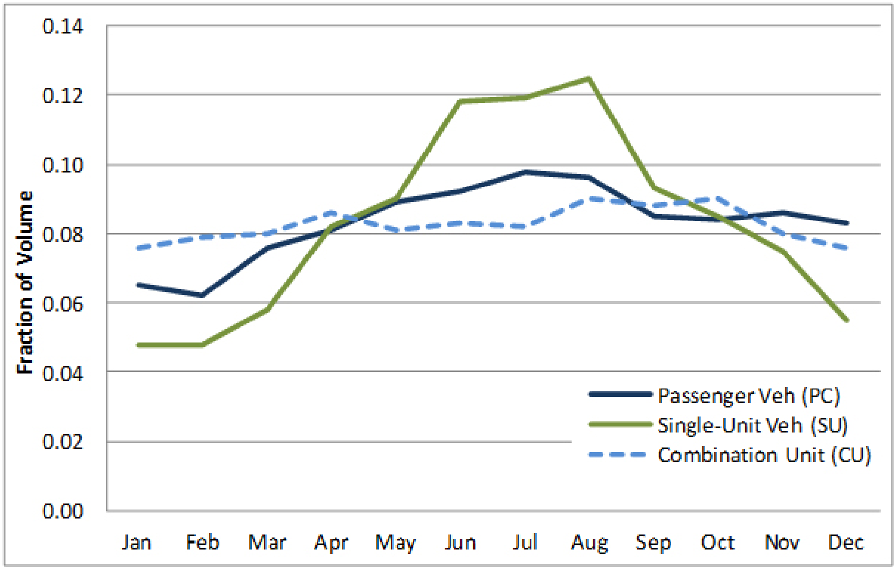


Figure 2. An Example of Monthly Travel Patterns by Vehicle Class ***(2)***

TMG presents alternative grouping procedures for factoring vehicle classification counts. The first procedure that is developed and used by Virginia Department of Transportation (VDOT) uses roadway specific factoring. This method requires extensive coverage of continuous vehicle classification stations, theoretically one for each roadway, and assigning short-duration classification counts to each roadway. VDOT currently operates more than 300 continuous vehicle classification sites in this program *(26)*. As expected, increasing the total number of vehicle classification sites will consequently increase the capital, maintenance and operating cost of vehicle classification stations.

The second alternative, the Traditional Factor Approach, uses grouping the roads whose truck traffic characteristics are similar. In this approach, prior knowledge on current truck traffic patterns, truck traffic generating locations in the state, composition of in-state and interstate truck traffic volumes, etc. are highly important. Understanding how these factors affect the composition of the vehicles and the spatial and temporal variation is the first step of developing truck factoring groups and respective procedures for developing adjustment factors. TMG recommends using functional classification to a limited extent for differentiating obvious truck traffic patterns if there is any, such as heavy-through truck traffic on Interstates and principal arterials. Cluster analysis can be used to identify the natural patterns of variation by using seasonal variation, day-of-week variation, and other quantifiable measures. Therefore, as also suggested for volume data programs, a combination of statistical procedures with prior knowledge should be used to establish the appropriate groups.

Additionally, other continuous vehicle classification data sources such as toll sites, TMC data sources, etc. should be considered in vehicle classification data programs. To incorporate these data sources, agencies need to establish working relationships with other governmental bodies, MPOs, and regional planning offices to coordinate the counting programs and to share the data. For example, DelDOT TMC has been collecting length-based vehicle classification data from major parts of the Interstates and some selected principal arterials in Delaware for the past few years. This data has never been part of DelDOT's traffic monitoring program.

Another important point to be mentioned is the popularity of length-based vehicle classification in recent years. State highway agencies have long been complaining about the current in-pavement sensors that require road/lane closures for installing and maintaining the sensors. Technological advancements brought an opportunity for utilizing non-intrusive technologies, placed either on the side of the roadway or at the top of the lane for vehicle detection. These technologies are being used for volume, speed and vehicle classification. However, this length-based classification and FHWA's axle-based classification bring another challenge on how to classify the vehicles.

FHWA is currently working on establishing length-based vehicle classification data collection and reporting standards *(2)* due to wide availability of non-intrusive length-based classification technologies such as microwave radars. FHWA requires states that are proposing to report length-based classification data to HPMS to provide the following information *(2)*:

- A description of the length categories to be used and how they relate to the FHWA's 13 vehicle classification categories (Figure 1);
- A description of the method used to test how well each of the length categories captures the vehicles classes identified in point 1 and the results of those tests;
- If a State intends to disaggregate length based data into the FHWA's 13 categories, the imputation method must also be described; and
- Documentation on the situations in which length classification will be used. (e.g. a State may propose to use such techniques only on high volume urban streets)

FHWA recommends using six generalized vehicle classes that are also used for reporting travel activity in the Vehicle Summary dataset for HPMS reporting. These six classes are presented in Table 2. As stated previously, TMG allows combining these vehicle class groups for those have similar seasonal patterns to minimize the likely errors on low volume roads.

Table 2. HPMS Vehicle Class Groups and Respective FHWA 13 Vehicle Classification Category Numbers *(2)*

HPMS Summary Table Vehicle Class Group*	FHWA 13 Vehicle Category Classification Number
Group 1: Motorcycles (MC)	1
Group 2: Passenger Vehicles equal to or under 102” (PV)	2
Group 3: Light trucks over 102” (LT)	3
Group 4: Buses (BS)	4
Group 5: Single-Unit Trucks (SU)	5,6,7
Group 6: Combination Unit Truck (CU)	8,9,10,11,12,13
* These groupings are used to report travel activity by vehicle type in the Vehicle Summaries dataset for HPMS.	

The validation of the determined VCGs can be accomplished by using the mean and standard deviation of each group, and examining the variation graphically. However, inclusion of all vehicle classes and their statistics makes this process complex and difficult for analysis. For this reason, analysis should be carried out by concentrating on the most important/observed vehicle classes. For instance, if single-unit truck volume comprises 80% of the total truck traffic in the state, then the single-unit trucks temporal and spatial variation should be the primary factor for generating the VCGs *(2)*.

The number of continuous classification stations in each group is highly dependent on the primary vehicle class used for developing the groups and respective statistics. This calculation should be carried out similar to volume data program by assuming the data are normally distributed and using student’s *t* distribution. TMG recommends using a minimum of six continuous classification stations in each group, and considering additions to minimize the affect of equipment failures or other problems *(2)*.

In case of adding a new continuous vehicle classification site, it is recommended to check if the new site fits well with any of the current VCGs. If the spatial and temporal variation of new site shows similar truck traffic patterns with other sites in a group, then the new site can be placed in this group and adjustment factors should be recalculated accordingly. Otherwise, revising the groups, creating a new group or revising the entire vehicle classification grouping may become necessary *(2)*.

2.2.4 Truck Weight Data

Truck weight data program is one of the complex and costly programs among the primary data collection activities in all states. Truck weight data and calculated summary statistics are used as a key input in pavement and bridge design, pavement and bridge maintenance treatments, estimating the value of freight travelling on roadways, determining the cost of congestion, and planning and operational activities. In addition to internal use of the data, weight data is also submitted to FHWA to meet federal needs and used for the calculation of W-table reports, which provides a standard summary statistic from states' vehicle classification and weight data *(27)*.

Similar to volume and vehicle classification counts, truck weight counts are used for monitoring the spatial and temporal variation of the truck weights, and determining the traffic patterns of loaded and unloaded trucks. These counts are performed either by using weigh-in-motion (WIM) sensors or static weight stations.

WIM sensors record instantaneous dynamic axle loads, number of axles and speed of vehicle as a vehicle is passing over the sensors. The weight of vehicles can even be calculated by the direction of the roadway and by lane depending on the placement of the WIM sensors. Then, multiplying the number of vehicles in a class with average vehicle weight yields the estimation of total weight exerted on roadways. Of all the traffic monitoring technologies, WIM involves the most sophisticated and costly data collection sensors that require high capital, operating and maintenance cost *(28)*.

Accuracy and reliability of the weight estimations are primarily dependent on the placement of the WIM sensors and truck dynamics. The location and placement of a WIM site should minimize the dynamic motion of the vehicles such as acceleration or breaking, condition of vehicle suspension system, and roadway geometries that can cause weight shifts from left to right or from axle to axle *(2)*. States are recommended to consider these factors while selecting the proper location for WM sensors. Additionally, states are only able to maintain limited number of stations due to high cost of WIM sensors. Therefore, location of the WIM stations should be strategically selected to monitor truck traffic between neighbouring states, seasonal variations of heavy loaded trucks, and monitoring of facilities that generates substantial truck traffic.

Most research has been done on using different technologies (e.g. bending and load cell plates, strip sensors, multi-sensors and bridge sensors, etc.) for improving the accuracy and reliability of WIM sensors. Each technology has its own strengths and weaknesses. Jacob and Feypell-de La Beaumelle. *(29)* evaluated WIM sensors in low-speed and high-speed accuracy categories and well-summarized the current applications and potential improvements. Additionally, research has been done on

WIM sensor calibration methods regarding which truck types or classes should be used for calibrating the WIM sensors *(28, 30, 31)*. However, in the context of this dissertation, the emphasis will be more on the data processing of the WIM sensors, specifically evaluation of spatial and temporal variation of WIM sensors and data.

Prior knowledge on truck traffic generating facilities, truck traffic patterns, and state's regulations on truck loadings contribute to the success of the truck weight data program. Truck traffic patterns and weight loads in urban areas often present different characteristics than those in rural areas *(2)*. Roads that serve in urban areas tend to carry moderately loaded trucks, where agricultural and industrial regions often require large and heavy trucks. Thus, states should be able to identify and consider these differences for an effective and successful truck weight data program.

It is also critical to examine the composition of vehicles and truck weight loads by direction of the roadway to identify the directional differences. This evaluation is critical specifically for the pavement design process. In this regard, roadways that are separated by a median can be assigned into different groups if the weight load characteristics are considerably different. If both directions share the same pavement design, then the heavier directional load should be used as a pavement design input *(2)*.

Grouping the roadways whose vehicle classification, truck weight and seasonal variation characteristics are similar enables establishing identifiable roadway groups that can be applied to all other similar roadways in a state. Therefore, summary statistics calculated from WIM stations in each group are used for estimating the truck weight measures of roadway segments where WIM stations are not available. However, the decision of whether different truck weight groups will be created for each vehicle class (at least for heavy vehicles), or groups will be established based on primary truck classes is challenging. For instance, if different truck weight groups will be created for each heavy vehicle class, a WIM station can be placed into group A for class 9 trucks and group B in class 11 trucks. However, if only one grouping will be established for all vehicle class types, then the observed most common truck class type(s) should be used for determining the groups. Obviously, the first example is more complex and difficult to assign roadway segments without WIM stations into proper groups. It is critical to emphasize that the primary goals in creating truck factor groups are capturing the spatial and temporal variation as well as creating easy-to-apply groups.

As similar to volume and vehicle classification grouping procedure, mathematical and statistical methods can be used in addition to descriptive and graphical evaluation. Besides, prior knowledge on truck traffic generating facilities, and local and regional truck traffic patterns should also be considered. TMG recommends creating intuitive groupings such as interstate/non-interstate or urban/rural and applying mathematical and statistical procedures to refine these groups *(2)*. It is also recommended that defined truck weight groups should be consistent with vehicle classification groups. Yet, in some cases, state highway agencies combine the vehicle classification and truck weight data for the purpose of TPG analysis and generating adjustment factors.

2.3 Short-Duration (Coverage) Data Programs

Short-duration traffic counts are one of the fundamental parts of the state traffic monitoring programs that provide extensive spatial coverage in states' roadway network. Short-duration data programs ensure that all roads under the responsibility of state highway agencies are covered and required data obtained for state and federal needs. Type, extent and duration of collected data are highly dependent on state agencies' data needs, available resources and policy perspectives. However, FHWA provides recommendations to ensure that states meet federal requirements.

Vast majority of the roadways are covered with short-duration data program in most states because continuous monitoring of each roadway segment is simply impractical and unaffordable. For instance, approximately among the 3,500 segments in Delaware, 90 segments are monitored with continuous count stations (including vehicle classification and WIM stations) and Interstates are monitored with non-intrusive data collection means. All remaining segments (approximately 3,350 roadway segments) are covered through short-duration data program. Additionally, these short-duration counts are mostly contracted to third-party data collection firms. Therefore, both in-house operations (e.g. QC/QA procedures, coordination and communication with contractor(s), etc.) and data collection in the field require extra attention. Short-duration counts are highly labor intensive requiring the data collection staff working frequently to place and retrieve the data collection equipment.

There are different practices among the state highway agencies for the length and frequency of short-duration counts. Length of short-duration counts varies from 24-hour to one week. While some highway agencies perform short and frequent data collection (24-hour every three years), some use longer duration counts with less frequent intervals (weeklong data every six year). Some research has been done on comparing the accuracy and reliability of 24 and 48-hour short-duration counts. Hall et al. *(22)* presented that there is not significant difference between 24 and 48-hours short duration counts (results are only 0.5% different from each other) and emphasized the possibility of using 24-hour data. On the other hand, Krile et al. *(32)* showed that AADT estimation error is significantly lower in 48-hour duration counts compared to 24-hour counts and stated that longer duration counts provide a more precise AADT estimation. Similarly, TMG recommends a minimum of 48-hours for the duration of the counts *(2)*. TMG recommends establishing the short-duration data program based on agency's need and priorities while meeting the federal reporting requirements.

Frequency of short-duration counts varies from one year to six years. TMG recommends counting each roadway segment in a maximum of a six-year cycle *(2)*, and HPMS further requires a three-year cycle for higher roadway functional classes *(1)*. Moreover, state agencies are encouraged to exceed this goal by performing more frequent short-duration counts if possible. State agencies are also recommended to perform minimum of 25-30 percent of their total short-duration counts as vehicle classification counts *(2)*.

Spacing between short-duration counts is another key factor for a successful short-duration data program. States are encouraged to select the appropriate length of roadway segments so that the volume and vehicle classification characteristics stay homogenous. This consideration is relatively easy for limited access highways since between interchanges can be considered as one segment. However, specifically in urban arterials, this task requires detailed evaluation to increase the accuracy and quality of the collected data. Therefore, state agencies should examine the roadway and traffic characteristics to determine the length of the roadway segments. This process should also be repeated if there is a change in the vicinity of the segment such as new developments or significant change in traffic volume, etc. A rule of thumb that has been used is defining the segment where the traffic volume in each segment stay within 10 percent of each other.

2.4 Other Traffic Measures

In addition to previously mentioned traffic measures, there are some other measures that require particular attention in states traffic monitoring program. Some of these measures are: travel time, vehicle occupancy counts, pedestrian counts, bicycle counts, traffic speed counts, etc. These measures are not required to be reported to federal agencies, but are found useful for planning and operation of the roadways. States should develop their own data collection principles and procedures for evaluating these traffic measures.

Collection of speed data has gained increasing attention in recent years, and extensively used by TMCs for operational purposes. Similarly, non-motorized traffic (bicycle and pedestrian) measures are widely used in planning and design of the roadways, and safety studies. Hence, FHWA included speed and non-motorized traffic sections in the recent release of Traffic Monitoring Guide (TMG) to provide necessary background information and to present used methods by other states.

2.5 Traffic Monitoring Survey: Determination of Issues and Challenges in States' Traffic Monitoring Program

2.5.1 Survey Design and Target Audience

Traffic monitoring survey is designed to identify the common problems that state highway agencies are facing in the perspective of traffic monitoring program in their respective states. Survey results are then evaluated to see if the problems identified by survey respondents coincide with the experiences during the study of *"Comprehensive Review and Update of the Traffic Monitoring Program at DelDOT"*.

The survey includes a total of eight questions. The questionnaire and exemption letter from Institutional Review Board (IRB) are provided in Appendices A and B respectively. Two of the eight questions are related to demographic data (state and position in the state DOT) and six of them are related to traffic monitoring program in the state highway agencies. These six open-ended questions are aimed at investigating the issues and challenges in states' traffic monitoring programs, specifically in volume, vehicle classification and truck weight programs focusing on continuous and short-duration data collection and data processing. In addition to issues and challenges, respondents are also asked to provide possible ways to improve the traffic monitoring program in their respective states.

The survey was sent out to the divisions responsible for handling the traffic monitoring program in each of the 50 state DOTs. Thirteen states responded and completed the survey. The survey was answered mostly by supervisors or program managers who have full knowledge of the traffic monitoring program in their respective states. The purpose of using open-ended questions was to make the respondents flexible with their answers rather than limiting them with few selected common issues and challenges. Since the respondents are experts in traffic minoring program, it is assumed that they all are well aware of problems and challenges to freely express their thoughts.

After the two demographic questions (state and respondent's role), the next question is aimed at understanding the organizational structure of the state highway agency in regards to traffic monitoring program. It is found that all responding state DOTs use both in-house workforce and contractors during the different stages of traffic monitoring. Continuous counts are generally obtained from states' continuous count stations and processed in-house. Short-durations counts are normally contracted due to high labor requirements. Depending of the size of the roadway network, some states perform the data collection within districts and share it with a central office for further processing and reporting. The remaining questions were designed to identify the issues and challenges in states traffic monitoring programs and discussed below in detail.

2.5.2 Issues and Challenges in States Traffic Monitoring Programs

In the survey, two questions are asked to understand the issues and challenges in continuous and short-duration data collection in traffic monitoring program. In continuous data collection, the most common problem indicated by participating states is troubleshooting and maintenance issues with old in-pavement sensors, specifically in vehicle classification and WIM sensors. These sensors are widely exercised in 1990s and require constant maintenance and calibration to ensure the accuracy of collected data. This issue also brings up the lack of funding for purchasing or upgrading the technology for continuous data collection.

After this very common problem, respondents pointed out two very important issues: First one is increased data request from federal agencies while states face financial problems to improve/renew data analysis means and/or to hire more staff. FHWA has been continuously updating the HPMS Field Manual and increasing the data coverage and data types such as ramp data, per vehicle data, and optional (but soon to be mandatory) data on non-motorized traffic. These modifications require constant changes and improvements in states' traffic monitoring programs, and data collection and processing efforts. Second issue pointed here is the lack of centralized data management system that enables "upload/download, pre-screen, analyse and store the data". Such systems can help improving the data sharing within and between agencies, and eliminating the multiple/redundant data collection by different governmental bodies within state boundaries.

Most shared issue with the short short-duration data collection is the lack of or inefficient quality control procedures to ensure the performance of the data. Within this problem, some states mentioned the lack of quality control procedures after state forces or contractors collecting and submitting the data to the office, and some others mentioned the inefficient procedures for defining the correct location for the data collection and making sure it is collected properly. Considering almost all states collect significant amount of short-duration data, even in thousand locations in a year, this issue can significantly affect the accuracy and reliability of AADT estimates. Respondents are also mentioned the limited financial resources and coordination with contractors and other governmental bodies such as municipalities are common problems in terms of short-duration traffic data collection.

In the next question, respondents are asked about the problems in the data processing phase of the traffic monitoring program. Majority of states put emphasize on software/programming issues from different perspectives. Some highlighted the lack of well-developed software or data analysis tools for incorporating variety of data format from different sensors. If the existing software is developed by a consultant and not well maintained, incorporating new data formats or meeting the new requirements become challenging. Additionally, some states indicated that they manually perform the data processing with available Microsoft office products such as MS Excel and Access, which requires significant time.

After asking about the issues and challenges in data collection and data processing phases of traffic monitoring program, another question asked respondents to identify the leading causes of inefficiencies in the traffic monitoring program in their states. Most respondents emphasized the lack of support/understanding from upper management, funding issues and staff turnovers as inefficiencies of overall traffic monitoring program in their respective states. Additionally, lack of well-designed software/programs or well-documented procedures for increasing the quality of data is highlighted for increasing the efficiency of traffic monitoring program. One respondent stated that “lack of support from computer technology personnel in the Department to create programs that would automate current manually intensive processes” is one of the potential issue KBES can be helpful with.

2.5.3 Potential Improvements Stated by Respondents

Last question in the survey asked about the possible ways to improve the traffic monitoring program in their states. Most respondents emphasized the importance of required funding for new equipment/technologies and additional personnel for meeting the federal and state needs. After the financial initiatives, few responded states specifically pointed out the importance of "a browser based application/web portal" that is expected to improve quality of collected data and advance the capability of performing QC/QA procedure. For instance, a KBES application that helps deciding the location of short-duration counts (distance from intersection, number of lanes should be covered, etc.) can be a great example of this "browser based application" to improve the data collection and/or perform the QC/QA procedure since most short-duration counts are contracted in most states.

Integration of new technologies into the traffic monitoring program is also emphasized specifically for collecting traffic data in urban areas since states struggle collecting quality data – specifically vehicle classification data, in high traffic volume urban areas. Additionally, communication and collaboration with other agencies in the region is mentioned for reducing the collection of duplicate data. Different agencies can collect same or slightly different data without knowing that the data is being collected by another agencies. Although it is not in the scope of this study, as an example, a KBES can help defining the needs and requirements of different agencies for different traffic data types, and consequently initiate the communication/collaboration between these agencies.

The survey questionnaire and primary responses provided by state DOTs are summarized in the Table 3. Items marked with (*) represent the issues and challenges that KBES can be helpful with.

Table 3. Summary of Survey Responses

Survey Questions	**Participants Primary Responses**
Organizational structure of State Highway Agency	In-house continuous data collection, in-house and contacted short-duration data collection
Challenges in continuous data collection	Difficulty of maintaining in-pavement sensors Communication issues (cell/IP based data transfers) Limited staff for data processing Funding for new equipment and software Increased data requests from federal agencies require more data
Challenges in short-duration data collection	Contractor issues (establishing well coordination and quality of data collection personnel) Coordination of other governmental bodies for data collection (city, county, MPO, etc.) Staffing issue (low wages, limited staff) Quality of the counts (optimum location for the count, difficulty of collecting urban arterials) Safety of the workers
Challenges in data processing	Issues with current data analysis tools/software (dated/not well maintained) Updating the data analysis tools to meet the increased data requests Inadequate resources for QA/QC procedures Diversity of equipment and data / integration of data
Primary factors of inefficient TMP	Funding issues (equipment renewal, hiring more staff) Lack of / inefficient QC/QA procedures Lack of programs/tools to automate manually intensive processes Increased data requests from federal agencies require more data
How to improve TMP	Funding increase Applications/tools to upload/review/process collected data Improving QC/QA Better/easier methods for volume estimation and adjustment factors Utilizing new non-intrusive technologies

2.5.4 Possible Role of Knowledge-Based Expert Systems

Survey responses revealed few problems that KBES can be helpful with. These contributions are more towards increasing the efficiency and quality of the traffic monitoring programs by providing decision support tools and easy to use guidelines for performing the necessary procedures for data analysis. These aforementioned issues and possible KBES solutions are explained here:

One of the issues stated by survey respondents was the problems with current in-pavement sensors and requirement of updating/renewing the data collection technologies. Therefore, an expert system application can help in evaluating the different technologies to contribute to the decision making process. Possible intrusive and non-intrusive technologies can be assessed based on accuracy and reliability measures, capital and maintenance cost requirements, different weather and temperature performances, etc., and listed for the selection of appropriate technologies.

Lack /inefficiency of QC/QA procedures and communication issues are highlighted as experienced problems in short-duration data programs in states. KBES can be helpful with the determination of optimum locations for the placement of short-duration data collection equipment. In short-duration counts, there are certain criteria that the data collection team should follow for the accuracy and reliability of collected data such as distance from intersections, avoiding merging/dividing lanes, appropriately fastening the tubes, data collection days/times, etc. These criteria can be tabulated in a computer-based platform that can provide a guidance/checklist type of application for data collection team in field and can also be used for estimating the reliability of the data by giving different weights for each item and determining and overall score for the short-duration count.

Another possible improvement can be in initiating communication/collaboration between and within agencies to reduce the collection of redundant or duplicated data. For instance, TMC at DelDOT has been collecting real-time volume data on major corridors in New Castle County (NCC) for operational purposes. Moreover, DelDOT Planning Division has been using volume data from continuous count stations for establishing traffic pattern groups and estimating traffic statistics for all roadways in Delaware. Analysis of this data, which is explained in Chapter 4 of this dissertation in detail, reveals that NCC roads are not well represented in volume data program and recommended to increase the incoming data. However, TMC has been collecting the necessary data in real time. Therefore, an expert system application can incorporate data needs of different transportation agencies and other governmental and non-governmental agencies for creating a web-based application to use evaluating the possible data sources of other agencies for further collaboration.

The final example is more related to the context of this study. Due to increased data needs both in federal and state level and shortage of available personnel, data analysts in traffic monitoring programs are not able to perform some necessary analysis such as traffic pattern group analysis, evaluation of monthly variations, detection of anomalies in data, etc. Therefore, an expert system application can provide guidance and decision support tool for some key parts of the traffic monitoring program in states to ensure the quality of the data and produced summary statistics. This support can be explaining the details of the procedures with step-by-step to the responsible personnel and/or performing some procedures for them with limited data input.

2.6 Summary of Chapter 2

This chapter presented the concept of traffic monitoring program in state highway agencies with different aspects. The chapter started with introducing the traffic monitoring program, how it is structured, types of traffic measures collected and how these measures are used. Continuous and short-duration data programs are explained with highlighting the benefits and limitations of each, and emphasizing the tradeoff between these programs.

Three primary data programs (volume, vehicle classification and truck weight data programs) are then explained in detail in continuous data program section. Most important measures that are obtained through continuous data collection and analysis such as AADT, AADTT, MADT, Truck percentages, TPGs, etc. are explained and necessary mathematical and statistical procedures are presented.

This chapter also presented a survey that is designed to identify the issues and challenges in states traffic monitoring programs. The survey sent out 50 State Departments of Transportation traffic monitoring related offices and 13 responses received. The results revealed that traffic monitoring programs are under the pressure of budgetary constraints to renew/update the data collection technologies and improving data analysis methods. Additionally, lack of /inefficient QC/QA procedures, increasing data requests from federal agencies, lack of/insufficient quality staff are some of the issues highlighted by state agencies.

Last, the chapter summarized the potential improvement areas in the traffic monitoring program to improve the understanding and decision making capability of state DOT personnel who are responsible of data collection, processing and reporting.

Chapter 3

OVERVIEW OF KNOWLEDGE-BASED EXPERT SYSTEMS

Expert systems, a sub-discipline in the research discipline of Artificial Intelligence (AI), are computer systems that emulates the cognitive skills of human experts to guide users thorough complex decision-making processes *(33, 34)*. Expert systems and Knowledge-Based Expert Systems (KBES) are often used interchangeably to represent the most common type AI applications *(34)*. Moreover, Feighenbaum et al. *(34)* distinguished the slight difference between two concepts as the knowledge base in expert systems “contains the knowledge used by human experts, in contrast to knowledge gathered from textbooks or non-experts”. Therefore, the term “expert systems” is used to represent the general concept of the expert systems, and the term “Knowledge-Based Expert Systems (KBES)” is used to represent the related methodology used to develop the TMDEST framework since the knowledge base contains knowledge from both human experts and other documentation.

Expert systems can make inferences and reach a conclusion, similar to a human expert, and if necessary, explains the logic behind the conclusion. Turban and Watkins *(35)* states that the explanation mechanism is one of the key features of the expert systems that distinguishes from conventional computer programs.

KBES allow building an interactive and computer-based system that helps end users to solve a decision-making task. The system dynamically asks relevant and focused questions, and derives precise reasoning conclusions. KBES could be as simple as creating a selection-aid tool for users to make the most accurate selection such as choosing a digital camera based on technical features, price, user expertise level, etc. Moreover, it can get as complex as requiring to be developed by a professional team and can include evaluation of possible solutions with different level of confidence. These more complex systems are widely used in medical diagnostic applications and customer service relations.

Jackson *(33)* separates KBES from conventional programs and artificial intelligence in that the KBES performs "*reasoning over representation on human knowledge*". It can perform numerical calculations and data retrieval, and reaches the conclusion by "*heuristic or approximate methods*". Therefore, success in terms of finding the solution is not guaranteed. However, KBES must convince the user regarding the facts and reasoning behind the conclusion.

Expert systems have been in use since 1960s, and two well-known applications (MYCIN and DENDRAL) are accepted as the early successful attempts of expert systems. In early 1980s, commercial applications were becoming more popular and successful. Liao *(36)* successfully summarized the methodologies and applications of expert systems between 1995 and 2004, the next decade after the Internet use was opened to public in 1994. This extensive evaluation led classifying the expert system methodologies and applications and helped researchers understand the differences between these methods. The research however suggested that some methodologies have "*common concepts and type of methodology.*" Therefore, some applications could be seen in multiple methodology categories. For instance, both rule-based and knowledge-based methodologies can include development of advisory systems, knowledge representation, and decision support. *(36)*.

Expert systems in general have some benefits over the use of actual experts in problem solving and decision support systems. Benefits can be listed as:

- **Availability** – Expert systems are easily available since it is used as either online or desktop version programs, and can capture the scarce expertise of an individual.
- **Error Rate** − Error rate is low in a well-designed expert system, as compared to human error rate.
- **Consistency**− Expert systems make consistent recommendations and work steadily without getting tensed, emotional, etc.
- **Speed**− Expert systems can complete a task much faster than a human expert.
- **Production Cost** − Production cost is reasonable, otherwise building an expert system may not be practical.
- **Reducing Risk** – Expert systems can work in environments hazardous for humans.

On the other hand, expert systems have some limitations that need to be considered. As similar to benefits, limitations can also be highly dependent on the purpose and objectives of the expert system to be built. Multi-level and complex expert systems may require high development time and cost. Some of the limitation in expert systems can include:

- Limitations of the technology
- Difficulty of knowledge acquisition
- User's cognitive limitations
- High development costs
- High development time
- Difficulty of maintaining an expert system
- User's potential lack of trust on the advise/decision

3.1 Roles in Expert System Development and Use

3.1.1 Expert

Success of a KBES depends on the knowledge of the "expert(s)" that forms the "knowledge base" in any KBES. This knowledge can sometimes be a set of rules and documents prepared by a group of experts to perform a certain task. Manuals and guidelines can be examples of these well-prepared documents, but in a complicated process, these guidelines can be long and hard to follow. In addition to the knowledge of the experts, "how experts reason with their knowledge to reach a conclusion" is an important aspect to build the rules in KBES.

3.1.2 Knowledge Engineer

Knowledge acquisition is one of the key stages in the development of a KBES. Knowledge acquisition is explained as transforming the knowledge and problem-solving capability of an expert to a computer systems *(33)*. This important task involves obtaining and classifying expertise from miscellaneous sources such as books, guidelines, manuals, human experts, etc.

Knowledge engineer is the person or group of people to transform the knowledge of the experts into an interactive computer-based application that end-users can easily utilize and perform the specific tasks. Knowledge engineer should be able to perform all necessary tasks (interview, observe, understand, etc.) to learn about "how experts reach to a conclusion and how they reason with their knowledge." The knowledge engineer should work very closely both with experts and end users for a successful KBES development.

Wagner *(37)* also discussed the concept of *"end user developers"* as a combination of experts and knowledge engineers. The end user developers are considered as experts or have enough knowledge on the subject to obtain the necessary knowledge to construct the knowledge base in a KBES. At the same time, they can build a KBES by using simple and easy-to-use development tools.

> **"End user developers in our consideration are professionals and managers whose primary function is not information system development. These individuals will usually select a lower-end development environment (e.g. M.4, Exsys, or similar), based on**

simplicity and cost, and choose application areas according to their knowledge and interests *(37)***.”**

3.1.3 End User

End user of an expert system is the person that will be benefiting from the development of the expert systems. End users interact with the user interface to follow on-screen instruction and provide input, if necessary, to reach a conclusion.

3.2 Components of Knowledge-Based Expert Systems

A KBES consists of three main components: knowledge base, inference engine, and user interface, as shown in Figure 3. The first component, knowledge base, contains all the knowledge where the KBES is designed to work within such as knowledge, facts, rules, etc. Inference engine executes the rules if the information provided by users fulfils the conditions in the rules. Lastly, user interface offers interaction with non-expert users, where users answer the questions or input data to start the logical process in inference engine.

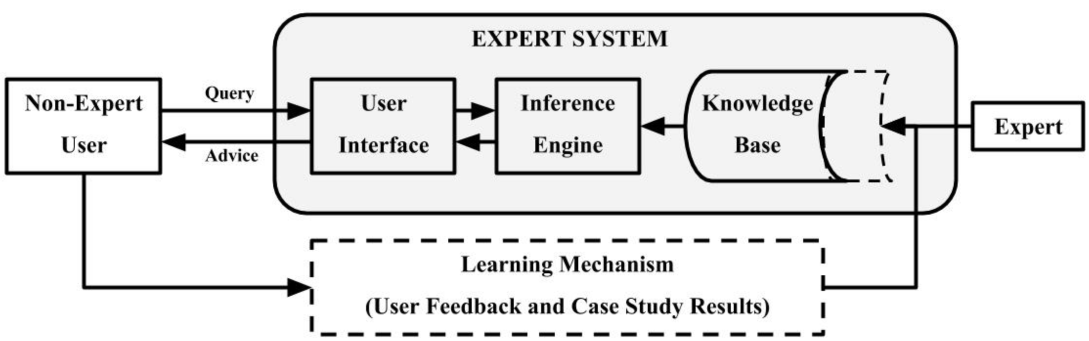


Figure 3. Typical Architecture of an Expert System

3.2.1 Knowledge Base

KBES include a knowledge base containing all the necessary domain-specific and quality knowledge. The success of a KBES is primarily depends on the collection and representation of accurate and precise knowledge. This knowledge can be both factual (widely-accepted knowledge, mathematical and statistical procedures, etc.) and heuristic (expert's judgments). Quality, completeness and accuracy of the data and information stored in the knowledge base significantly impact the accuracy and usefulness of any KBES.

3.2.2 Inference Engine

Inference engine has two primary tasks:

1. Utilizing the necessary rules and procedures to acquire and use the knowledge stored in the knowledge base to reach a particular conclusion.
2. Controlling the user interface and acquiring the necessary information and data from end user.

Inference engine enables combining the appropriate facts, rules and knowledge for a specific case as the expert system runs. The facts related to a specific case are stored in a *working memory*, which accumulates the knowledge about this specific case at hand. Then, the inference engine applies the appropriate rules to the working memory, adding new information and data until a conclusion is reached. The execution of rules are called "firing a rule" meaning when the entire IF parts of a rule are satisfied, then the inference engine "fires the rule" and executes the THEN part of the rule. This simple concept is presented in Figure 4.

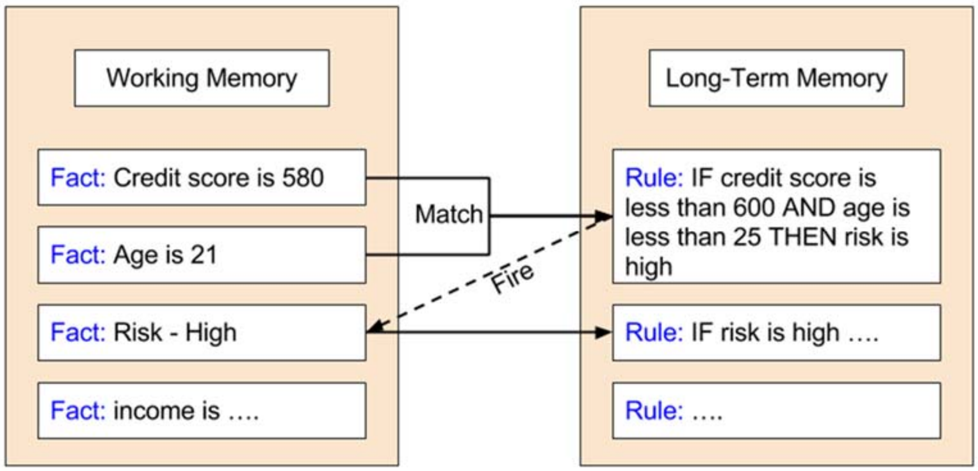


Figure 4. Concept of "Firing a Rule" in Expert Systems

Inference engine can use forward and/or backward chaining production methods for applying the rules to derive a conclusion. Jackson *(33)* explains the concept of forward and backward chaining as follows.

> **"We can chain forward from conditions that we know to be true towards problem state which those conditions allow us to establish, or we can chain backward from a goal state towards the condition necessary for its establishment."**

Forward chaining approach uses a strategy to check if each rule happens and answer the question "*what can happen next?*" This strategy follows the set of conditions and reaches to a conclusion until all rules are tested or reached to a rule to end the system. Forward chaining method is based on testing the rules in sequential order, from top to bottom in a logic block for each logic block. In this method, when the IF condition in a rule is true, then the inference engine fires the rule and apply the THEN part of the rule. Then, the inference engine moves to the next rule until the end. All this fired rules and knowledge/data brought by the fired rules are stored in working memory until the system reaches to a conclusion. Forward chaining is very procedural and order dependent and helps successfully applied to convert procedural operations to web-based interactive systems. The following diagram presents the simple concept of the forward chaining approach.

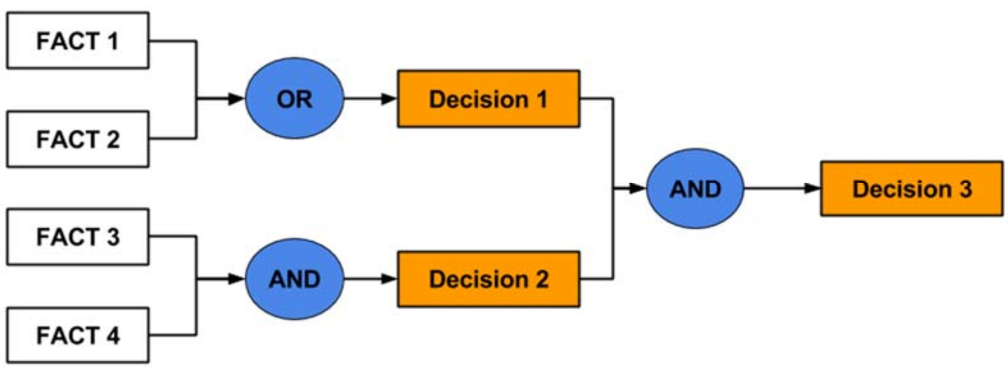


Figure 5. A Simple representation of Forward Chaining

Backward chaining, also called "Goal Driven Approach" uses a given "goal" to achieve a specific conclusion. In this approach, inference engine finds and fires all the relevant rules to achieve a goal rather than following the rules in a sequential order. The inference engine first finds the rule(s) that can assist to achieve the given goal. Then, if any of these rules require another rule to derive a specific value to be used, inference engine again finds and executes these rules. These secondary rules brings the concept of "immediate goals", not replacing the "final goal" but defining “temporary goals” to be used within the rules to reach the “final goal.” This process continues until the inference engine reaches to a conclusion, which is the given goal at the beginning of the process. Following diagram presents the simple concept of backward chaining approach.

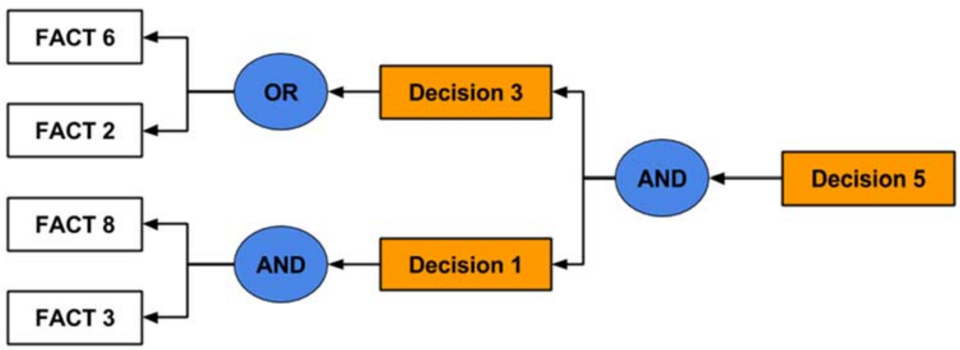


Figure 6. A Simple Representation of Backward Chaining

Backward chaining has many advantages for the KBES including multilevel and complex logic, since the goal changes dynamically. The inference engine starts with a given “final goal” and move forwards with “immediate goals” and only ask relevant questions to the end user. Therefore, in a complex system that includes very large number of rules, backward chaining can significantly eliminate asking unnecessary questions to the users.

3.2.3 User Interface

User interface enables the interaction between KBES and the end user. Therefore, user interface should be simple enough to ensure the successful communication with end users since end users are not necessarily to have any knowledge on the internal components of the KBES such as rules, logic blocks, and knowledge base. This interaction can be provided via dialog boxes, command prompts, or other input methods.

Explanation mechanism is one of the key features of the KBES distinguishes it from conventional computer programs. The method and procedure KBES uses to reach a conclusion may not be obvious to an end user. Thus, it is critical to employ an approach for explaining the reasoning behind the decision in a way that non-experts can understand.

The design of the user interface sometimes become challenging considering the variety of the inputs provided by user, list of rules fired to reach a specific conclusion and necessary details to explain the reasoning behind the conclusion. Therefore, user interface should be designed in a way to ask questions that the users will be comfortable with answering, and to provide reports clear enough to understand the conclusion.

3.3 Applications of Expert Systems in Transportation

One of the well-known and early expert system applications from medical field, PUFF, is successfully used for the interpretation of the measurements from respiratory tests applied to patients. This application helped improving the diagnosis decisions of less-experienced physicians by using the methodology developed by expert physicians *(38)*.

Faghri and Demetsky *(39)* designed a prototype KBES (called TRANZ) for evaluating and selecting the appropriate traffic control strategies around highway work zones. In this prototype, range of control options is evaluated to produce control requirements to the end user.

PAVER and Micro PAVER are another well-known expert system application in pavement management developed in early 1990s. The system provides pavement engineers to determine and prioritize the maintenance and rehabilitation needs by using Pavement Condition Index (PCI) and pavement rating procedures *(40)*.

In another study, Frey et al. *(41)* used the KBES for improving the safety at rural, unsignalized intersections by incorporating the quantitative assessments of the potential design and safety options. This system guides end-users for selecting the proper design features and crash statistics, such as if the intersection is two-way or all-way stop controlled, most common crash types, time of day and weather conditions, etc. and provide countermeasures for improving the safety at these rural, unsignalized intersections *(41)*.

Falamarzi et al. *(42)* developed a web-based advisory system (CALMSYS) for the implementation of different traffic calming strategies. The authors incorporated variety of traffic calming strategies with the knowledge and experience of the domain experts to design a web-based advisory system. The system enables end users to select pre-defined problems (e.g. speeding in urban streets, accident rate, width of street, street with sharp turns, etc.) and provide different traffic calming strategies to the users.

3.4 Verification, Validation and Evaluation (VV&E) of Expert Systems

One of the important tasks in building expert systems is the verification, validation and evaluation (VV&E) of the system. Without performing these important checks, the system may be malfunctioning, misleading or totally useless. Depending on the size of the expert system, complexity of rules and logic blocks, different approaches could be used for verification and validation process. Wentworth et al. *(43)* discussed these processes in following three main categories, and explained the purpose of each category as well as listed different approaches for verification and validation of expert systems.

3.4.1 Verification

The purpose of verification of an expert system is to check if the exert systems works efficiently without producing any errors, the results are consistent and the user interface is well designed. All expert systems are required to be investigated whether the system is consistent and stable. Verification process should deal with following questions *(43)*:

- Does the design reflect the requirements? Are all of the issues contained in the requirements addressed in the design?
- Does the detailed design reflect the design goals?
- Does the code accurately reflect the detailed design?
- Is the code correct with respect to the language syntax?

3.4.2 Validation

The validation process simply answer the question of "is the program doing the job it was intended to do?" Thus, validated expert system ensures that the system is usable for the intended purpose. However, as similar to human experts, expert systems also do not guarantee an absolute solution and provide an advise/guidance with a degree of confidence. Wentworth et al. *(43)* listed the issues addressed during the validation process:

- How well do inferences made compare with knowledge and heuristics of experts in the field?
- How well do inferences made compare with historic (known) data?
- What fraction of pertinent empirical observations can be simulated by the system?
- What fraction of model predictions are empirically correct?
- What fraction of the system parameters does the model attempt to mimic?

3.4.3 Evaluation

Evaluation process measures the value of an expert system and simply answers the question of "is the system valuable?" Some researchers include this evaluation process in validation part and some investigates separately. A verified and validated expert system might fail in evaluation step simply because being too complicated to use, doesn't save any effort or cost, or produces results that are not universally accepted *(43)*. As similar to validation and verification process, Wentworth *(43)* identified the questions should be answered in the evaluation step:

- Is the system user friendly, and do the users accept the system?
- Does the expert system offer an improvement over the practices it is intended to supplement?
- Is the system useful as a training tool?
- Is the system maintainable by other than the developers?

3.5 Summary of Chapter 3

This chapter provided the necessary background on expert systems. The chapter explained the expert system as a part of Artificial Intelligence (AI) and the concept of Knowledge-Based Expert Systems (KBES), and provided a concise historical development. Then, roles and contributors are explained as experts, knowledge engineers and users. It is also highlighted the "*end user developer*" concept, which KBES are developed by professionals who are not information system professionals but working in a field where experts constitute the knowledge base. So these end user developers may have both expert and knowledge engineering role.

The concept of the KBES and its components explained in detail. Differences of forward and backward chaining emphasized. Importance of user interface and explanation mechanism stressed to produce a practical and easy to use KBES and inform users regarding the reasoning behind the given conclusion. Lastly, Verification, validation and evaluation process is explained.

Chapter 4

A COMPREHENSIVE REVIEW AND UPDATING OF TRAFFIC MONITORING PROGRAM AT DELDOT

The University of Delaware Center for Transportation has published two reports related to Delaware Department of Transportation (DelDOT) Traffic Monitoring program. The first, published in 1991, entitled “Development of an Integrated Traffic Monitoring System in Delaware” reviewed the methods and procedures, and developed statistical methods consistent with the federal guidelines for improving the precision of data collection and reliability of the data. Phase two, published in 1995, entitled “Traffic Monitoring in Delaware” further reviewed the improved the procedure in previous report and compared the current practices with other state highway agencies such as Vermont and Rhode Island. The second study also reviewed the number and location of all traffic volume, classification and vehicle weight sites throughout the state.

Since the publication of the Phase-2 report in 1995, traffic characteristics have changed. Now there are 10 traffic lanes on a significant portion of I-95, and SR 1 is fully functional. Lanes have been added for capacity enhancement throughout the state. Furthermore, land-use patterns have changed. Areas that were considered rural 20 years ago are now suburban. Areas that were suburban are now urban. Moreover, not only there is more technologically advanced data collection equipment available, but other DelDOT divisions and agencies, such as the Traffic Management Center (TMC), are conducting data collection on a regular basis.

The next sections in this chapter will provide an overview of traffic monitoring program at DelDOT. Then, volume, vehicle classification and weight data programs are studied thoroughly, seasonal variations are evaluated and traffic pattern groups are established. Current numbers of continuous count stations and their locations are evaluated, and few new stations suggested. Last, short-duration data program is reviewed.

4.1 Overview of DelDOT Traffic Monitoring Program

DelDOT has been collecting, summarizing and reporting highway traffic data and information for more than 50 years. The collected data is primarily used to assess transportation needs and system performance.

4.1.1 Traffic Monitoring and Data Collection Technologies

DelDOT has been using variety of technologies for the collection of volume, vehicle classification, and weight data on Delaware roadways. Among all different technologies, few of them are extensively used and worth to mention.

ATR stations have long been used to continuously monitor traffic on Delaware roadways covering majority of roadway functional classes. Variety of loop detector configurations have been used to collect different type of traffic measures such as volume, vehicle classification, and vehicle speed. ATR stations collect traffic data on 24 hours per day, 7 day per week and transmit the collected data to ITMS (Integrated Transportation Management System), which is the data retrieval system of TMC.

DelDOT currently has 84 operating continuous count stations providing traffic data as of 2014, excluding few malfunctioning and require maintenance/renewal. Among these, 15 are volume-only (ATR); 45 are volume and speed (VSP); 2 are volume, classification and speed (VCS); and 22 are Weight-In-Motion (WIM) stations. DelDOT also has 7 toll sites that also provide volume and vehicle classification data in some extent. A map of currently operating continuous count stations is presented in Figure 7. The continuous count stations are both randomly and strategically placed throughout the Delaware roadway network. Strategic locations typically cover the state borders for the monitoring of interstate traffic movements.

Current Continuous Count Stations in Delaware

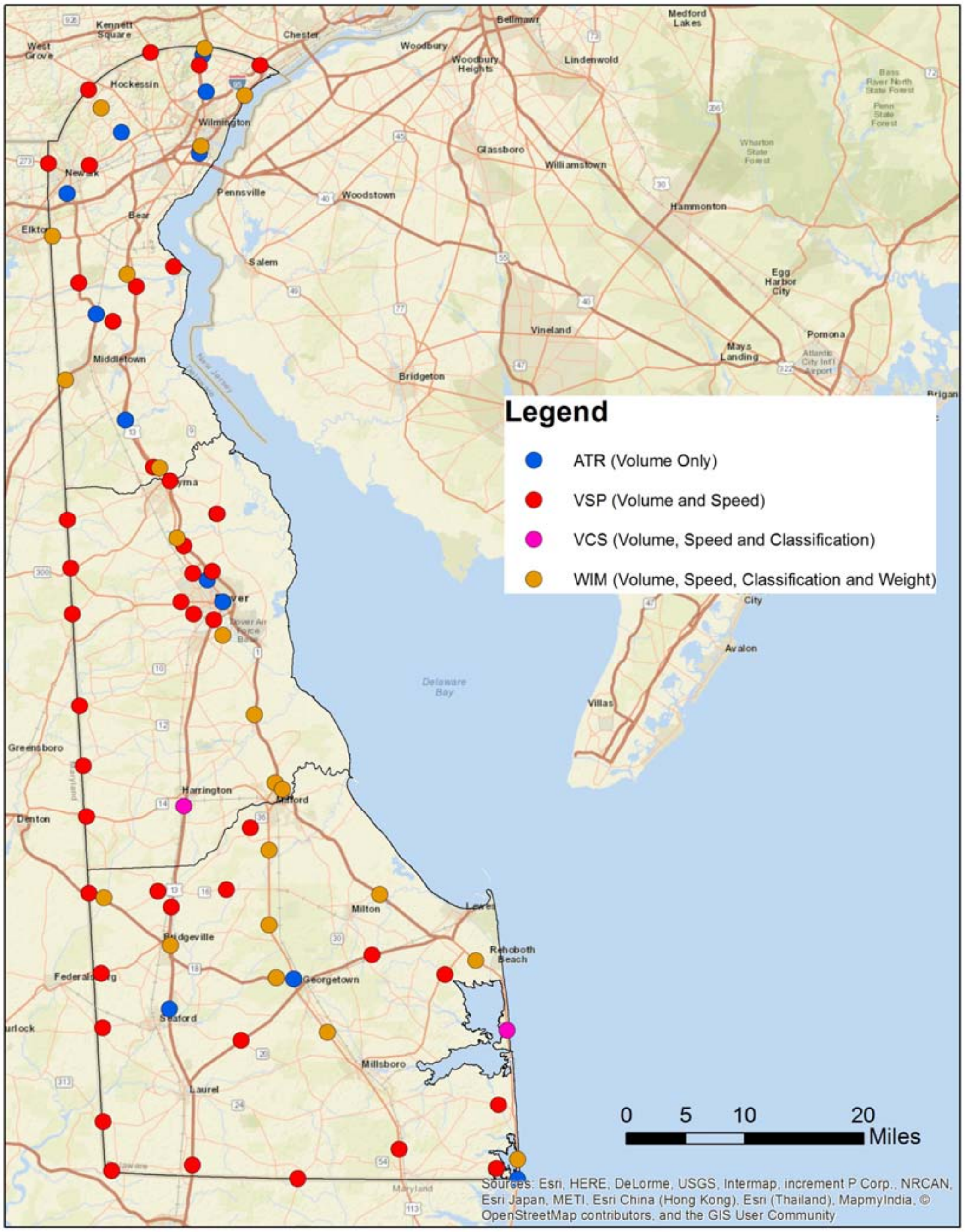


Figure 7. DelDOT's Current Continuous Count Stations

The Transportation Management Center (TMC) at DelDOT utilizes inductive loop detectors (6'x6') to collect real-time traffic volume data along major signalized corridors. The so-called system loops are placed downstream of each lane where vehicles typically reach free flow speed. Then, collected volume data are generally used to manage signal-timing operations within traffic-responsive signal system deployed corridors. Relevant to the context of this study, detected traffic volume has the potential to contribute to the continuous and short-duration traffic volume counts *(44)*.

DelDOT also utilizes Real-time Traffic Microwave Sensors (RTMS) for the collection of real-time traffic data along interstates and major corridors. These microwave sensors are placed on the side of the roadways, and are able to collect traffic volume, length-based vehicle classification, individual vehicle speed and average travel speed. Additionally, these sensors are able to measure the aforementioned traffic data types by each lane. However, these microwave sensors use length-based classification and currently not compatible with FHWA's 13-category vehicle classification. Although collected length-based data is useful for internal use, it is required to develop appropriate methods to convert collected length-based classification data into FHWA's 13 vehicle axle-based categories to be used in HPMS reporting.

In addition to widely used technologies mentioned above, there are more sensors and detector for obtaining traffic, weather, and infrastructure related data. Bluetooth technologies have been lately used for the collection of travel time along major roadways; CCTV cameras for monitoring congestion, accidents, etc.; changeable message signs for informing/warning travellers; and weather stations to collet real-time weather and pavement surface condition information (surface temperature, freezing points, etc.).

4.1.2 Roles and Responsibilities in DelDOT

DelDOT consist of many divisions and sections within its organizational structure to perform different tasks more effectively. Among all, the following DelDOT divisions and sections are described for their participation and contribution to the traffic monitoring program.

DelDOT Planning Division has many responsibilities to provide and maintain the quality of service in transportation. The Planning Division is the primary actor for collecting, analysing, and publishing transportation-related data, including submitting necessary data to the federal agencies and establishing customer relations. The Planning Division is the responsible DelDOT section for administering the DelDOT Traffic Monitoring Program. The Traffic Count Coordinator is the main responsible personnel for the coordination and control of the traffic monitoring data in the Planning Division.

DelDOT Traffic Section is responsible for designing, maintaining and operating all traffic system devices that are owned and maintained by DelDOT. Traffic system devices refer to a variety of devices used for monitoring and managing the traffic flow on roadways such as traffic signals, traffic cameras, Automatic Traffic Recorders (ATRs), data communication systems, etc. DelDOT's 2015 Traffic Design Manual *(44)* covers the types and specifications of traffic system devices in detail.

DelDOT TMC is the responsible Traffic Section group for the operation of all traffic system devices throughout the state. TMC also serves as a data communication center in DelDOT. All ITS devices owned and operated by DelDOT are connected to DelDOT's Integrated Transportation Management System (ITMS), which is the data retrieval and communication system of TMC. Therefore, all ITS devices, including continuous count stations send data to TMC. Then, other divisions/sections within DelDOT can coordinate with TMC to access collected traffic data.

DelDOT Office of Information Technology (OIT) is responsible for establishing a communication bridge between TMC and DelDOT Planning Division in traffic monitoring program. OIT obtains traffic volume, vehicle classification and weight data through TMC's data communication system. OIT data analyst(s) also receive short-duration (coverage) counts from vendor(s) who perform the short-duration counts. Then, both continuous and short-duration traffic monitoring data are validated and processed by OIT data analysts in coordination with DelDOT Planning Division. OIT also reports the monthly traffic volume data to FHWA where data is used for generating Traffic Volume Trends Report.

4.1.3 Traffic Monitoring Program Workflow in DelDOT

The traffic monitoring program requires the effective communication and collaboration between key personnel from different DelDOT divisions, sections and private companies. Figure 8 outlines the key personnel and workflow in a diagram. Continuous counts such as volume, vehicle classification and weight data are extracted through TMC's data servers, and short-duration data obtained through vendor(s). Then, OIT data analyst performs the validation process for short-duration and continuous data thorough data analysis software. Anomalies and errors are reported to the responsible parties. Afterwards, OIT analyst submits monthly summary of ATR data to the Traffic Count Coordinator.

Once the data is processed and finalized, it is shared with relevant DelDOT groups such as HPMS coordinator, publication and reporting personnel, and federal agencies. OIT Analyst submits monthly ATR data to FHWA through FHWA's Travel Monitoring Analysis System. On the other hand, Traffic Count Coordinator shares relevant data with HPMS team for the preparation of HPMS reporting and manages the preparation of Traffic Summary Book.

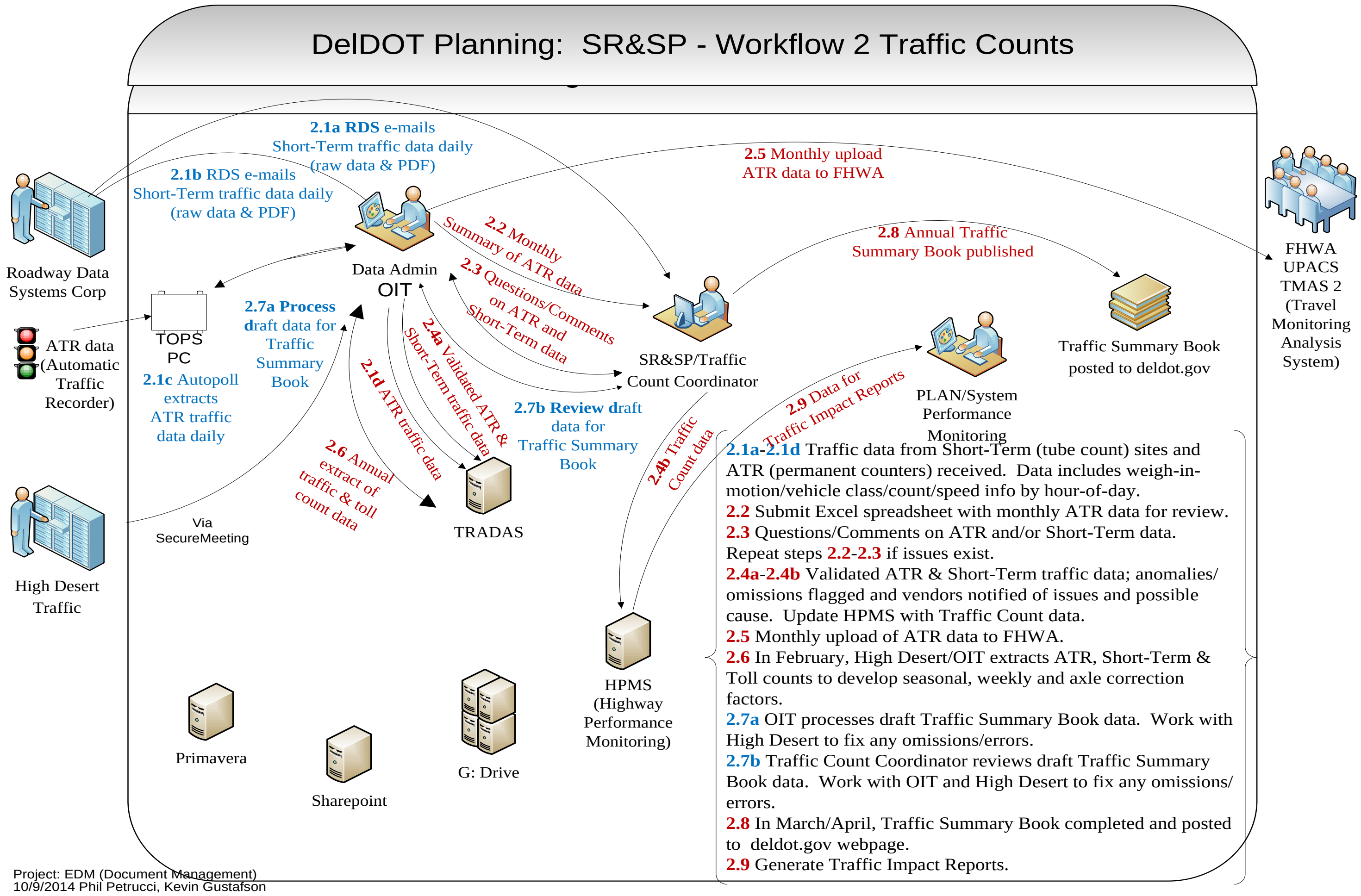


Figure 8. DelDOT Traffic Monitoring Workflow *(Source: DelDOT-OIT)*

4.1.4 Traffic Monitoring Data Processing Efforts at DelDOT

DelDOT publishes The Traffic Summary Report, which is an annual publication that contains updated traffic data such as seasonal traffic patterns, adjustment factors, growth factors, K- and D-factors, and other pertinent information about the traffic in Delaware. The report also briefly outlines the data collection and analysis process, and reporting of traffic data. DelDOT Division of Planning has been using a commercial software package to validate and analyse the collected volume, vehicle classification and weight data *(45)*.

DelDOT currently assigned 8 Traffic Pattern Groups (TPG) to represent the traffic characteristics of all roads in the Road Inventory Network. These TPGs, ranging from TPG 1 through TPG 8 are established based on functional classes of the roadways and similar traffic characteristics such as seasonal volume trends. Table 4 presents the list of TPGs with corresponding functional classes and number of continuous count stations in each TPG.

Table 4. Traffic Patterns Groups and Represented Functional Classes *(45)*

Traffic Pattern Group	Functional Classification	Number of Continuous Count Stations
TPG 1	Interstate, Freeways & Expressways	8
TPG 2	Other Urban Arterials	18
TPG 3	Urban Collectors	3
TPG 4	Urban Local Street	None
TPG 5	Rural Arterials	29
TPG 6	Rural Major Collectors	6
TPG 7	Rural Minor Collectors & Local Roads	2
TPG 8	Recreational Routes	16

It is reported that there were 3,459 roadway segments on the Road Inventory Network in 2015 where 86 of them are supported by continuous count stations and remaining 3,373 segments are covered by short-duration data program. DelDOT performs approximately 900 short-duration volume counts for a one-week period at most locations. Among 900 counts, 100 of them are 48-hour duration vehicle classification counts, mainly at HPMS locations. DelDOT short-duration data program covers all roadway segments in maximum of six-year cycle, while some segments are collected in annually or three-year cycles *(45)*.

4.2 Description of Empirical Data Setting and Initial Data Processing

The data provided by the DelDOT OIT and consists of:

- Daily volume counts from continuous count stations for the years 2012, 2013 and 2014,
- Vehicle classification count data from continuous vehicle classification count and WIM stations for the years 2012, 2013 and 2014,
- Weight data from WIM stations for the years 2012, 2013 and 2014,
- Short-duration volume data for the years of 2012, 2013 and 2014.

Additionally, FHWA's VTRIS W tables are used for incorporating the truck weights and loaded truck percentages in each vehicle classification category. FHWA Office of Highway Policy Information (OHPI) has developed the VTRIS W tables to present the vehicle classification and weight summary statistics.

The entire dataset includes volume data from 84 stations, classification data from 24 stations and weight data from 22 stations.

Initial data processing started with evaluating the list of continuous count stations, their locations and respective roadway functional classes from various DelDOT sources for creating a base file for further analysis. During this step, the following three sources are used and data from these sources are combined in one spreadsheet. These sources are:

- DelDOT Traffic Summary Book
- ATR location map file obtained from DelDOT website
- Functional Classification maps of New Castle, Kent and Sussex Counties obtained from DelDOT website

There were some inconsistencies discovered while comparing these three data sources. 2014 Traffic Summary Book was taken as a base file and updated based on functional classification maps. For example, station 8084 - DE 9 / 404 E of Harbeson was listed as ‘minor arterial’ in the Traffic Summary Book. However, Sussex County functional classification map indicates that this station should be listed as ‘principal arterial’. Similarly, stations 8066, 8067, and 8068 located on DE 10, DE 12, and DE 14 respectively near the Maryland state line in Kent County are listed as ‘principal arterial’. All three stations are presented as ‘major collector’ in Kent County functional classification map and have less than 3,500 AADT. After these minor changes, a final version of the continuous count station list and respective roadway functional classes are used in the analysis.

4.3 Volume Data Program

Volume data from continuous count station are investigated for the evaluation of spatial and temporal variation and establishing TPGs. These TPGs help accumulating continuous count stations whose roadway functional classes, seasonal variation characteristics and volume trends are similar. Then, each TPG group is graphically studied for monthly volume trends and tested to ensure if each group include the minimum number of continuous count stations for statistical accuracy.

4.3.1 Calculation of MADT, AADT and CV

Monthly Average Daily Traffic (MADT) is calculated for each continuous count station for 2012, 2013 and 2014. In this calculation, an average of three years is used to reduce the effect of variation produced by single events in any individual year. This approach provided more robust dataset for establishing the groups.

There are different approaches regarding the calculation of AADT and MADT to reduce the effect of missing data as discussed in Chapter 2 of this dissertation. The following TMG recommended procedure is used for the calculation MADTs.

$$MADT = \frac{1}{7}\left[\sum_{i=1}^{7}\left(\frac{1}{n}\sum_{j=1}^{n} VOL_{ij}\right)\right]$$

Where:

VOL = daily traffic for day j, of DOWi

i = day of the week

j = 1 when the day is the first occurrence of that day of the week in a month, 4 when it is the fourth day of the week

n = the number of days of that day of the week during that month (for which you have data)

In this formula, an average day of week average daily traffic (ADT) is first computed for a given month, and then all seven-day values are averaged. This approach effectively removes the biases produced by missing days, especially if those missing days are unequally distributed across days of the week. Then, AADT is calculated by averaging the MADT for each continuous count station by using the following formula:

$$AADT = \frac{1}{12}\left(\sum_{i=1}^{12} MADT_i\right)$$

Where:

AADT = Annual Average Daily Traffic

MADT = Monthly Average Daily Traffic for month *i*

i = month of year

Then, monthly adjustment factors (MAF) for each continuous count station are calculated by using the ratio of AADT to MADT.

$$MAF_i = \frac{AADT}{MADT_i}$$

Once the monthly factors are calculated, coefficient of variation can be easily obtained by using the ratio of standard deviation of monthly factors to mean of monthly factors.

$$CV = 100 * \frac{S_{MAFi}}{X_{MAFi}}$$

Where:

CV = Coefficient of Variation of monthly factors

S_{MAFi} = Standard deviation of monthly factors

X_{MAFi} = Mean of monthly factors

4.3.2 Graphical Evaluation of AADT and CV for the Volume Data

The 3-year average of AADTs and CVs are graphically evaluated to see if there is any visible trend in the data. Figure 9 presents the AADT and CV of 84 stations included in the analysis. It is clearly visible that some group of roadways are accumulated towards the higher AADT values (> 50,000 AADT), and some of them towards higher CV values (> 0.20 CV) where higher AADTs are from Interstates and northern sections of DE 1 in NCC, and higher CVs are from predominantly recreational roads.

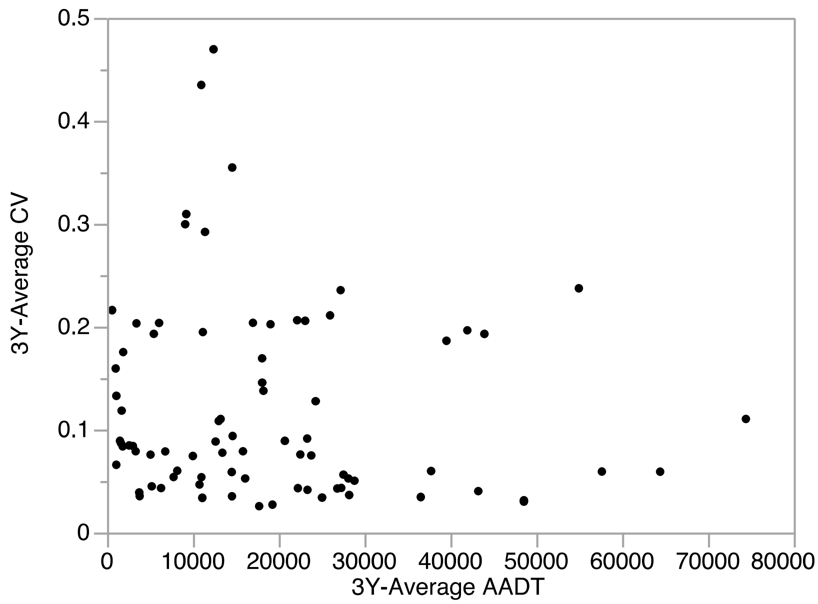


Figure 9. Distribution of AADT and CV for 83 Continuous Count Stations

Then, the data set is divided into two groups as 'urban' and 'rural' to evaluate the same visible trends in the data by urban/rural typology and monitor if there is any change. Distribution of AADT and CV are presented by urban and rural areas in Figure 10. The following effects are considered worth mentioning:

- Interstates present higher AADT and lower CV and accumulated towards the right end of the distribution.
- Major parts of DE 1 near urban, small urban and rural areas present higher CV due to the variation of the seasonal traffic volume.
- Remaining arterials and collectors are accumulated in moderate volumes and low CVs in urban areas.

- Recreational roads in rural areas present higher CV values compared to recreational roads in urban areas.
- Majority of rural roadways – excluding predominantly recreational roads that show CVs over 0.3 and high volume DE 1 Freeway/Expressway section, are aggregated into two groups: lower AADT (<10,000) with moderate seasonal variation and moderate AADT (10,000 – 20,000) with moderate seasonal variation. Moreover, the first group includes the majority of the major collectors and second group includes majority of rural arterials.

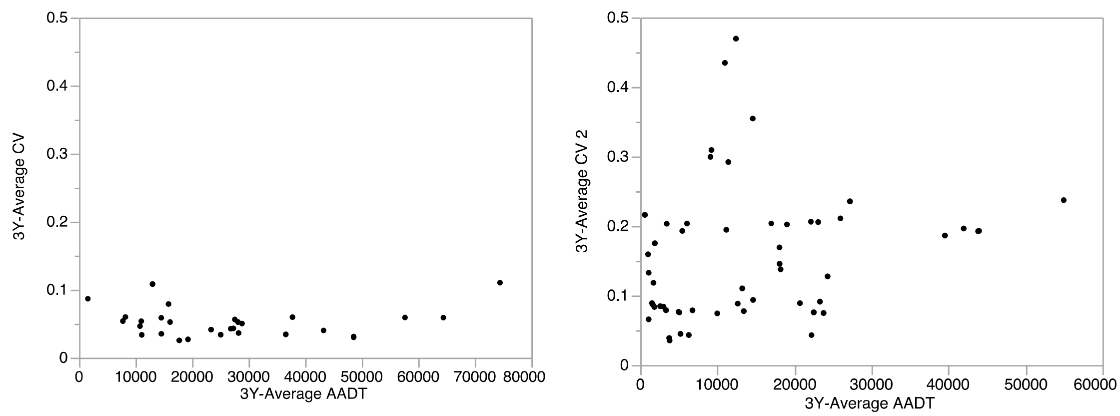


Figure 10. Distribution of AADTs and CV in Urban (Left) and Rural (right) Areas

Since the CVs will be used to generate the TPGs by including the effect of monthly variations, distribution of CVs over the roadway functional classes are also graphically investigated (Figure 11). This evaluation helped identify the outliers and boundaries in each functional classification.

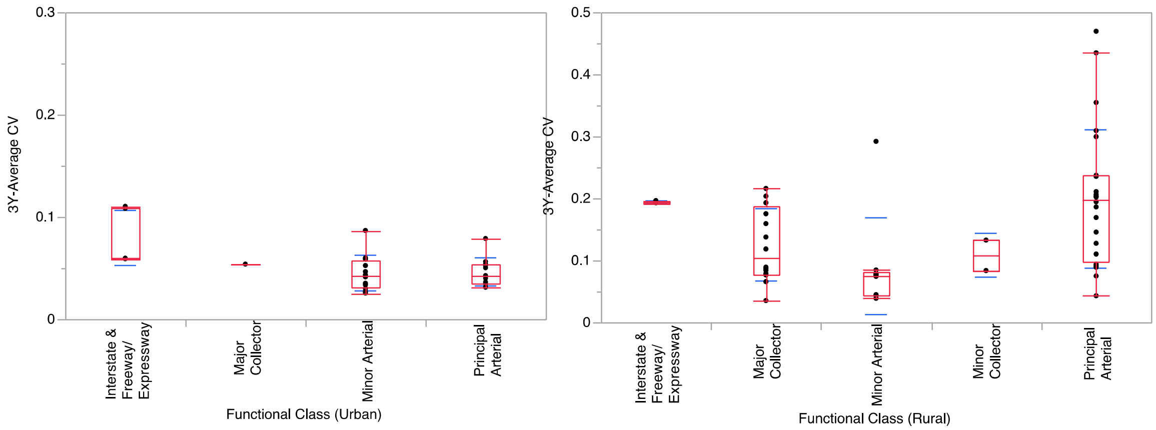


Figure 11. Distribution of CVs by Roadway Functional Classification in Urban and Rural Areas

These graphical evaluations increase the understanding of dataset before applying statistical methods. From Figure 11, it is clearly visible that majority of roadways which are from same roadway functional classification show similar seasonal variations. The roadway functional classes that show higher range in CVs are due to the effect of recreational roadways in the group.

4.3.3 Determination of Traffic Pattern Groups

Hierarchical clustering was applied to CVs and AADTs for 3-year average data for 83 continuous stations. Only station 8053 – State Fair VCS was excluded due to special use of the site and its distinct traffic pattern. Figure 12 presents the dendogram of hierarchical clustering, where each different color represents different clusters.

Both scree plot and Cubic Cluster Criterion (CCC) are used for determination of optimum number of clusters in the dataset. Figure 13 presents the scree plot for hierarchical clustering where elbows in the graph indicate the possible optimum number of clusters. Visual interpretations of scree plot shows one clear elbow that points out the noticeable increase in the coefficient as presented in Figure 13. The turning point of arrow indicates 10 clustering groups. Similarly, CCC indicated that 10 clustering is the optimum based on given dataset. Then, the it is decided to start with 10 clustering groups and make necessary adjustments if necessary to create identifiable TPGs.

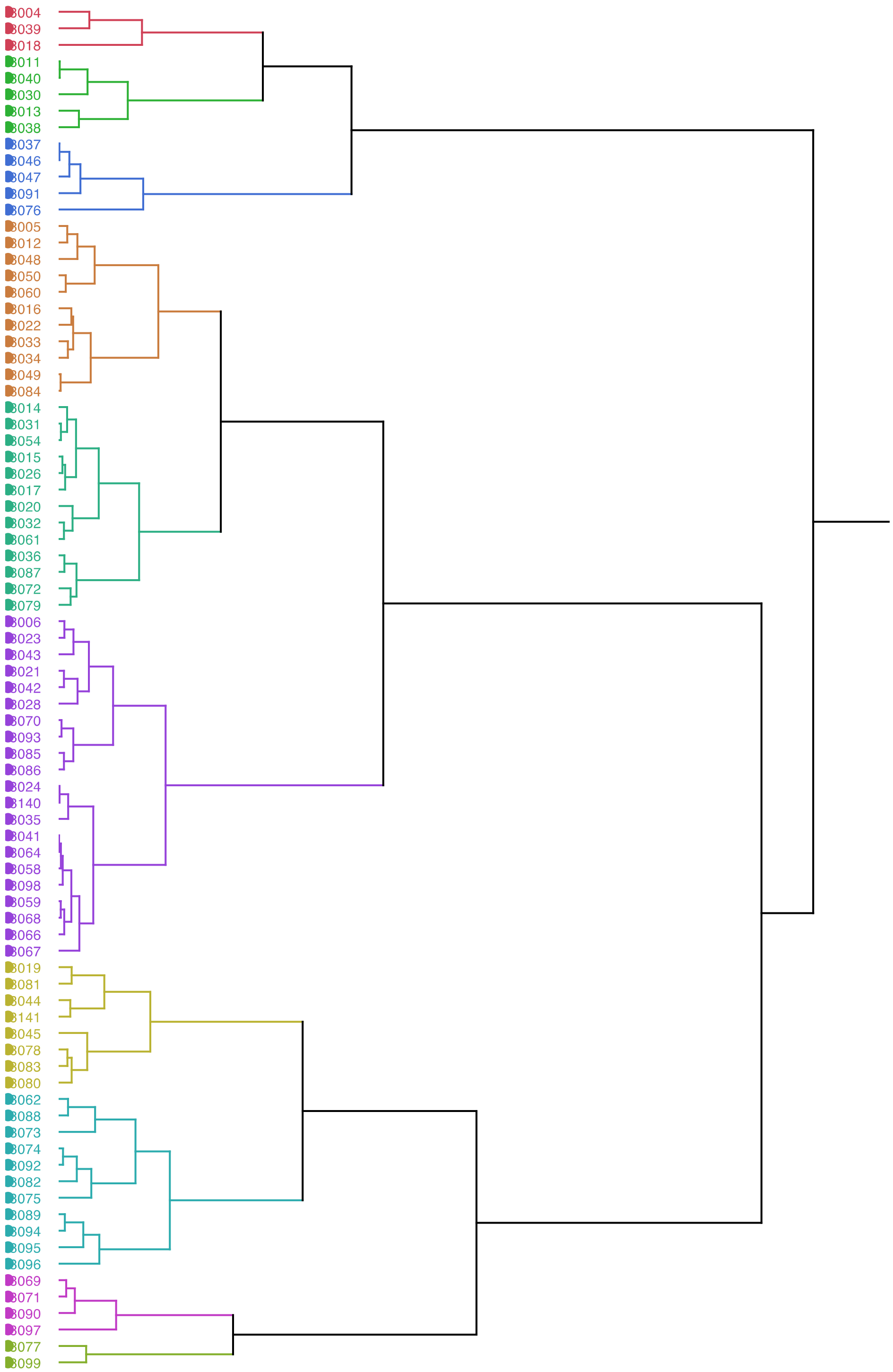


Figure 12. Hierarchical Clustering of Volume Continuous Count Stations

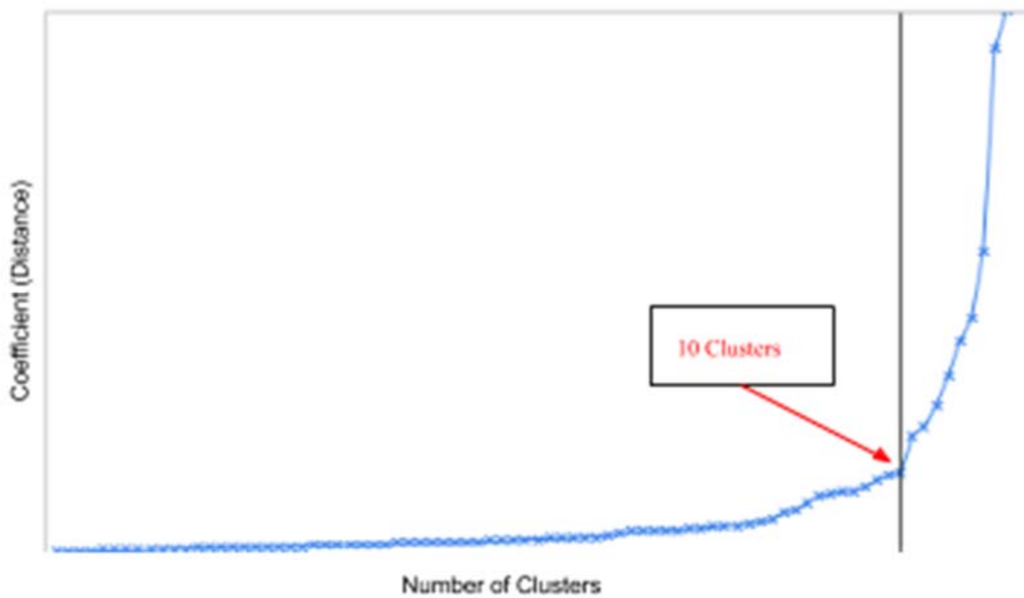


Figure 13. Scree Plot of Hierarchical Clustering

Among 10 clustering group, further detailed graphical evaluation and urban/rural differences were investigated based on the following rules:

- If there is a continuous count station that is placed in an urban clustering group while it is geographically located in rural area, it can be placed in a rural clustering group whose group members show similar AADT and CV characteristics or vice versa.
- If there are two groups whose monthly variations present similar trends, and placed in the same urban or rural area, and have the same or similar roadway functional classification, these groups can be merged together.

- If there is a continuous count station whose roadway functional classification is significantly different from other continuous count stations in the same clustering group, it can be placed into a different proper clustering group. For example, removing a major collector from a principal arterial group.

These adjustments are made for generating identifiable traffic pattern groups which are also consistent based on same or close roadway functional characteristics and are placed in the same urban/rural settings in addition to monthly variation similarities. Moreover, it will improve the assignment of short-duration counts into proper traffic pattern groups.

Initial clustering groups 3 and 8 show very similar monthly variations with a CV ranging between 15% and 24%, and only placed in different groups due to their AADT differences (Figure 14). Moreover, all stations placed in these two groups are rural arterials. Therefore, these clusters are merged into one clustering group and named as Traffic Pattern Group 5 – Recreational Rural Arterials. Monthly variations of continuous count stations that are placed in TPG 5 are presented in Figure 15. Vertical axis presents the monthly adjustment factors (MAF) for each station. It is also important to emphasize that MAFs have an inverse relation with MADT, so low monthly factors indicates high traffic volume in summer months for the given location in this specific group.

Specific roads that are placed in this group are identified as:

- DE 1 north of Rehoboth Ave (Rehoboth Beach)
- US 113

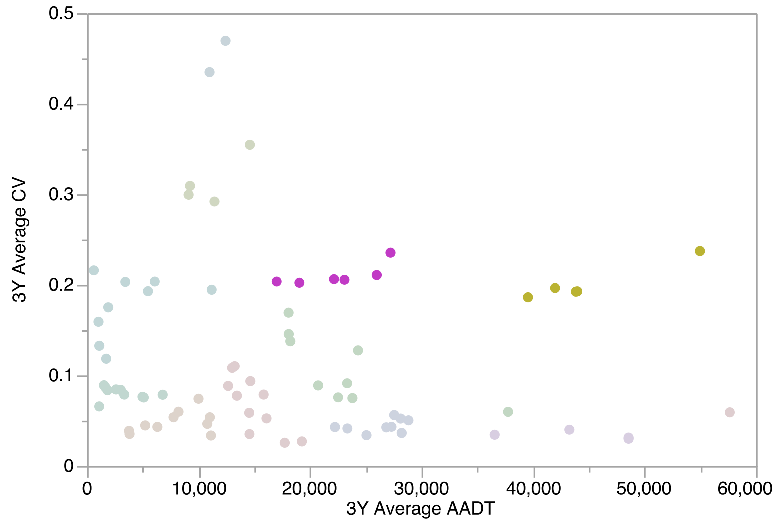


Figure 14. Graphical Evaluation of Initial Clustering for Groups 3 and Group 8

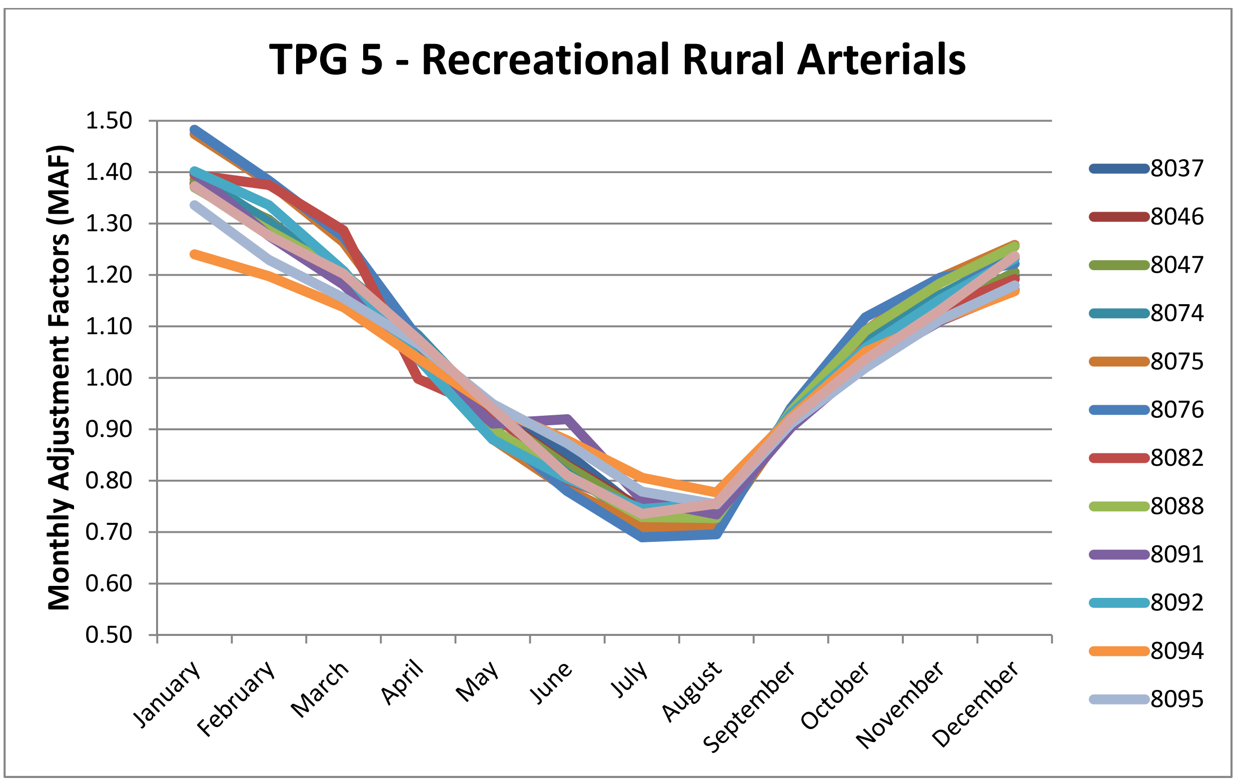


Figure 15. Monthly Variations in TPG 5 – Recreational Rural Arterials

Another clear merging opportunity is observed between initial clustering groups of 9 and 10. As presented in Figure 16, these two groups are accumulated far away from other clustering groups and have slightly different CVs from each other based on monthly variations. These stations are merged into a single cluster and named Traffic Pattern Group 8 – Recreational Routes. Later, four other stations (CVs around 20%) are also added to this group considering the roadway functional classification and geographic location where stations are mostly placed along same roadways with initial six stations in the group. Monthly variations of total of ten continuous count stations placed in TPG 8 are presented in Figure 17. These stations are placed where seasonal variation is significant. Specific corridors in this group are identified as:

- DE 1 south of Rehoboth Avenue (Rehoboth Beach)
- DE 54
- DE 26
- DE 16
- DE 404 between MD line and US 13

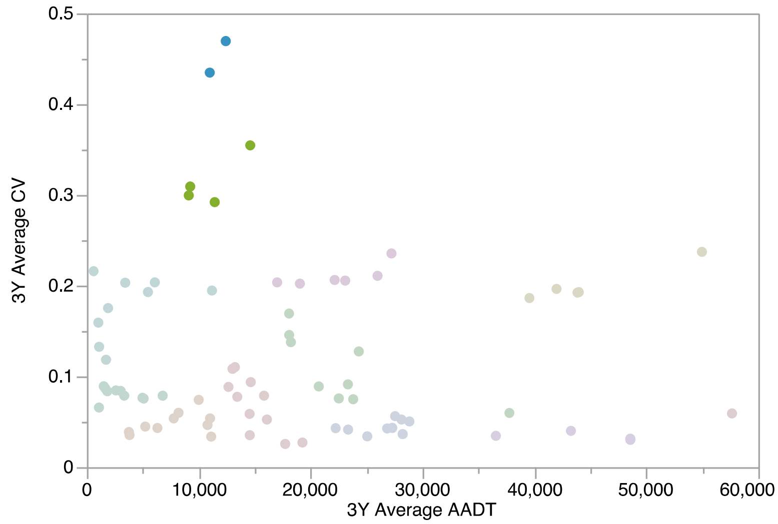


Figure 16. Graphical Evaluation of Initial Clustering Groups 9 and 10

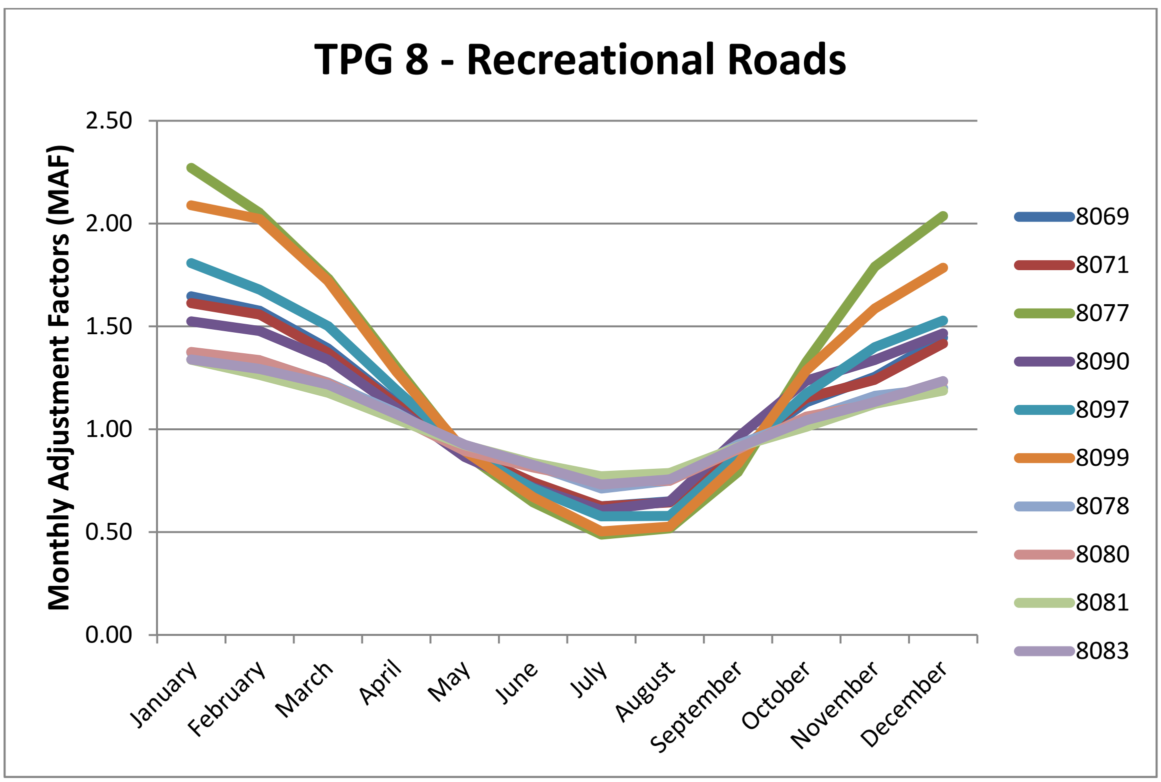


Figure 17. Monthly Variation of TPG 8 – Recreational Roads

It is also observed that there is another clustering group that contains rural arterials with low coefficient of variation compared to previously named TPG 5, and this group is named TPG 6 – Non-Recreational Rural Arterials (Figure 18). It is further investigated if there is a clear distinction between these two groups or they should be merged to eliminate the confusion of having two rural arterial groups. Then, the average monthly variation of rural arterials and recreational roads are compared in Figure 19 and decided not to merge the rural arterial groups due to differences in seasonal variations. It was decided to name the TPG 5 as Recreational Rural Arterials and TPG 6 as Non-recreational Rural Arterials to differentiate these two groups.

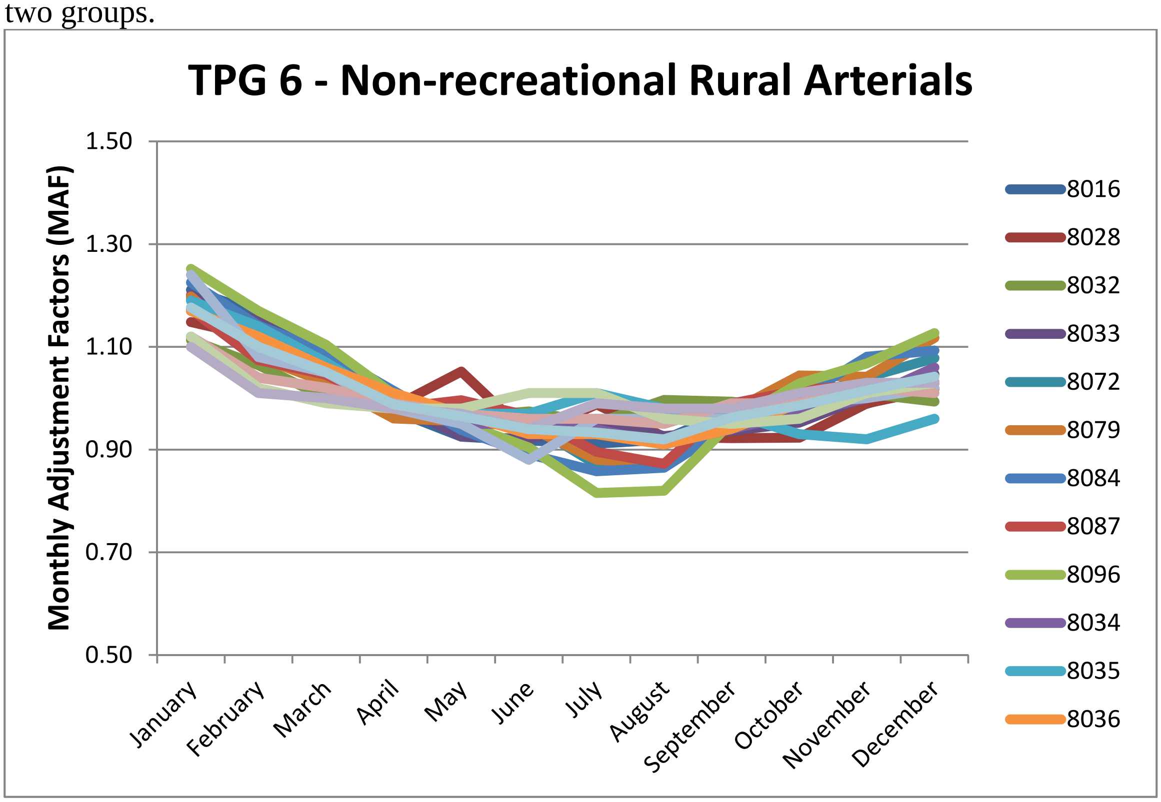


Figure 18. Monthly Variation of TPG 6 – Non-Recreational Rural Arterials (Low CV)

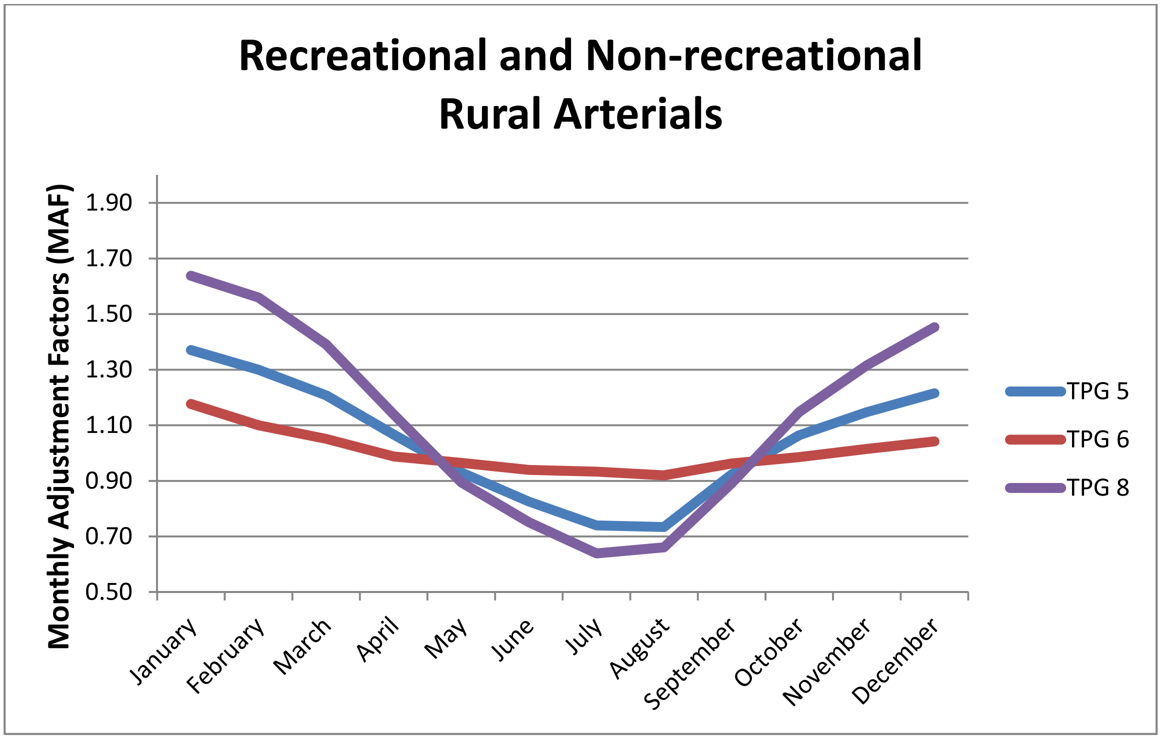


Figure 19. Comparison of CVs for TPG 5, 6 and 8

TMG recommends establishing separate groups for Interstates and Freeways/Expressways both in urban and rural areas. Therefore, three continuous count stations from I-95 and I-495, and one station from DE 1 (north of St. Georges Bridge) are placed in a single group called TPG 1 –Interstates & Freeways and Expressways. The one station from DE 1 (station 8018) is located in urban area and shows similar traffic characteristics with Interstates. However, three stations that are located on I-95 and I-495 near the PA line and does not reflect the traffic characteristics on remaining sections of Interstates such as the MD line to DE 1 interchange, and DE 1 to I-295 split/merge. Therefore, monitoring the Interstates requires further evaluation.

After finalizing the transfers and merges, continuous count stations are placed into 8 traffic pattern groups as similar to DelDOT's current TPGs with slight differences. The following Table 5 presents the list of traffic pattern groups, continuous count stations placed in each group, and total number of stations in each group. It is important to note that fewer number of continuous count stations are observed in recreational roads in the current TPG distribution. TMG recommends using CV higher than 25% as recreational roads, and only 10 stations are observed in this category. This shift in travel pattern can be explained as traffic volumes on non-summer months are also increasing in southern Delaware.

Table 5. Final Traffic Pattern Group Assignment

Traffic Pattern Groups	Continuous Count Stations	Number of Total Stations
TPG 1 – Interstates, Freeways & Expressways	8004 8018 8038 8039	4
TPG 2 – Urban Principal Arterials	8011 8013 8014 8015 8017 8020 8022 8023 8026 8030 8031	11
TPG 3 – Urban Minor Arterials and Urban Collectors	8005 8006 8012 8021 8040 8041 8042 8043 8048 8050 8054 8060 8061	13
TPG 4 – Urban Local Roads	-	-
TPG 5 – Recreational Rural Principal Arterials	8037 8046 8047 8062 8073 8074 8075 8076 8082 8088 8091 8092 8094 8095	14
TPG 6 – Non-recreational Rural Arterials	8016 8028 8032 8033 8034 8035 8036 8059 8072 8079 8084 8085 8086 8087 8093 8096	16
TPG 7 –Rural Collectors and Rural Local Roads	8019 8044 8045 8058 8064 8066 8067 8068 8070 8089 8098 8140 8141	13
TPG 8 – Recreational Roads	8069 8071 8077 8078 8080 8081 8083 8090 8097 8099	10
Excluded: 8024, 8049, 8053 TPG 5: DE 1 North of Rehoboth and US 113 TPG 8: DE 1 South of Rehoboth, DE 16, DE 26, DE 54, and DE 404 between MD Line and US 13		

TPG 1 is dedicated to Interstates. TPG 2 and TPG 3 cover the urban arterials and collectors. TPG 2 includes continuous count stations that are placed on urban principal arterials. TPG 3 covers urban minor arterials and collectors. All short-duration counts from urban arterials and collectors should use adjustment factors developed for TPG 2 and TPG 3.

TPG 4 is designated for Urban Local Roads. Although there is not any continuous count station placed on urban local roads, it is kept in TPG groups to be consistent with DelDOT's current traffic pattern group list.

TPG 5 and TPG 6 cover rural arterials. TPG 5 specifically designated to rural principal arterials (DE 1 – north of Rehoboth Avenue and US 113) that have higher seasonal variation compared to other rural arterials, except recreational roads. TPG 5 and TPG 6 have 20% and 8% CV values respectively. Therefore, adjustment factors that are developed for TPG 5 should be used to expand the short-duration counts obtained from DE 1 (north of Rehoboth Avenue) and US 113. All remaining rural principal and rural minor arterials should be factored by using adjustment factors developed for TPG 6.

TPG 8 is established to represent the recreational roads in the state. A total of ten continuous count stations in this group show high seasonal variability with an average of 29% CV. These stations are located on roadways that are primarily used for beach traffic in the summer months. These specific roadways are DE 1 (south of Rehoboth Avenue), DE 26, DE 54, DE 16 and DE 404 (between MD line and US 13). All short-duration counts obtained from aforementioned roadways should be factored by using the TPG 8 adjustment factors.

After TPGs are finalized, monthly adjustment factors are calculated for each group. Figure 20 presents the monthly variation of TPGs and Table 6 presents monthly adjustment factors for each TPG for each month based on three-year average dataset.

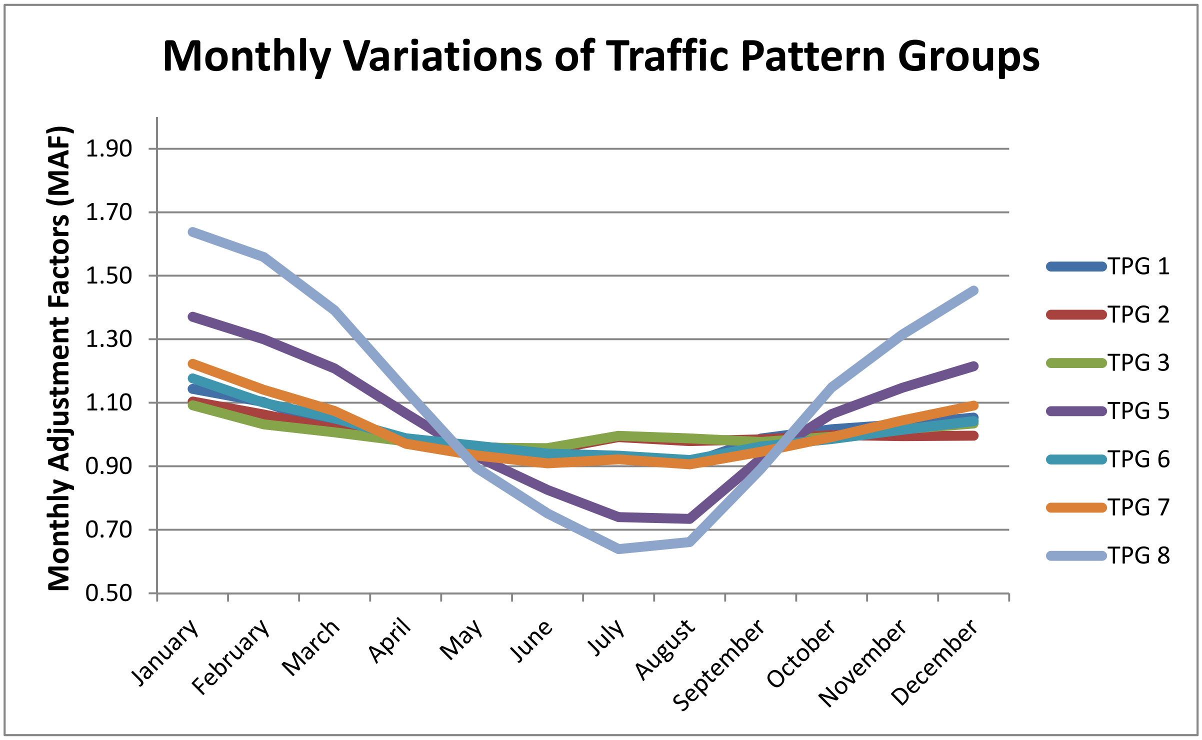


Figure 20. Monthly Variation of Traffic Pattern Groups

Table 6. Monthly Adjustment Factors (MAF) for TPGs

Traffic Pattern Groups	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
TPG 1	1.14	1.10	1.02	0.98	0.96	0.94	0.93	0.91	0.99	1.02	1.03	1.05
TPG 2	1.10	1.06	1.02	0.99	0.96	0.95	0.99	0.98	0.98	1.00	0.99	1.00
TPG 3	1.09	1.03	1.01	0.98	0.96	0.96	1.00	0.99	0.98	0.99	1.02	1.03
TPG 4	No Station in this group											
TPG 5	1.37	1.30	1.21	1.07	0.93	0.83	0.74	0.73	0.92	1.06	1.15	1.21
TPG 6	1.18	1.10	1.05	0.99	0.96	0.94	0.93	0.92	0.96	0.99	1.01	1.04
TPG 7	1.22	1.14	1.07	0.97	0.93	0.91	0.92	0.91	0.95	0.99	1.04	1.09
TPG 8	1.64	1.56	1.39	1.14	0.89	0.75	0.64	0.66	0.89	1.15	1.32	1.45

4.3.4 Sample Size Estimation

One of the most important issues related to continuous traffic monitoring is the number of stations needed for each traffic pattern group for statistical accuracy. Determination of appropriate number of continuous count stations required for each TPG is calculated by using the procedure recommended by TMG. It is assumed that the traffic dataset has a normal distribution. The student t-distribution is used to determine the minimum sample size needed to obtain selected level of accuracy.

The required minimum number of stations for each traffic pattern group in varying precision intervals are calculated and presented in Table 7. TMG recommends 10% precision with 95% confidence for each group, excluding recreational groups where no precision requirement is specified. The concept of precision intervals and confidence level explains how much our sample represents the true population statistics. For example, 10% precision intervals with 95% confidence means, we are 95% confident that population statistics are expected to be within ±10% of the calculated sample statistics. It is also important to note that higher confidence levels and lower precision intervals require increasing the sample size.

It is clearly visible that all traffic pattern groups satisfy the recommended precision interval with 95% confidence, and some of the groups (TPG 2, 3, 6, and 7) are even with 99% confidence. TPG 5 and TPG 8 are not subject to this criterion as suggested by TMG due to high coefficient of variation in recreational roads.

Table 7. Number of Continuous Count Stations Required for Varying Precision Intervals

Traffic Pattern Group	Number of stations	**Precision Intervals (<10% recommended)**		
		99% Confidence	95% Confidence *	90% Confidence
TPG 1 – Interstates, Freeways & Expressways	4	21%	10%	8%
TPG 2 – Urban Principal Arterials	11	5%	3%	3%
TPG 3 – Urban Minor Arterials and Urban Collectors	13	4%	3%	2%
TPG 4 – Urban Local Roads	-	-	-	-
TPG 5 – Recreational Rural Principal Arterials	14	17%	12%	10%
TPG 6 – Non-recreational Rural Arterials	16	8%	5%	4%
TPG 7 –Rural Collectors and Rural Local Roads	13	9%	7%	5%
TPG 8 – Recreational Roads	10	36%	26%	21%

* Recommended confidence level by TMG

4.3.5 Selection of New Site Locations

Evaluation of generated traffic pattern groups and analysis of placed continuous count stations in each group revealed that all TPGs satisfy the minimum number of station required for statistical accuracy. However, distribution of continuous count stations in the New Castle County require further evaluation, considering the amount of traffic on the roadways in this area.

In Figure 21, it is presented that some major roadways in NCC have either one or no continuous count stations. Roadways such as SR 72, SR 273, SR 41/48, SR 141 are in this category. These roadways carry significant traffic and are under-represented in the calculation of traffic pattern groups. There are two possible approaches to overcome this issue:

Figure 21. Current Continuous Count Stations in NCC

First, it involves placing appropriate continuous count stations on selected roadways. In this approach, continuous count stations should be placed either randomly or strategically. The following locations are recommended to increase the accuracy and reliability of TPGs. The locations are selected to cover the higher AADT roadways near borderlines and major traffic routes carrying significant traffic.

- SR 41/48 near PA line
- SR 261 near PA line
- SR 2 – Elkton Road near MD line
- SR 896 – New London Road near MD/PA line
- SR 273, US 40, SR 141 (locations should be selected based on traffic characteristics, availability of power and communication lines, and appropriateness for right of way)

The second alternative is integrating other data sources into the traffic monitoring program. Figure 22 presents the data sources utilized by TMC. It is clearly visible that the majority of arterials and interstates are covered by different type of sensors to provide data. Some of these sensors are system loops and microwave sensors. The traffic monitoring program can utilize data generated by these sensors (few selected sensors if not all) to increase the volume data coverage in New Castle County for the generation of TPGs and estimation of AADTs and respective adjustment factors.

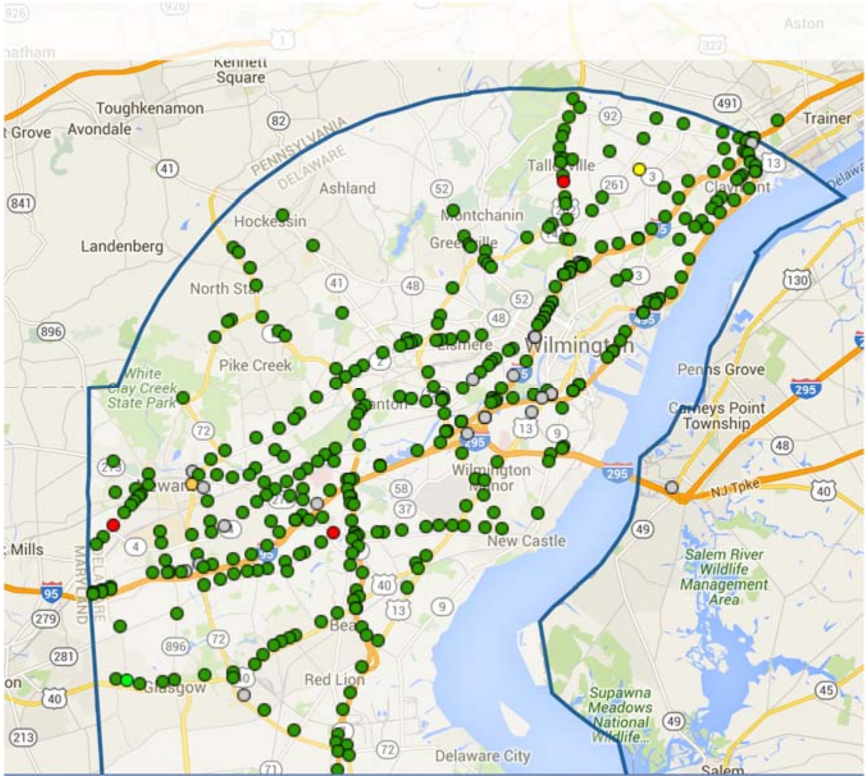


Figure 22. TMC Volume Data Sources in NCC ***(46)***

Consequently, current continuous count stations and proposed seven new continuous volume count stations are presented in Figure 23. In this figure, green triangles represent the proposed seven locations as listed previously.

Current and Proposed Volume Stations in DE

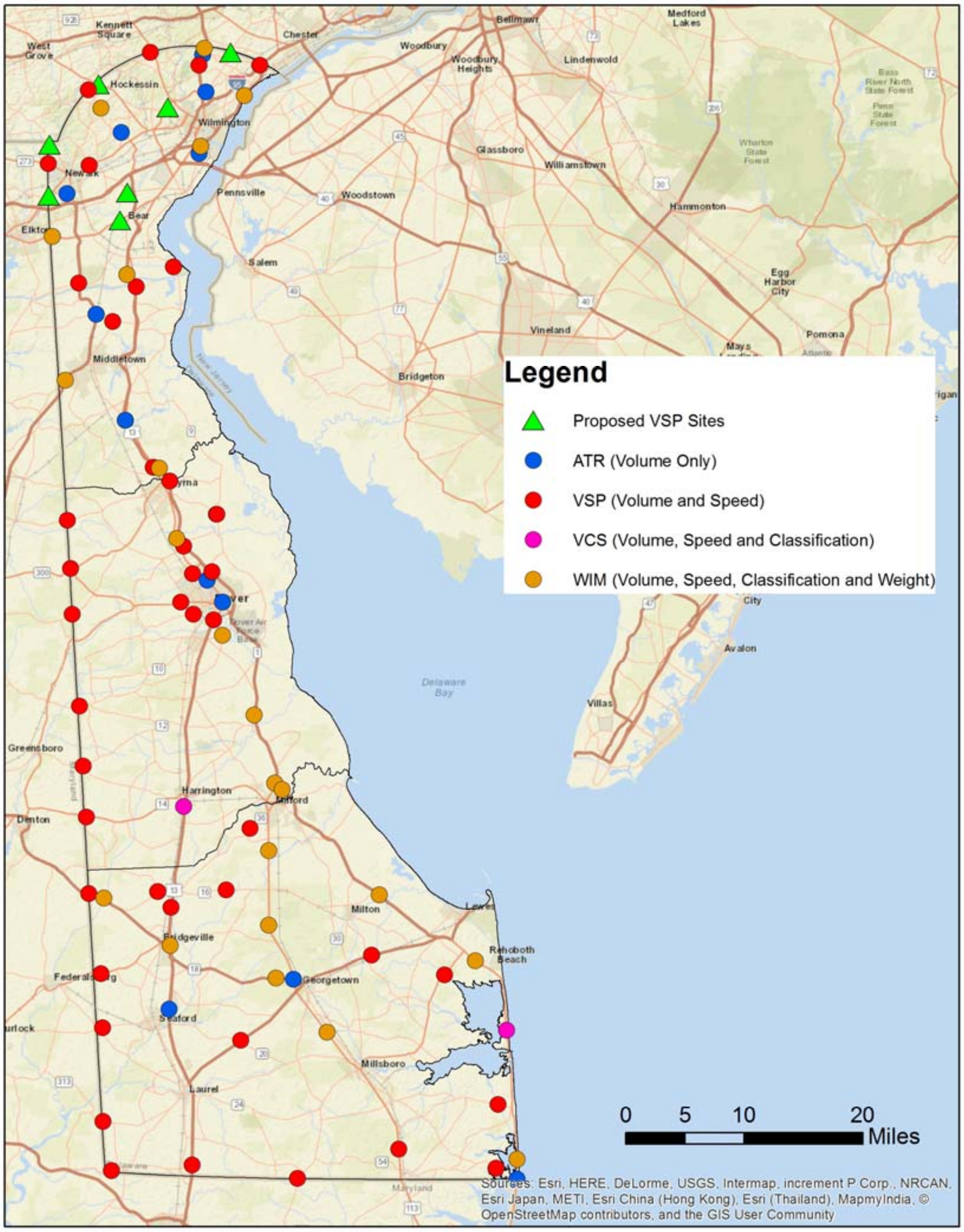


Figure 23. Current and Proposed Volume Stations in DE

4.3.6 Summary of Findings in Volume Groupings

Evaluation of volume data program, determination of traffic patterns groups, estimation of required continuous count stations for each TPG and selection of new site locations are studied in this section. Analysis results revealed that:

The number of recreational continuous count stations is decreased from 15 to 10 compared to current TPG in the DelDOT traffic monitoring program. This can be explained with shifted traffic characteristics on selected Kent and Sussex County roadways that currently carry high traffic volumes on non-summer months.

Proposed TPGs satisfy the required minimum number of station criteria, and no new sites are needed for statistical accuracy and reliability. However, it is observed that major roadways in NCC are under-represented in the determination of TPGs and respective adjustment factors. Therefore, it is recommended to increase the coverage in NCC for volume data. Two approaches proposed in this regard: installing new sites, integrating other data sources.

Installation of new sites includes strategically and randomly selected locations to increase the coverage near borderlines and ensure major roadways are well represented.

Integration of other data sources proposes using TMC's system loop and microwave sensors at selected locations. DelDOT needs to develop the appropriate methods and algorithms for retrieving the TMC data for use in the traffic monitoring program. But until that is done, increasing the number of continuous count stations is highly recommended.

Interstates I-95, I-295 and I-495 are not extensively covered with continuous count stations. Three stations are located on the northern part of I-95 and I-495 near the PA line and do not reflect the traffic characteristics on the entire 40.6 miles of Interstates in Delaware. Therefore, it is suggested to further evaluate the Interstates whether it can be monitored with conventional ATR stations or new technologies should be incorporated.

DE 1 has been increasingly changing from principal arterial to limited access freeway/expressway over the last two decades. Northern part of DE 1 (north of CD Canal) is included in TPG 1 with urban Interstates. Other three stations (8037, 8046 and 8047) that are located on DE 1 (between CD Canal and Dover) show very similar characteristics with recreational rural arterials and are included in TPG 5. It is suggested to re-evaluate the traffic pattern on these three stations in near future, possibly in five years, to see if these stations present different traffic pattern and require separate rural freeways/expressways traffic pattern group.

4.4 Vehicle Classification and Weight Data Program

Vehicle classification counts are used to determine the type of vehicle at a count location and are useful in evaluating the composition of vehicles on roadways, and their spatial and temporal variations. These counts can be performed manually or by automatic counters that measure the number of axles on a vehicle or the length of a vehicle depending on the type of sensor used. FHWA's 13 vehicle classification categories are primarily used for classifying vehicles and reporting to federal agencies through HPMS. However, different vehicle classification categories can be used to accommodate other data and reporting needs, such as monitoring a special facility generating truck traffic, monitoring a roadway or corridor where conventional vehicle classification technologies cannot be used, etc. FHWA recommends states to develop appropriate conversion methods and factors for using length-based classification in HPMS reporting *(2)*.

Truck weight counts are used to determine truck weight loads exerted on pavement and primarily used for pavement and bridge design. Similar to volume and vehicle classification counts, truck weight counts are also used for determining the traffic patterns of loaded and unloaded trucks and their spatial and temporal variations. These counts are performed by either using static weight stations or weigh-in-motion (WIM) detectors. States are able to maintain limited number of stations due to high capital, operational and maintenance cost of these stations. Therefore, locations of the WIM station are more strategically selected to monitor truck traffic between neighbouring states, seasonal variations of heavy loaded trucks, and monitoring of facilities that generates substantial truck traffic.

DelDOT has 24 continuous count stations that collect axle-based vehicle classification data compatible with FHWA's 13-vehicle classification category. 22 of these stations are WIM stations and also provide axle-based weight, and 2 provide only vehicle classification, volume and speed data (no weight). According to the 2014 Traffic Summary Book *(45)*, DelDOT vehicle classification data program uses roadway functional classification as a method for generating weighted average composition of vehicle classes at all sites within the functional system. It is also presented that the calculated vehicle classification does not reflect the seasonal variations and are not supported with statistical analysis. Therefore, evaluating the seasonal variations by vehicle class and assessing possible traffic patterns with statistical and mathematical procedures is necessary. Figure 24 presents the location of continuous count stations that provide vehicle classification and weight data in Delaware.

The evaluation process starts with determination of truck percentages (single unit (SU) an combination unit (CU) percentages) and seasonality of the truck traffic in Delaware. Then, vehicle classification groups (VCG) are established based on truck percentages and seasonal variation. Afterwards, WIM stations are investigated to identify the truck types/classes that are exerting most weight on roadways, and examine if there is seasonality on loaded truck weights. Final step of this evaluation includes evaluating if VCGs also represent the truck weight characteristics or different truck weight grouping is necessary.

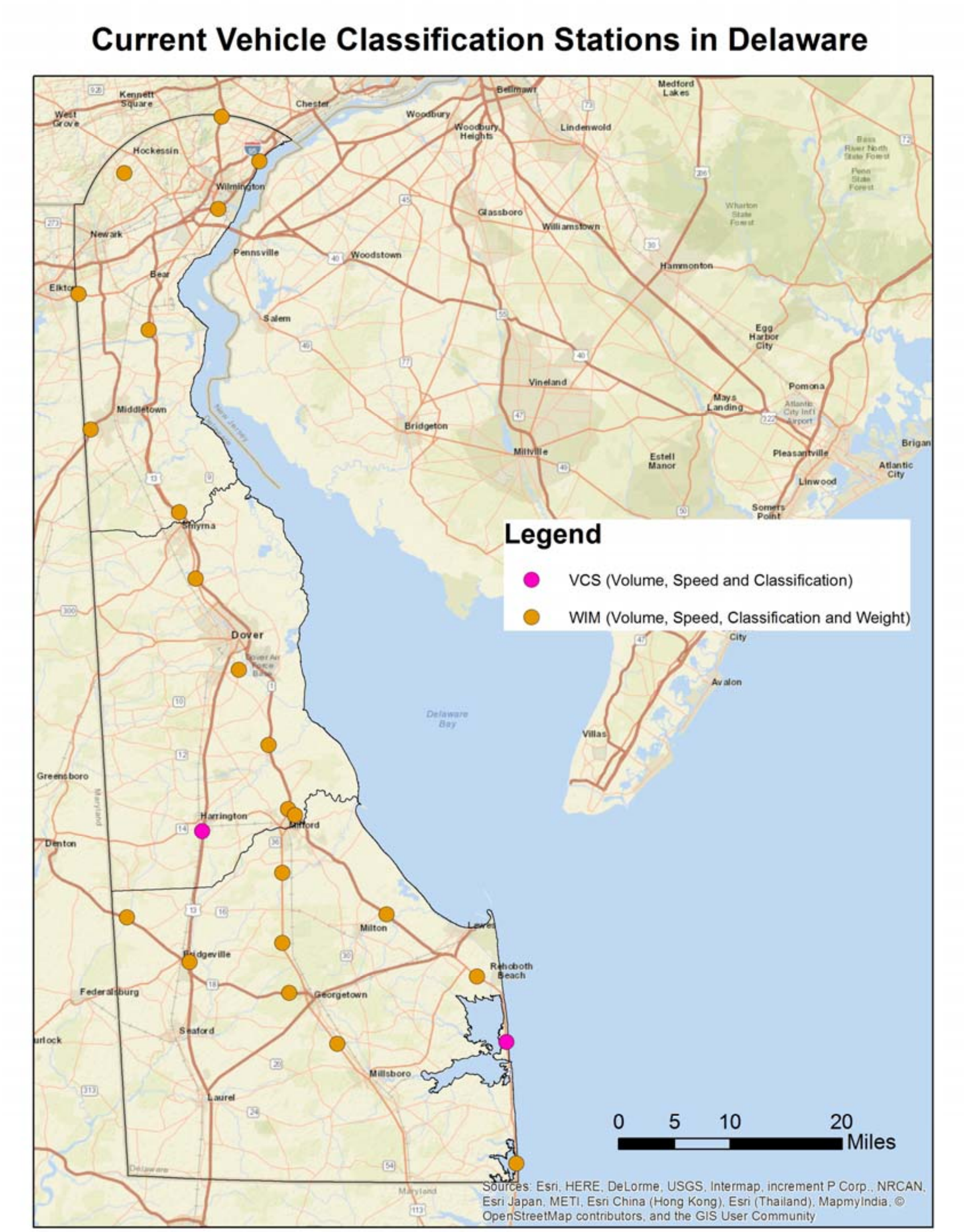


Figure 24. Current Vehicle Classification Continuous Count Stations in Delaware

4.4.1 Evaluation of Truck Traffic Patterns and Empirical Data

It is important to understand the truck traffic patterns in Delaware before moving forward to data analysis. The following two figures (Figure 25 and Figure 26) obtained from WILMAPCO Regional Freight and Goods Movement Analysis Report *(47)*, presents the Annual Average Daily Truck Traffic (AADTT) routes and patterns in Delaware.

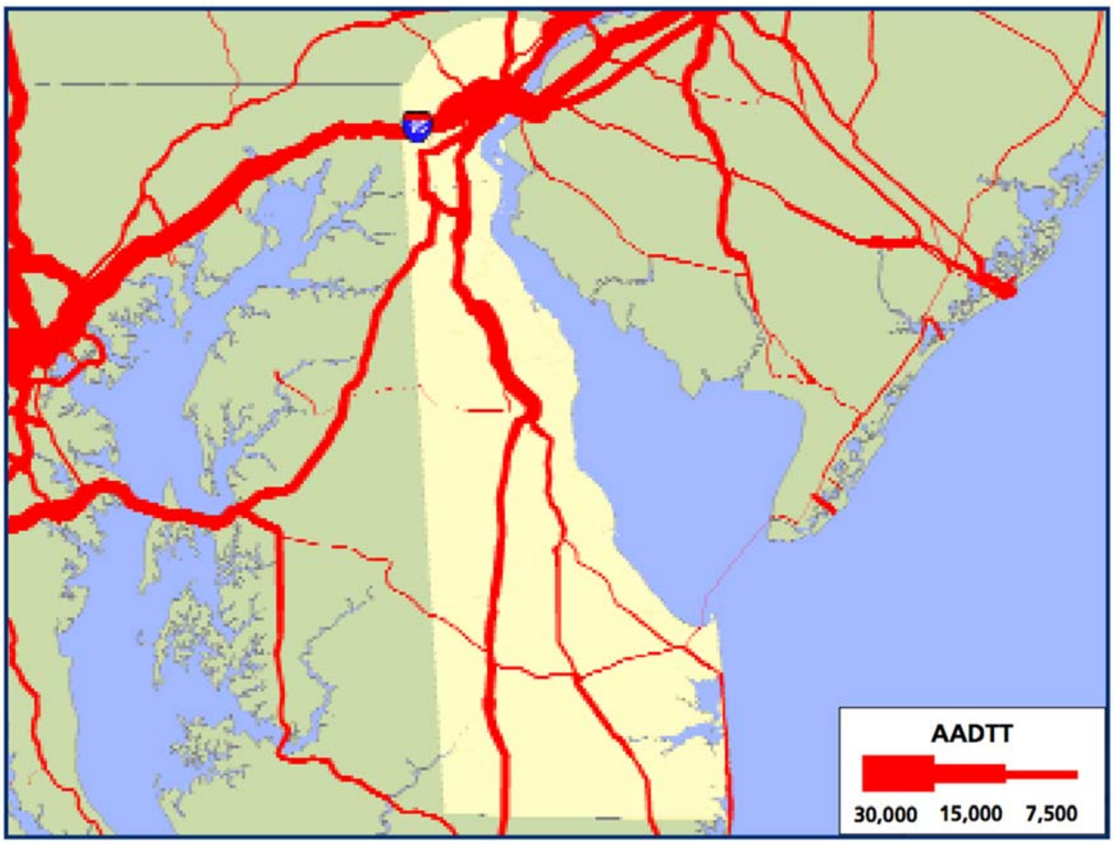


Figure 25. Estimated Average Annual Daily Truck Traffic: 2020 ***(47)***

Obvious truck traffic patterns can be identified as:

- High truck traffic on Interstates and northern part of SR 1;
- North/south truck traffic pattern on US 13, US 113 and SR 1;
- Moderate truck traffic to and from US 301;
- Moderate truck traffic on connecting roads to Interstates such as US 202, US 13, SR 41, SR 896, and SR 4.

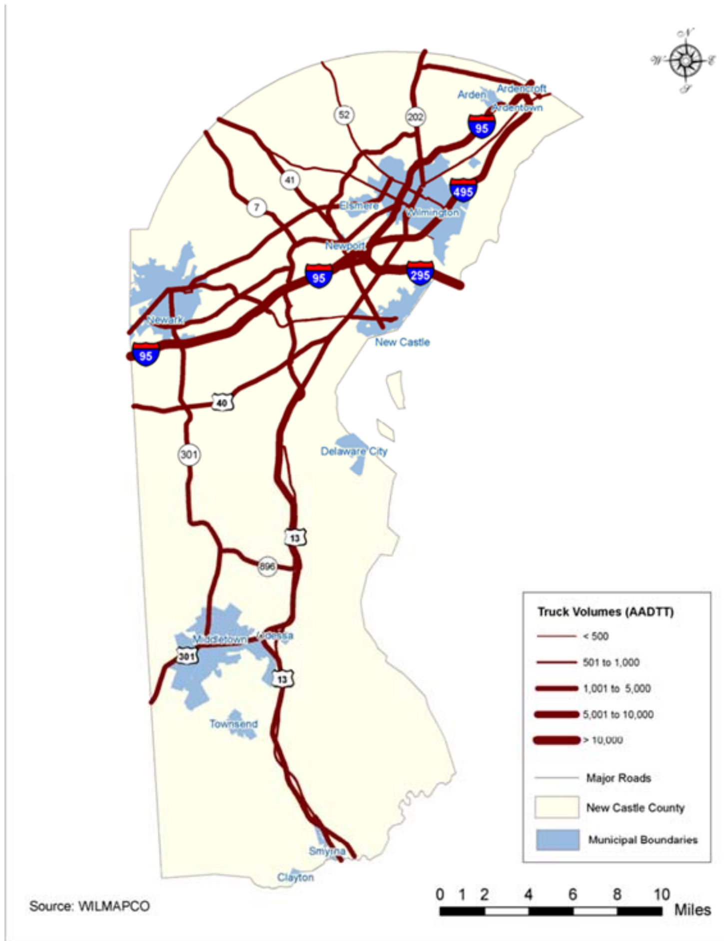


Figure 26. Average Annual Daily Truck Traffic in NCC – 2005 ***(47)***

Among 24 continuous vehicle classification sites, two of them (stations 8004 and 8062) are not included in the analysis due to high percentage of missing data where data was producing unexpected results. Remaining 22 sites are evaluated based on graphical examination, and statistical and mathematical procedures in addition to the dynamics of the truck traffic patterns presented here. Monthly variation of recommended six groups and total truck volumes are graphically examined for each continuous count stations. Among 22 stations, two of them (Statiosn 8016 and 8053) were also excluded due to observed substantial differences in track traffic patterns.

WIM station 8016, located on US 301 near the MD line, carry significant truck traffic between neighboring states Delaware and Maryland. This station has a moderate seasonal variability (CV=7%). However, approximately 16% of the total volume is composed of single and combination unit trucks. Among 16% truck traffic, combination unit trucks are consist of 75% of the truck traffic based on 2012, 2013 and 2014 data. This high percentage of combination unit truck traffic is not recognized in any of the vehicle classification sites. Moreover, US 301 is emphasized as one of the high volume truck traffic routes in truck travel pattern studies conducted by WILMAPCO *(47)*.

WIM station 8053 located in Tower Hill Rd. (State Fair) present high seasonal variability (CV=16%) in addition to high percentage of truck traffic (19%). Additionally, traffic pattern significantly changes in July due to State Fair and increased traffic. Furthermore, traffic volume in this site is significantly low (AADT =1005) compared to other vehicle classification and WIM sites. As a result, this site is excluded from the determination of VCGs.

In addition to the data set used in vehicle classification data program, truck weights are also incorporated in truck weight data program. Monthly summary statistics from WIM stations and FHWA's W tables are used for investigating the truck weights for each WIM station and anomalies detected in Station 8096 and 8026.

Station 8026 (DE 7 at South of Little Baltimore Road) present inconsistent data specifically in summer months. A dramatic change was observed in weight loads in both class 5 and class 9 trucks. Average truck weight of class 9 trucks drops from approximately from 22 tons to 12 tons in June and to 16 tons in July. However, this change is not consistent for the years 2012, 2013 and 2014.

Similar anomalies are also observed in WIM station 8096 (US 13 near Bridgeville), and inconsistency among years is presented in Figure 27 and Figure 28. Therefore, it is recommended to further evaluate these sites with WIM data prior to 2012 to decide if there is a noticeable change in truck weight patterns or the WIM stations require calibration. However, considering the class 5 and class 9 trucks present similar axle spacing and combination, asymmetrical graphical trend can be a sign for a calibration issue. Because, a noticeable decrease in average class 9 truck weights present a parallel trend with an increase in average class 5 truck weights.

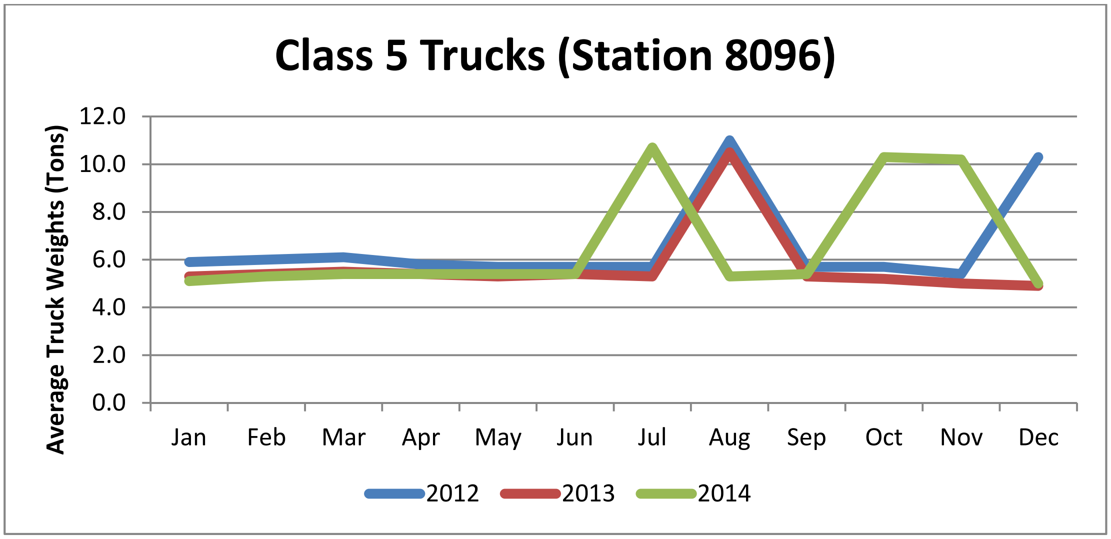


Figure 27. Average Truck Weights of Class 5 Trucks in Three-Year Time Frame

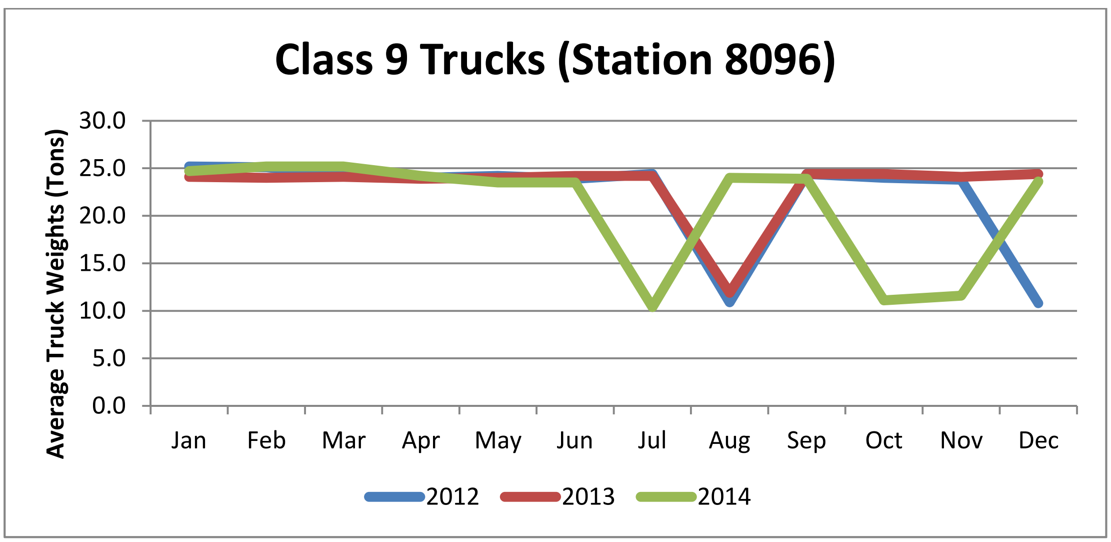


Figure 28. Average Truck Weights of Class 9 Trucks in Three-Year Time Frame

4.4.2 Determination of Vehicle Classification Groups (VCG)

First, monthly distribution of traffic among six vehicle class groups (Table 2) is evaluated by using monthly variation graphs for each station. This evaluation revealed that:

- Motorcycle traffic patterns and monthly variations are significantly different from other vehicle classes. However, motorcycle traffic constitutes less than 1% of the total traffic and is not included in determination of VCGs. But, it is recommended to evaluate the motorcycle traffic individually in each site to gain an insight, and further study the traffic patterns if necessary.
- Buses present different seasonal patterns in few sites. However, due to low percentage of total traffic volume as similar to motorcycle traffic, bus traffic pattern is also excluded while establishing VCGs.
- Single unit (SU) and combination unit (CU) truck percentages constitutes between 3% and 19% of the total traffic. Therefore, SU and CU traffic patterns are primarily considered for determination of VCGs.

Then cluster analysis is applied to the data obtained from vehicle classification and weight-in-motion stations for determination of Vehicle Classification Groups (VCG). These datasets include percentage of trucks, percentage of SU and MU trucks, and respective CVs. Although cluster analysis did not provide satisfactory results, it helped to shape the possible VCGs. The following Figure 29 presents the initial groupings suggested by cluster analysis. Results suggested four distinct groups with some outliers. However, cubic clustering criteria (CCC) could not provide strong suggestion for the number of groups. Therefore, the result of cluster analysis is used as a starting point for considering the number and size of the VCGs. Then, sites in each group have individually investigated based on SU and CU truck percentages and monthly variations (CV). Additionally, functional classification of the roadway segments where continuous count stations are placed and geographical location of the sites are also considered for creating identifiable groups.

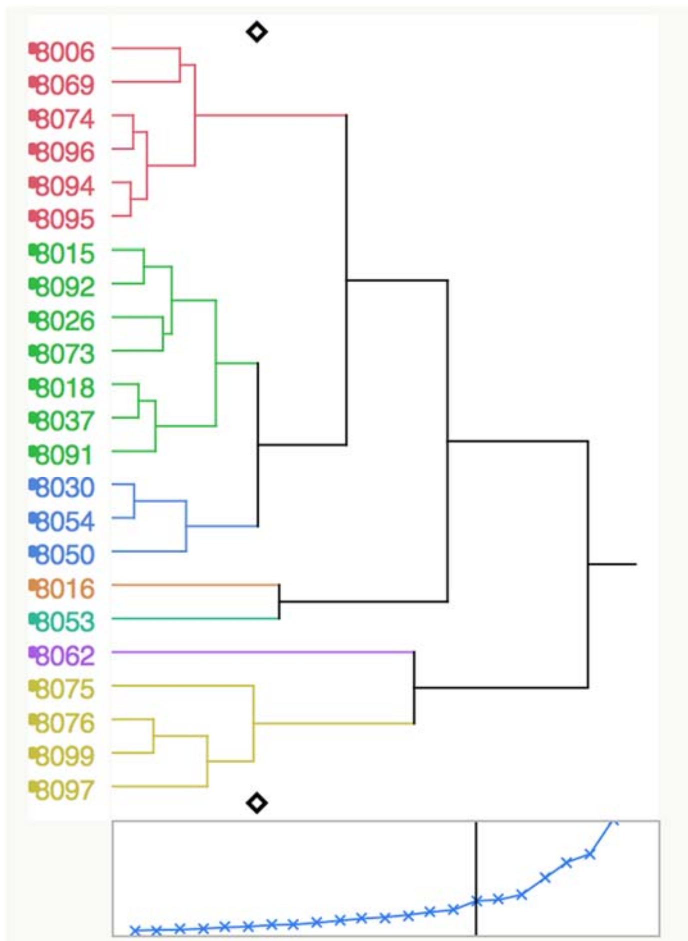


Figure 29. Dendogram of Hierarchical Cluster (SU and CU percentages and CVs)

The coefficient of variation of monthly average daily truck traffic varies between 7% and 24% with an average of 12%. On the other hand, percentage of truck traffic varies between 3% and 19% with an average of 7%. The following Table 8 presents the variation in selected vehicle classification groups based on percentage of total volume and seasonal variation.

Table 8. Range in Truck Percentages and Seasonal Variation

		Average	**Min**	**Max**
CV of MADTT	Single Unit	12%	6%	24%
	Combination Unit	15%	6%	36%
	Total Truck	12%	7%	24%
Percentage of Total Volume	Single Unit	4%	2%	8%
	Combination Unit	3%	1%	16%
	Total Truck	7%	3%	19%

There is a clear difference between some recreational roadways and remaining roadways for seasonal variation. These continuous vehicle classification stations (8075, 8076, 8097, and 8099) show a high variability in seasonal variation between 20% and 35% coefficient of variation for single unit and combination unit truck traffic respectively. However, percentage of truck traffic in total volume is relatively low – between 3% and 5%.

After examining the sites and making the necessary adjustments, final VCGs are considered in four groups. Table 9 presents this four group and respective stations within each group.

Table 9. Final Vehicle Classification Group (VCG) Assignment

Vehicle Classification Groups (VCG)	Continuous Count Stations	Number of Total Stations
VCG 1 – Interstates & Freeways and Expressways	8000* 8001* 8002* 8003* 8004**	5
VCG 2 – Urban Other Roads (Arterials)	8006 8015 8026 8030 8050 8054	6
VCG 3 – Rural Other Roads (Arterials)	8069 8073 8074 8094 8095 8096 8062**	7
VCG 4 – Rural Recreational Arterials	8018 8037 8075 8076 8091 8092 8097 8099	8
Sites Excluded	8016 8053	2
Total Sites:		28

*Toll Sites
**8062 and 8004 are not calculated due to limited available data and assigned into groups based on roadway functional classes

VCG 1 includes interstates where truck traffic is expected to be significant. Unfortunately, there was not enough data from interstates for further developing the monthly adjustment factors. Therefore, VCG 1 is created considering the TMG recommendations to have a vehicle classification group for interstates and other freeways/expressways.

VCG 2 consist of Urban Arterials that carries truck traffic to and from Interstates and Freeways in urban areas in New Castle and Kent Counties. Five continuous count stations in this group present similar seasonal variation as presented in Figure 30. Combination of these stations produces 2.5% SU and 1.3% CU truck traffic. Thus, truck traffic constitutes 3.8% of the total traffic in urban other roads. VCG 2 stations are placed on selected NCC roadways such as US 40, US 202 and SR 7, and urban minor arterial near Dover such as SR 10 and US 13.

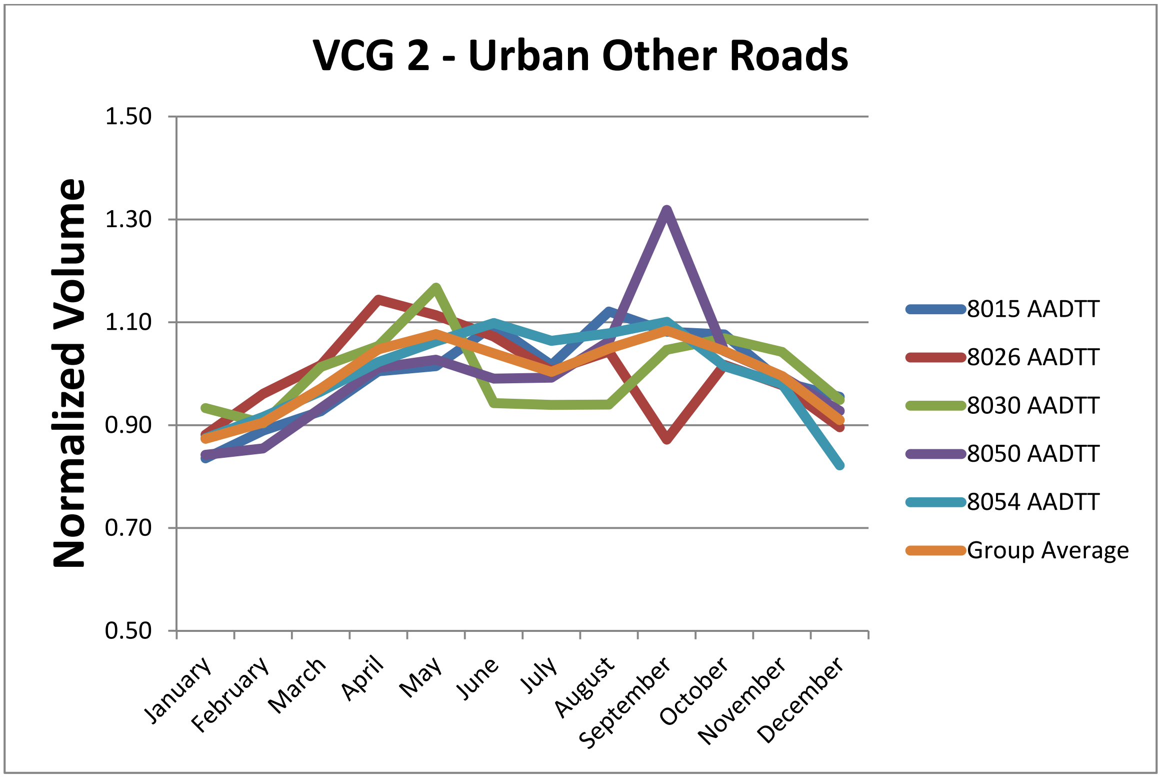


Figure 30. Monthly Variation of VCG 2 – Urban Other Roads

Rural other roads constitute VCG 3 in proposed vehicle classification groups. Six continuous count stations located on other principal arterial in Sussex County presents considerably similar seasonal variation (Figure 31). Additionally, single unit and combination unit truck traffic constitutes 4.5% and 4.6% of the total traffic respectively in VCG 3. Thus, total truck volume is estimated as 9.1% of the total traffic in rural other roads with moderate seasonal variability (CV=12.4%).

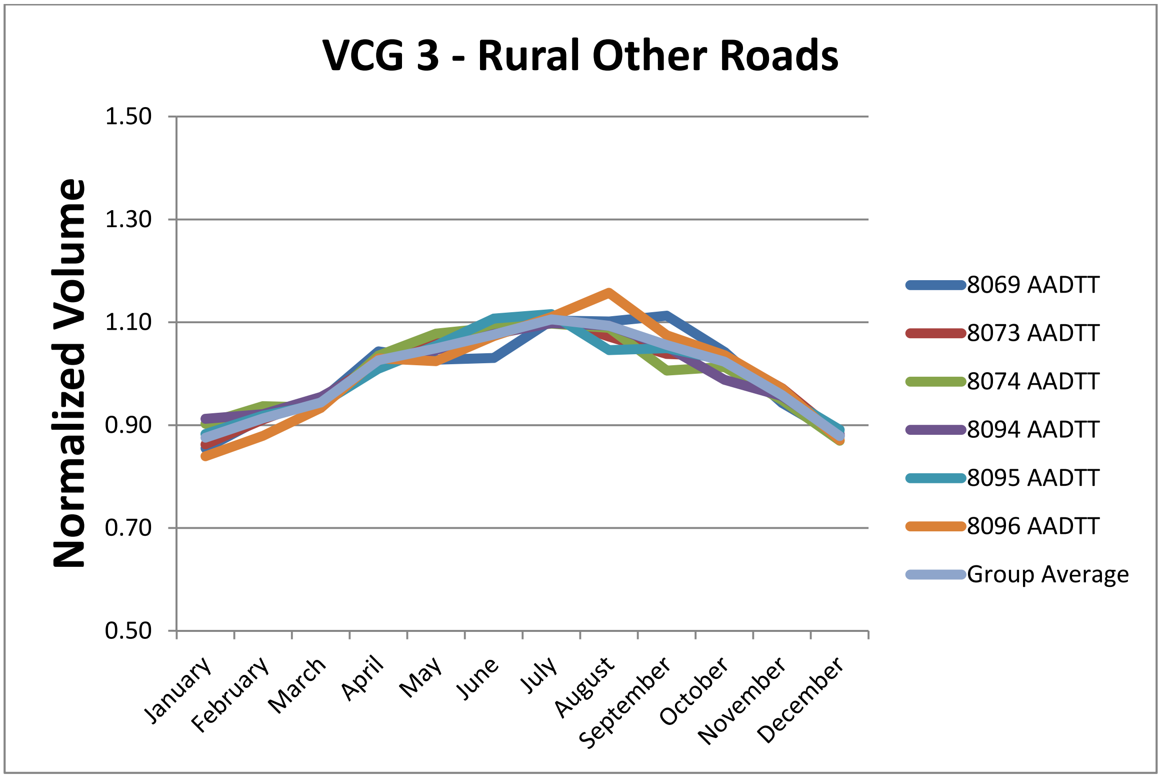


Figure 31. Monthly Variation of VCG 3 – Rural Other Roads

The final classification group VCG 4 includes rural recreational roadways that present high seasonal variation in addition to similar truck traffic percentages. Seasonal variation of eight stations in this group is presented in Figure 32. These continuous count stations are placed on DE 1 in all three counties: NCC, KC and SC. Single unit and combination unit truck traffic constitutes 3.4% and 2% of the total traffic respectively in VCG 4. Therefore, truck percentage in VCG 4 is calculated as 5.4% of the total vehicle volume.

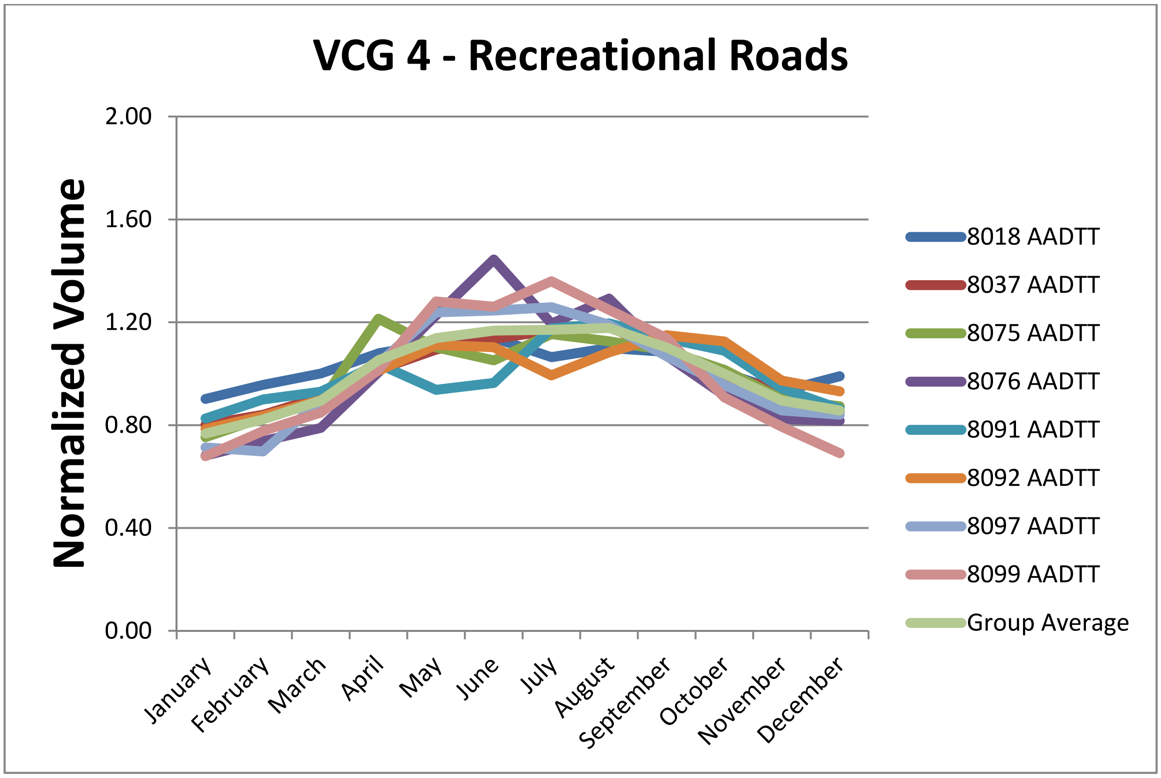


Figure 32. Monthly Variation of VCG 3 – Rural Recreational Roads

Previous figures indicate the similar seasonal variation in each VCG. It is also important to understand how these groups are different from each other. Thus, group means are compared and presented in Figure 33. It is obvious that monthly variation of these groups present noticeable difference. Recreational roads (VCG 4) present high seasonal variability with increased traffic in summer months. Urban arterials (VCG 2) present less monthly variation and a distinct pattern in summer months, where truck traffic is relatively low in mid-summer compared to late Spring and early Fall.

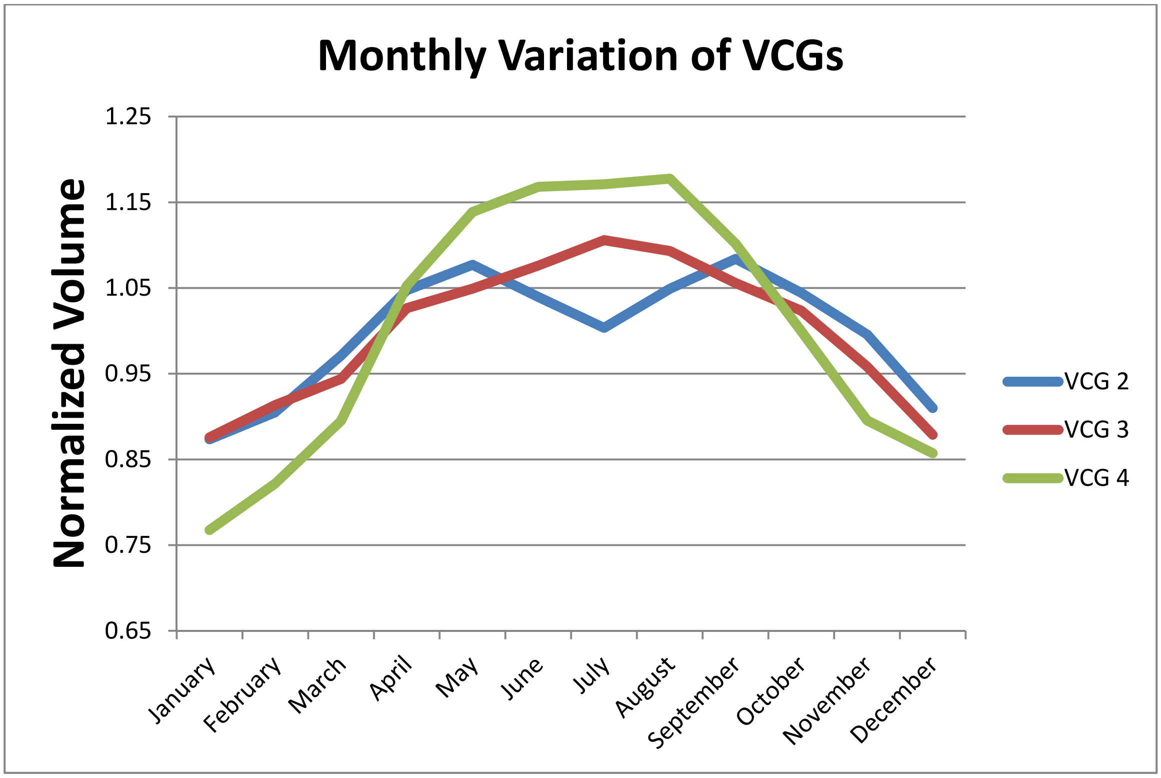


Figure 33. Monthly Variation of VCGs

4.4.3 Incorporating Truck Weight Data into VCGs

Preliminary truck weight evaluation started with determining truck types that are exerting most weight on roadways. For this evaluation, FHWA's W tables are used. The following Table 10 presents the distribution of trucks among vehicle classes. From the table, it is clear that Class 5 (Single Unit Trucks - 2 axle, 6 tire) and Class 9 (Single Trailer Trucks - 5 axle) trucks are dominating the truck traffic in Delaware by generating the approximately 80% of the total truck traffic.

Table 10. Percentage Distribution of Trucks Among Vehicle Classes

FHWA Vehicle Class	2014		2013		2012		3-Year Average	
	Avg. Daily Count	%	Avg. Daily Count	%	Avg. Daily Count	%	Avg. Daily Count	%
Class 5	331	45.6%	335	40.8%	314	38.7%	327	41.5%
Class 6	64	8.8%	74	9.0%	81	10.0%	73	9.3%
Class 7	16	2.2%	22	2.7%	20	2.5%	19	2.5%
Class 8	47	6.5%	62	7.5%	66	8.1%	58	7.4%
Class 9	262	36.1%	315	38.3%	308	38.0%	295	37.5%
Class 10	3	0.4%	7	0.9%	11	1.4%	7	0.9%
Class 11	2	0.3%	3	0.4%	4	0.5%	3	0.4%
Class 12	1	0.1%	1	0.1%	1	0.1%	1	0.1%
Class 13	0	0.0%	3	0.4%	6	0.7%	3	0.4%
Total Truck Volume	726	100.0%	822	100.0%	811	100.0%	786	100.0%

Moreover, the weight exerted on each truck type examined and presented in Table 11 and Figure 34. It is critical to understand that Class 5 and Class 9 trucks apply significant total weight compared to other truck classes. Therefore, these two classes were selected to further investigate the seasonal pattern of truck weights. As presented in Table 11, class 5 vehicles apply approximately 2,377 tons daily (19% of the total weight) and class 9 vehicles apply approximately 7,665 tons daily (61% of the total weight), where these two classes compose 80% of the total weight applied to the roads.

Table 11. Weight Distribution of Trucks Among Vehicle Classes

FHWA Vehicle Class	Average Daily Truck Traffic AADTT	Average Truck Weight (kg)	Percentage of Trucks	Total Weight (kg)	% Loaded Trucks
Class 5	449	5,312	46.3%	2,377,000	44%
Class 6	89	14,218	9.2%	1,266,000	91%
Class 7	22	28,156	2.3%	621,000	97%
Class 8	62	11,874	6.4%	734,000	50%
Class 9	336	22,781	34.6%	7,665,000	87%
Class 10	6	24,051	0.6%	151,000	76%
Class 11	4	17,689	0.4%	65,000	82%
Class 12	1	16,819	0.1%	17,000	100%
Class 13	2	23,496	0.2%	47,000	33%
`	970	12,993	100%	12,611,000	65%
All Comb. Trucks		20,293		8,340,000	81%

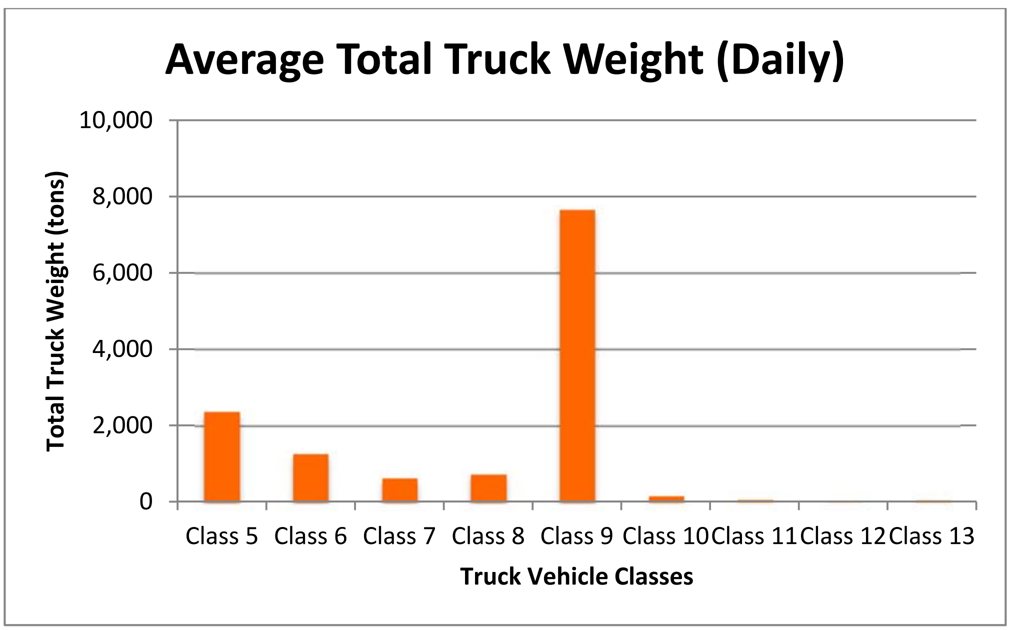


Figure 34. Average Total Truck Weights Applied to Roads (Daily)

Additionally, total truck weights by direction have evaluated to identify if there is a significant weight difference between opposite directions for class 5 and class 9 trucks (Figure 35 and Figure 36). Most WIM stations present similar weight loads in opposite directions.

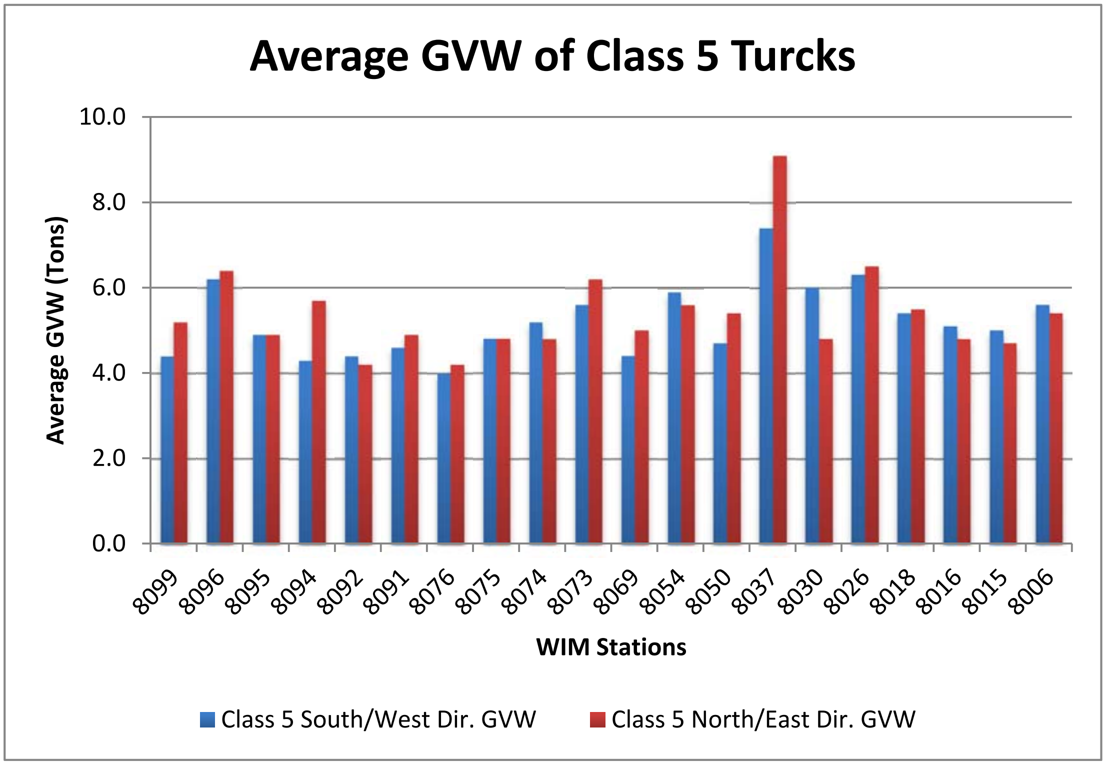


Figure 35. Average Truck Weights by the Direction of the Roadways at WIM Stations (Class 5)

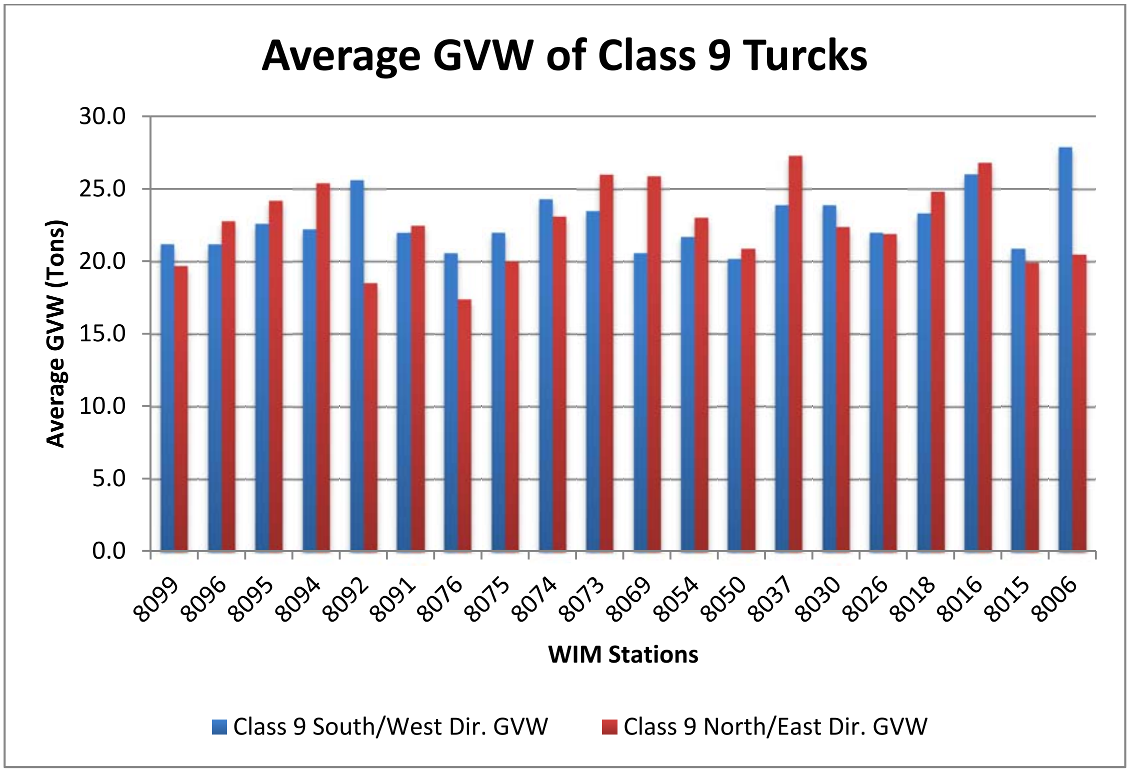


Figure 36. Average Truck Weights by the Direction of the Roadways at WIM Stations (Class 9)

Monthly variations of truck weights evaluated with CV of truck weights for Class 5 and Class 9 trucks. Although significant variation is not observed in monthly truck weight data, cluster analysis is applied to check if these similarities/differences are significant. Cluster analysis of average truck weights and CV of monthly truck weights did not reveal considerable groups. Both Cubic Clustering Criterion (CCC) and scree plot did not present a clear pattern to establish truck weight based groups. Then, average truck weights and CVs are graphically assessed and no significant seasonal variation observed in truck weight, specifically for Class 5 and Class 9 trucks. However, it is observed that truck weight patterns in rural and urban jurisdictions have different weight characteristics. Therefore, VCGs are used for representing the truck traffic patterns in Delaware due to:

1. VCGs represent the seasonal variation of truck volume in urban and rural areas, and
2. Truck weights do not presents seasonal variation and urban/rural variations can be represented with VCGs.

VCGs are used for producing truck weight graphs for Class 5 and Class 9 trucks and presented in the following graphs. Figure 37 presents the seasonal variation of different VCGs. It is clearly visible that urban roads present similar seasonal variation with rural roads with slightly higher average truck weights, which can be translated into that urban class 5 trucks are slightly heavier than rural class 5 trucks. Recreational roads present different seasonal variation where truck weights are higher in the first half of the year compared to second half of the year.

On the other hand, class 9 trucks present a significantly different pattern compared to class 5 trucks in urban and rural roads. As presented in Figure 38, class 9 trucks observed on rural roads are heavier than the urban roads. This difference can be explained with fully loaded class 9 truck travelling to and from industrial facilities and farmlands. Class 9 trucks present similar seasonal variation with class 5 trucks in recreational roads.

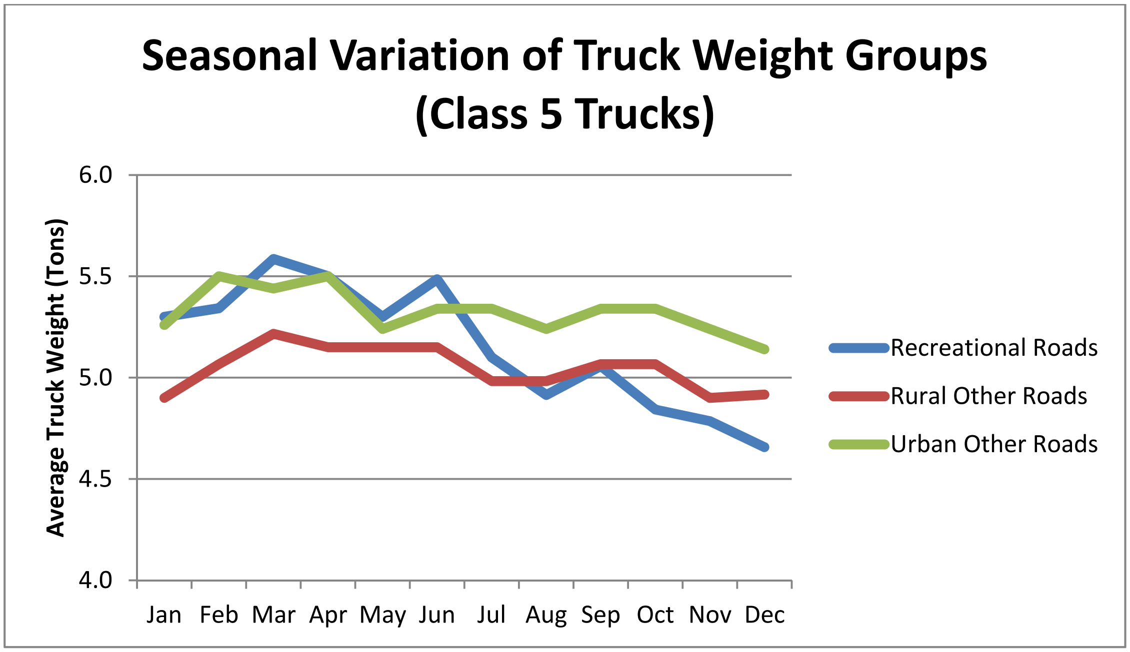


Figure 37. Seasonal Variation of Truck Weight Groups (Class 5 Trucks)

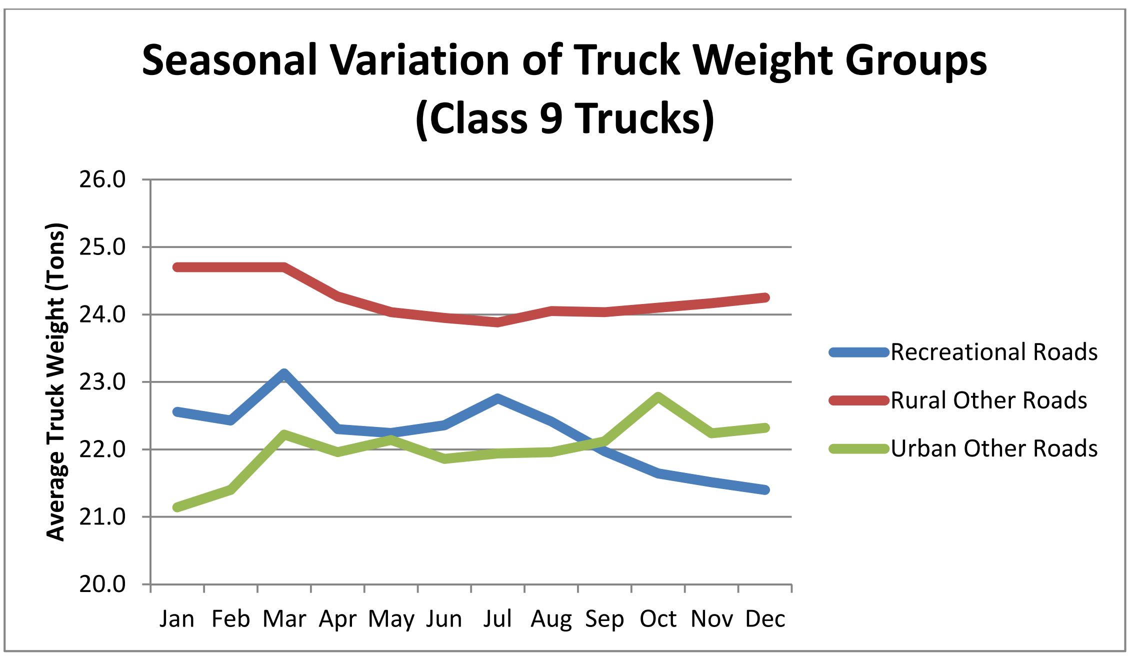


Figure 38. Seasonal Variation of Truck Weight Groups (Class 9 Trucks)

The final distribution of WIM stations into truck weight groups is presented in Table 12. It is also important to note that there is only one WIM station, which covers the Interstates in Delaware, where no data was available for analysis. As also discussed in VCG groupings, Interstates are not well monitored with continuous count stations in all volume, vehicle classification and truck weight programs. Thus, it is strongly recommended to establish a continuous data program for Interstates to supply necessary data for state and federal needs.

Remaining WIM stations are placed in accordance with VCGs and presented in Table 12.

Table 12. Final Truck Weight Group Assignment

Vehicle Classification Groups (VCG)	Continuous Count Stations	Number of Total Stations
VCG 1 – Interstates & Freeways and Expressways	8004*	1
VCG 2 – Urban Other Roads (Arterials)	8006 8015 8026** 8030 8050 8054	6
VCG 3 – Rural Other Roads (Arterials)	8016** 8062** 8069 8073 8074 8094 8095 8096**	8
VCG 4 – Rural Recreational Arterials	8018 8037 8075 8076 8091 8092 8099	7
Total Sites:		22

*No data
**Data anomalies observed and excluded from analysis, and placed into groups based on roadway functional classification.

4.4.4 Sample Size Estimation

The traffic monitoring guide recommends following the statistical procedures recommended in sample size estimation for the calculation of minimum number of station required in each group and further recommends a minimum of six stations for each group *(2)*. Therefore, a similar procedure is followed and precision intervals are calculated for each group based on proposed placement of the stations in each VCG (Table 13).

Calculation of precision intervals reveals that VCG 2 and VCG 4 do not meet the 10% precision interval with 95% confidence. Since TMG excludes recreational roads in this criterion due to high seasonal variability, it is not required to add more stations in VCG 4. Therefore, at least one additional vehicle classification station is recommended to increase the accuracy and reliability of the estimations in VCG 2.

Table 13. Number of continuous count stations required for varying precision intervals

		Precision Intervals (<10% recommended)		
Traffic Pattern Group	**Number of stations**	99% Confidence	95% Confidence *	90% Confidence
VCG 1 – Interstates & Freeways and Expressways	5	Not calculated due to limited data		
VCG 2 – Urban Other Roads (Arterials)	6	18%	11%	9%
VCG 3 – Rural Other Roads (Arterials)	7	11%	8%	6%
VCG 4 – Rural Recreational Arterials	8	20%	13%	11%

* Recommended confidence level by TMG

Same procedure is applied for Class 5 and Class 9 trucks and investigated whether the number of stations in each group also statistically enough to represent the variation in truck weights. Table 14 presents the analysis results for both class 5 and class 9 trucks. Since there is no noticeable seasonal variation observed in truck weights, calculated CVs are relatively low compared to volume and vehicle classification groups. Consequently, even small numbers of stations in each group meet the required precision levels. It is suggested that there is no additional WIM stations needed for non-Interstate roads.

Table 14. Number of WIM stations required for varying precision intervals

		Class 5 Trucks			**Class 9 Trucks**		
		Precision Intervals (<10% recommended)			Precision Intervals (<10% recommended)		
Traffic Pattern Group	**Number of stations**	99% Conf.	95% Conf.*	90% Conf.	99% Conf.	95% Conf.*	90% Conf.
Group 1 – Interstates & Freeways and Expressways	1	Not calculated due to limited data			Not calculated due to limited data		
Group 2 – Urban Other Roads	6	4%	2%	2%	4%	2%	2%
Group 3 – Rural Other Roads	8	3%	2%	2%	2%	1%	1%
Group 4 – Rural Recreational Arterials	7	8%	5%	4%	3%	2%	2%

* Recommended by TMG

4.4.5 Selection of New Site Locations

VCG 2 Urban Other Roads require at least one additional vehicle classification station. Considering the truck traffic patterns presented by WILMAPCO report, SR 41/48 near the PA line, SR 2 Elkton Road near MD line, and SR 141 are proposed for possible locations for new vehicle classification station. Current and proposed locations for vehicle classification stations are presented in Figure 39.

Remaining VCGs do not require additional new sites for statistical accuracy. However, one location requires particular attention in this regard. Station 8016 (US 301 near the MD Line) carries significant truck traffic in the region, specifically combination unit trucks – 12% of total volume. This distinct pattern requires further evaluation of the site and truck traffic patterns in the region. Therefore, it is recommended to monitor this truck traffic with longer period of short-duration counts (weeklong) in nearby roadways to help identify the movement of the trucks using US 301. Locations of these short-duration classification counts are highly associated with prior knowledge and engineering judgment. However, following locations are recommended due to possible connections to Freeways and Interstates in the region: SR 299, SR 896 (Boyd's Corner Road), and US 301 Summit Bridge Road.

Figure 39. Current and Proposed Locations for Vehicle Classification Stations

4.4.6 Summary of Findings in Vehicle Classification and Weight Groups

Evaluation of vehicle classification and WIM stations increased our understanding for the composition of the vehicles in Delaware. Prior knowledge on truck traffic patterns and individual evaluation of sites revealed that few locations present significantly different truck traffic patterns compared to others. One of these locations, station 8016 – US 301 near the MD line, was further discussed due to high percentage of combination unit truck traffic and recommended a comprehensive evaluation.

It is observed that class 5 (single unit, 2-axle trucks) and class 9 (single trailer, 5-axle trucks) trucks compose 80% of the total truck traffic in Delaware and apply 79.6% of the total weight exerted on roads. Thus, these two truck classes are primarily used for establishing truck weight groups. Both class 5 and class 9 truck did not reveal noticeable seasonal variation for truck weights and VCGs used for evaluating the truck weights.

A total of 22 WIM and 2 classification sites were examined in the determination of vehicle classification groups (VCG). Cluster analysis and graphical examination are used for determination of groups and assigning the stations into respective groups. Established four groups are:

- VCG 1 – Interstates
- VCG 2 – Urban Other Roads
- VCG 3 – Rural Other Roads
- VCG 4 – Rural Recreational Roads

Furthermore, the number of stations in each group is examined to meet the required confidence level and precision intervals. This evaluation revealed that VCG 2 requires at least one additional vehicle classification site in urban arterials. Considering the truck traffic patterns in the area, SR 41/48 near the PA line, SR 2 Elkton Road near the MD line and SR 141 are proposed for possible vehicle classification stations.

Evaluation of truck weight data shows that class 5 and class 9 trucks present different characteristics in urban and rural typology. Class 5 trucks present higher average truck weights in urban areas than in rural. Conversely, class 9 trucks show higher average truck weights in rural areas than urban.

Interstates are not well monitored with WIM stations regarding the evaluation of vehicle classification and truck weights. Considering the complexity of installing and maintain WIM station on interstates, it is recommended to investigate the other non-intrusive technologies that can be useful for determination of vehicle types and truck weights on interstates. Also, coordinating with neighboring states MD and PA and using available truck weight data near borderlines can help understand the truck weight patterns on Delaware interstates.

4.5 Short-Duration (Coverage) Data Programs

Short-duration counts are widely used by highway agencies to perform large number of counts every year. As mentioned previously, continuously monitoring each and every roadway segment is unrealistic and unaffordable, specifically considering the limited economic resources. Therefore, states balance limited number of continuous count stations with wide-coverage short-duration counts for the collection and analysis of required traffic measures. Two main reasons of using short-duration counts are:

1. Easy and inexpensive to perform the data collection, and
2. Provide wide geographic coverage.

However, this short-duration data program is also highly labor intensive requiring the data collection staff working frequently on placing and retrieving the data collection equipment. TMG provides two recommendations that can be considered for selecting the appropriate data collection equipment and establishing the short-duration data programs in addition to accuracy and reliability of the equipment. These features are:

1. Equipment that can be easily placed and calibrated (reducing the time spent for installation and calibration for each unit might have a significant impact on the overall cost of short-duration data program).
2. Equipment that maximize the safety of personnel during the placement and retrieval of the sensors. (Placement and retrieval of the equipment require data collection personnel to be on and/or near the roadways).

TMG recommends establishing the short-duration data program to cover all roadway segments within a state with a maximum cycle of six years. Furthermore, HPMS requires states covering higher functional classification roadways every three years. This short duration counting effort would be supplemented by special counts to meet the site-specific data needs. Additionally, it is also recommended to collect 25%-30% of the short-duration counts with vehicle classification counting equipment *(2)*.

Spacing between short-duration counts is another key factor for an accurate short-duration count. States are encouraged to select the appropriate length of roadway segments so that the traffic measures do not change significantly in the selected segments. A rule of thumb that has been used among state agencies is that defining the segment where the traffic volume in each segment stays within 10 percent of each other.

Duration of short-duration counts is also a critical factor for the accuracy and reliability of the collected data. TMG recommends minimum of 48-hours for the duration of vehicle classification counts, and encourages increasing the duration of count to cover weekends for a better estimation of Day-of-Week (DOW) variation. On traffic volume counts, duration of count can be varying from 48-hour to a weeklong count. Some agencies prefer 48-hour counts with a three-year cycle, while some perform 7-day counts with a six-year cycle. TMG recommends establishing the short-duration data program based on agency's need and priorities while meeting the federal reporting requirements.

The Delaware short-duration count program covers approximately 3,460 roadway segments on Delaware roadway network. Among 3,460 roadway segments, 91 segments are ATR locations, 44 segments are Interstates and DE 1 non-ATR locations. These 44 segments are covered by TMC sensors (Wavetronix) to provide data. Short-duration volume counts are performed for a one-week period and classification counts are performed for a 48-hour period. Additionally, approximately 1,350 segments (other principal arterial, minor arterial and major collectors) are covered in a three-year cycle, and approximately 2,000 segments are covered with a six-year cycle (minor collectors and local roads) are covered in a six year cycle.

The DelDOT Traffic Summary Book indicates that approximately 900 short-duration counts are performed every year where about 100 of them are classification counts mainly at HPMS locations. Volume short-duration counts are performed for a one-week period to increase the accuracy of AADT estimates. Classification counts are performed for a 48-hour duration. Considering FHWA's recommendations and other states' practices, DelDOT is one of the top states performing weeklong short duration data collection. The following Table 15 presents a sample short-duration count schedule for the year of 2013 and provides the details for volume and vehicle classification counts with respective roadway functional classes.

Table 15. Short-Duration Count Schedule (2013)

3 Year Cycle				
Roadway Functional Class	**Total Counts**	**Volume**	**Classification**	**Miles Covered**
Other Principal Arterial	154	121	33	93.65
Minor Arterial	154	97	57	83.96
Major Collector	152	109	43	161.19
Total 3 Year Cycle	460	327	133	338.79
6 Year Cycle				
Roadway Functional Class	**Total Counts**	**Volume**	**Classification**	**Miles Covered**
Minor Collector	17	12	5	26.04
Local Roads	323	311	12	351.62
Total 6 Year Cycle	340	323	17	377.66
Total Short-Duration	800	650	150	716.45

One major issue should be considered is that the percentage of classification counts within the total short-duration counts. TMG recommends 25-30 percent of the short-duration count should be performed as classification counts; however, DelDOT performs nearly 100 classification counts and 800 volume counts, which is between 10%-15%. Therefore, it is recommended to increase the number of short-duration classification counts to ensure different vehicle classes are well represented, specifically trucks summary statistics are accurately estimated.

4.6 Adjustment Factors to Expand the Short-Duration Count Data

Adjustment factors are used for expanding the short-duration counts into yearly averages by removing the biases caused by daily, weekly and monthly variations. For instance, average daily traffic for a Monday in February can be significantly different from a Monday in August on a recreational roadway segment. In this case, using the volume data from a Monday in February can result in underestimating the traffic volume, and using the volume data from a Monday in August can result in overestimating the traffic volume on this roadway segment. To overcome these limitations, continuous count stations are used for developing adjustment factors to correctly estimate the yearly averages. Therefore, deriving the accurate adjustment factors has a significant effect on the accuracy and reliability of the estimates.

After obtaining the short-duration count data, appropriate adjustment factors are applied to short-duration count for the estimation of AADTs. The following equation presents the estimation of AADT and possible factors that can be included in the calculation:

$$AADTij = VOLij * MAFj * DAFj * ACFi * GFj$$

Where;

AADTij = the annual average daily traffic at location *i* of factor group *j*

VOLij = the axle volume at location *i* of factor group *j*

MAFj = the applicable monthly (seasonal) factor for factor group *j*

DAFj = the applicable day-of-week factor for factor group *j* (if needed)

ACFi = the applicable axle correction factor for the factor group *j* (if needed)

GFj = the applicable growth factor for the factor group *j* (if needed)

Some of these adjustment factors are used if necessary. For instance, if the short-duration count is performed for a seven consecutive days (as in DelDOT short-duration volume data program), then day-of-week factor is not necessary. Seven consecutive days of data accurately removes the bias caused by day-of-week variation. Similarly, growth factor should be used only if the last available count was performed in previous years.

4.7 Summary of Chapter

Chapter 4 presented the evaluation of the traffic monitoring program at DelDOT. Volume, vehicle classification and truck weight data from 2012, 2013 and 2014 was analyzed to identify the spatial and temporal variation. Continuous count stations are grouped by using mathematical and statistical procedures based on seasonal variation, volume trends, vehicle classification types, truck weights and roadway functional classification characteristics.

Evaluation of volume data and established TPGs revealed that traffic characteristics on selected Kent and Sussex County roadways shifted from recreational to commuter and recreational, and carry more traffic volumes on non-summer months.

Proposed TPGs satisfy the required minimum number of station criteria, and no new sites are needed for statistical accuracy and reliability. However, it is observed that major roadways in NCC are under-represented. Therefore, it is recommended to increase the coverage in NCC for volume data either with installing new continuous count stations or integrating with data already collected by TMC.

Interstates I-95, I-295 and I-495 are not extensively covered with continuous count stations. Volume stations are located northern part of I-95 and I-495 near the PA line and do not reflect the traffic conditions on other parts of the Interstates. Moreover, WIM station 8004 placed on I-495, which is the only WIM station on Interstates in Delaware, is not providing accurate data. Considering the complexity of installing and maintaining in-pavement sensors on interstates, it is recommended to investigate other non-intrusive technologies for data collection.

In vehicle classification and truck weight data analysis, it is observed that class 5 (single unit, 2-axle trucks) and class 9 (single trailer, 5-axle trucks) trucks compose 80% of the total truck traffic in Delaware and apply 79.6% of the total weight exerted on roads. Thus, these two truck classes are primarily used for establishing truck weight groups.

Furthermore, three possible locations are proposed for a vehicle classification station to meet the required minimum number of station for urban other roads group.

Chapter 5

METHODOLOGY: DEVELOPING A DECISION SUPPORT TOOL FOR STATES' TRAFFIC MONITORING PROGRAM (TMDEST)

5.1 Concept of TMDEST

The Traffic Monitoring Decision Support Tool (TMDEST) is aimed at improving the overall quality of traffic monitoring program in states by providing an expert system-based decision support tool to guide responsible personnel during the collection and analysis of traffic monitoring data. The framework is not intended to replace the current data analysis and methods but rather contributes to particular functions in the traffic monitoring program, specifically establishing traffic pattern groups, and evaluating spatial and temporal variations for generating necessary adjustment factors to expand short-duration counts. Moreover, this approach contributes to the decision making process (e.g. selecting appropriate technologies for data collection and selecting proper locations for short-duration counts) and facilitating the data analysis and QC/QA procedures (e.g. determination of appropriate methods for MADT/AADT estimation and TPG methods, sample size estimation, and location determination for new CCS).

The primary target audience and potential end user of TMDEST are state DOT personnel who are responsible for collecting, analyzing and reporting traffic monitoring data. However, the proposed tool can also be utilized by any state or federal agency that is interested in traffic monitoring data, their spatial and temporal patterns, data collection and analysis methods, and the establishment of TPGs.

The TMDEST consists of two main sections: an informative tool and an interactive tool. The informative tool is dedicated to outlining and summarizing the user-requested information in a rule-based system, where the user is only required to select among presented on-screen options to reach the end product, which is mostly a set of recommendations. On the other hand, the interactive tool enables the user to input simple or complex entries in addition to the presented set of choices to make sophisticated analytical conclusions. The main differences between informative and interactive tools are enabling data entry from users and the complexity of background calculations. This structural separation becomes very useful while constructing the logic and command blocks during the system development. Both informative and interactive tools consist of sub-systems to reduce the complexity of verification and validation of the systems. Figure 40 presents the concept of TMDEST and its primary components.

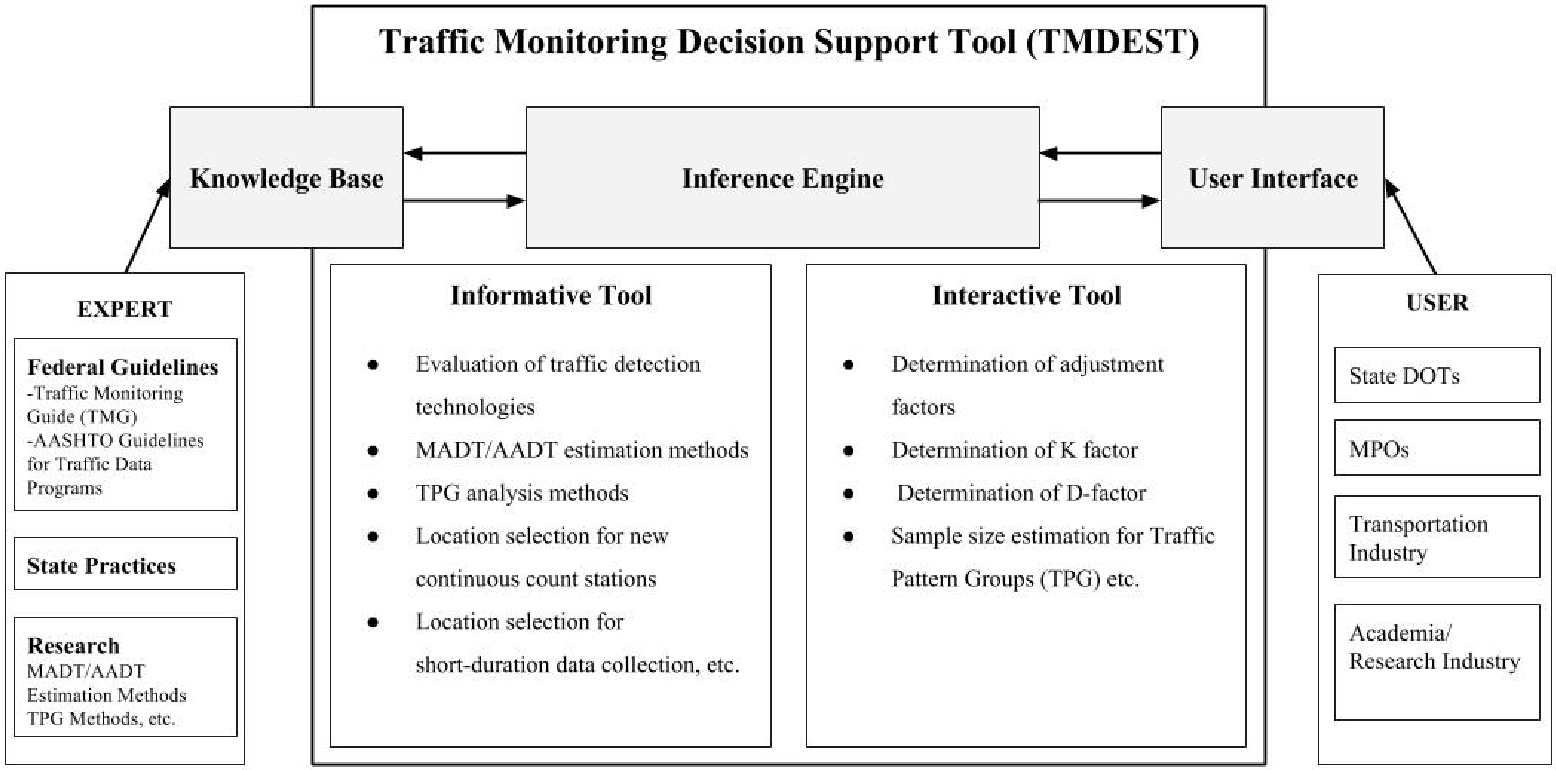


Figure 40. Concept of Traffic Monitoring Decision Support Tool (TMDEST)

5.1.1 Informative Tool

The informative tool predominantly provides filtered and summarized state-of-the-art information regarding the methods and technologies for traffic monitoring data collection and analysis. This includes recommended procedures by federal agencies such as FHWA and AASHTO, and other popular methods developed by researchers and used by state DOTs. Users are guided to situation specific information/recommendations by selecting among the provided on-screen options and following the instructions. For instance, if a user is interested in evaluating the possible methods in MADT/AADT estimation for a data set including non-random missing data, the expert system will ask particular questions and provide the most relevant recommendations regarding the appropriate methods and step-by-step instructions for applying the chosen method to the available datasets. A similar approach can also be used in evaluating the methods for TPG analysis, determination of appropriate locations for new continuous count stations, and location selection for short-duration count data.

The main reasons for considering such information in TMDEST framework includes but are not limited to:

- Providing summary information about the procedures for the collection and analysis of traffic monitoring data;
- Offering step-by-step instructions for performing selected procedures and calculations.

5.1.2 Interactive Tool

The interactive tool enhances the interaction created in the informative tool by enabling user input such as numerical input or data file in a certain format. These inputs are then used for necessary mathematical and statistical calculations to provide a recommendation to the end user. Data inputs can be as simple as numerical values or strings that could be entered through user interface, or file inputs might require further processing by using programming languages such as SQL to create the necessary database in the expert system. Data input methods may vary depending on the size and content of the data, and platform that the data is stored. Pavaloaia *(48)* presented common external file input methods and file types for Exsys Corvid® which is the platform used in this study.

In states' traffic monitoring programs, the interactive tool supports the execution of data driven decisions. However, one critical issue is that only small portions of data formats are common for all states based on HPMS reporting requirements. Likewise, data types vary among states considering the variation in data collection technologies and data processing methods used. Therefore, development of the interactive tool is highly dependent on the data setting and environment the expert systems will be used in. Hence, the primary focus of case studies here were common and simple data types that are well known by transportation professionals, such as MADT/AADT, and numerical values such as the total number of continuous count stations. Additionally, case studies emphasize the practicality of integrating other data sources by reading t-statistics from the file to be used in sample size estimation. Both data input methods can be modified and improved based on the needs and expectations of the transportation agency.

5.2 An Expert System Development Tool: Exsys Corvid Core®

The program used to design the expert system is called Exsys Corvid Core (will be named Corvid Core® in this dissertation) and developed by Exsys® Inc., which is one of the leading companies providing expert system development tools with over 30 years of experience. Exsys Corvid® is the main expert system development tool and compatible only with Windows platforms. Corvid Core® is the Mac OSX version of the Exsys Corvid® with slight differences for building and deploying online expert systems. The Corvid Core® version is capable of performing most important and "core" functions of the main platform, Exsys Corvid®.

Corvid Core® software provides an easy way for building interactive web-based expert systems. It is designed to provide a user-friendly graphical user interface and also aimed at non-programmers, which is critical for end user developers discussed by Wagner *(37)*. Corvid Core® enables creating IF/THEN rules, incorporation of mathematical expressions, designing user interface and explanation mechanism, and integrating with databases and other sources with SQL commands.

Among all, there are two primary limitations of Corvid Core® compared to the Exsys Corvid® worth mentioning in regards to system development. One is the lack of a dynamic variable feature that enables the creation of variables while executing rules. This feature simplifies the use of if/while loops and creation of variables within the loop for further processing. The second limitation is Corvid Core® can only use one command block for structuring the expert system, which limits the developer for building multiple user interfaces and logic processing methods (forward/backward chaining). These limitations affected the structure and number of steps required to develop the TMDEST. Instead of building a single large

KBES framework, multiple modules were designed to perform the different tasks (evaluation of methods, TPG analysis, sample size estimation, etc.). Moreover, considering relatively small modules to construct the KBES structure for each step also simplified the verification and validation process at the same time.

5.2.1 Major Components of Exsys Corvid Core®

Variables are the key design features of Corvid Core®, and used to ask questions, display results and describe the decision-making logic. Variables can be created in variable windows depending on the question being asked and type of response required by the end user, and then used for building Rules and Logic Blocks in an expert system.

There are six types of variables in Corvid Core®. These are multiple selection list, numeric value, string value, date value, collection/report, and confidence variables. Among these, multiple selection list, numeric value, string value and date value are used for creating expressions that are used in the "IF" part of the expert system. Remaining two variables, collection/report and confidence, are used in the "THEN" part of the expert system for presenting the results in different ways. Multiple selection list, which is generally the most used variable type enables selecting among given options such as Yes/No, A/B/C, etc. Additionally, this variable type makes the selection process much easier for end users. Numeric, string and date value variables enable end user to enter text and numeric inputs for a prompted question. Both multiple selection list and numeric variables are extensively used in TMDEST. Numeric variables are primarily used for asking numeric inputs from end users (e.g. CV values and number of TPGs).

Collection/report variable is primarily used for generating customized reports to the end users and can be designed based on end user needs and priorities. Additionally, collection/report variable is useful for displaying a recommendation or decision that also includes variables entered by the end user. For instance, in TMDEST sample size estimation module, the end user will be asked to enter the number of TPGs and CV values for each TPG. Collection variables are then used for displaying if the given “X” number of stations are statistically enough for a given “A” precision intervals, and “B” confidence levels.

Last variable, confidence variable, is used for giving a confidence rating for an outcome based on end users’ selections. These confidence ratings are then accumulated for a certainty score to enable producing a decision/advice to the end user. For instance, in the part for evaluating the appropriate methods for AADT and MADT estimation in TMDEST, a series of multiple selection list type of questions (e.g. *Do you regularly have missing data in your CSS data files?, What is the distribution of missing data?, What is the duration of your short-duration data? etc.*) will be asked to the end user. Then, a confidence score will be assigned to each possible method based on user’s response (e.g. if a user specifies the presence of non-random missing data, then a low confidence score will be assigned to “*simple average method*” and high confidence score will be assigned to “*AASHTO method*”). Then, accumulation of all scores given to each possible method will help to select and sort the appropriate methods for MADT and AADT estimations.

Another major component of Corvid Core® is logic blocks that allow building IF/THEN rules in a structured way. There are many equivalent ways of structuring the logic block as similar to different experts might solve a problem in a variety of ways. However, logic blocks should be structured in a way so that the rules cover all possible end user input values without causing any gap in the logic. The typical logic block structure is a branching tree diagram. A rule is made up of branching “nodes,” which are simply statements, conditions, or mathematical expressions. All these conditions are built by using the variables that must be created before they can be added to the logic chain. The logic blocks simply provide the rules and tell the Corvid Inference Engine “how” to do things.

In TMDEST, logic blocks are structured by following the general procedure outlined by FHWA’s TMG since the proposed framework is aimed at improving the traffic monitoring program in state highway agencies. Logic blocks are structured in small partitions and linked to a main module for enabling an easy selection of proper tasks and quickly performing the necessary actions. Moreover, small partitions facilitate the verification and validation process by allowing each partition be evaluated individually. For instance, evaluation of methods for MADT and AADT estimation, evaluation of methods for TPG analysis, sample size estimation, selection of location for new sites, and use of adjustment factors are individually structured in Corvid Core®, even with multiple logic blocks, and linked to a main module for enabling the end user to select and perform only the necessary tasks.

Corvid also has Command Blocks that is used to run the system and to design how the results will be displayed to the end user. The command block simply tells the Corvid Inference Engine “what” to do with these variables and rules. In many cases, specifically for small systems, command block can work with only a few commands. These commands can be used for creating loops for repeating the question or data entry, for using forward/backward chaining in different parts of the expert system, displaying the results in different ways, and many other functions to run the system. In TMDEST, multiple command blocks are used for different components of the system. In sample size estimation module, command block is used for creating a loop for repeating the data entry and necessary calculations for each TPG (e.g. number of stations, CV values). Moreover, command block is also used for reading data from an external file for incorporating the t-statistic values for a given confidence level and degrees of freedom.

KBES may contain a large amount of information, which could be extended and/or updated. However, due to the fact that KBES are created by rules and facts, they do not learn from mistakes, so user feedback and an on-going development process are needed. Therefore, a long-term plan is necessary for collecting feedback from users and developing appropriate strategies for improving the content and rules of the system if necessary.

5.3 Development of TMDEST Modules and Case Studies

The total of six modules was developed in two categories to present both information and interactive tools to further the TMDEST concept and demonstrate the use in states traffic monitoring programs. Federal guidelines, state practices, and research studies were used to construct the necessary knowledge for the TMDEST framework in addition to the experience gained during the “evaluating and updating the traffic monitoring program at DelDOT” project. This knowledge is then categorized within the concept of traffic monitoring to identify the possible parts that TMDEST can be helpful with. Among these possible parts, following two case studies are chosen to demonstrate the capabilities of the developed framework.

The first case study is designed to explain and guide the TPG analysis based on temporal and spatial variations as an illustration of the informative part of the TMDEST. This case study includes multiple subsections for the evaluation of data sources and methods for selected tasks and explanation of the appropriate procedure for applying adjustment factors. Recommendations provided to the user integrate constraints and limitations provided by the user with federal guidelines and well-accepted methods.

The second case study provides an opportunity to demonstrate the data input and numerical calculations in addition to the features presented in the first case study. Both simple data entry through the user interface and incorporating with a data file are emphasized in this second case study. It explains the process for estimating the sample size for each TPG and included the mathematical and statistical calculations. The Table 16 presents the purpose of each module that will be discussed in the following section.

Table 16. Purpose of the TMDEST Modules

TMDEST Module	Purpose of the Module
Class/Weight Trend Module	Guide the user to identify the most common truck types and trucks that exert the most weight to be considered in establishing vehicle classification and truck weight groups.
MADT/AADT Methods Module	Evaluate different MADT and AADT estimation methods based on presence and extent of the missing data, and inclusion of temporal variations to recommend the most appropriate methods to the user.
TPG Methods Module	Evaluate four TPG analysis methods (Traditional Approach, Cluster Analysis, Cluster Analysis with Roadway Functional Classification, Volume-based Groupings) based on seasonal variation, volume trends and geographic coverage to recommend the most appropriate methods to the user.
TPG Groups Module	Establish the TPGs with an approximate cluster analysis and functional classification method by asking the seasonal variation and urban/rural typology questions to the user for each roadway functional class.
Adjustment Factor Module	Improve the decision on which adjustment factors are necessary to be used to expand the collected short-duration counts for the estimation of AADTs.
Sample Size Estimation Module	Evaluate the number of continuous count stations (CCS) in each TPG for statistical significance and suggest the required additional number of stations if necessary.

5.4 Case Study One: Step-by-Step Traffic Pattern Group (TPG) Analysis

Traffic pattern group analysis is used to explore spatial and temporal variation of traffic in a study area or state. These variations are then used for establishing TPGs and deriving adjustment factors to be used for estimating of necessary summary statistics. The concept of TPG analysis and available methods were discussed in

Chapter 2, and DelDOT case study was presented in Chapter 4 of this dissertation. This section presents the development of TPG analysis module within TMDEST framework by using Corvid Core® expert system development tool.

The case study is constructed in six modules where each module is designed to provide solutions/recommendations for different tasks. Users can either follow the order of the modules or select the appropriate module from a menu provided in the main module. Figure 41 presents the modules and respective tasks of each module for TPG analysis and its components.

This case study extensively used the list variables to allow users to select among provided on-screen options where each selection contributes to the decision in different weights. Final recommendations are provided with the reasoning behind the decision. The six modules provide an example for an overall evaluation of vehicle classification and weight monitoring program. Starting with identifying the certain vehicle classes that have a significant contribution to the traffic, the TMDEST evaluates and recommends the appropriate methods for MADT/AADT estimation and TPG analysis; establishes TPGs with approximate seasonal variation and roadway functional classification; tests the sample size in each group, and recommends necessary adjustment factors to be used.

These six modules are presented in detail in the following sections.

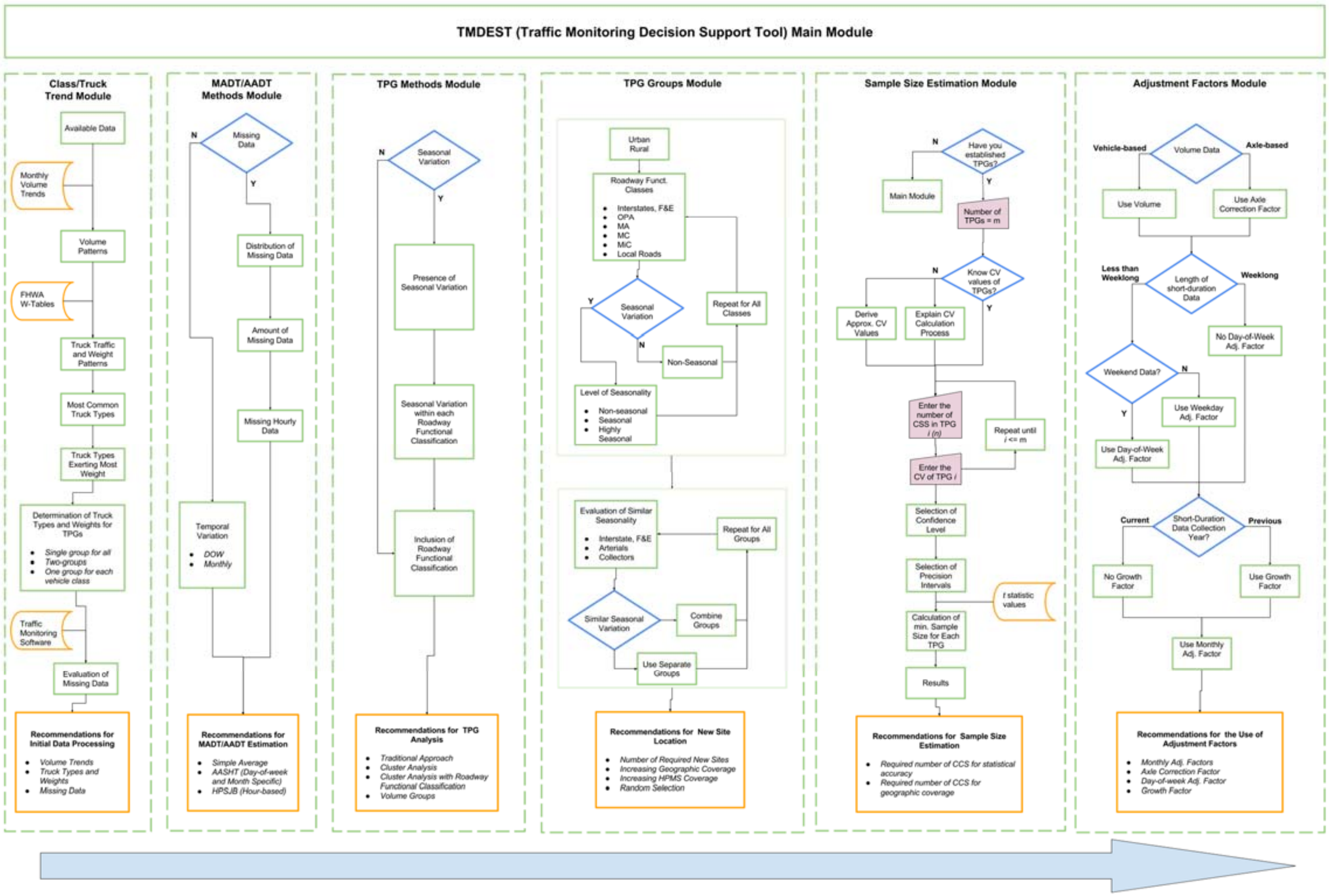


Figure 41. Process Flow for Step-by-Step TPG Analysis

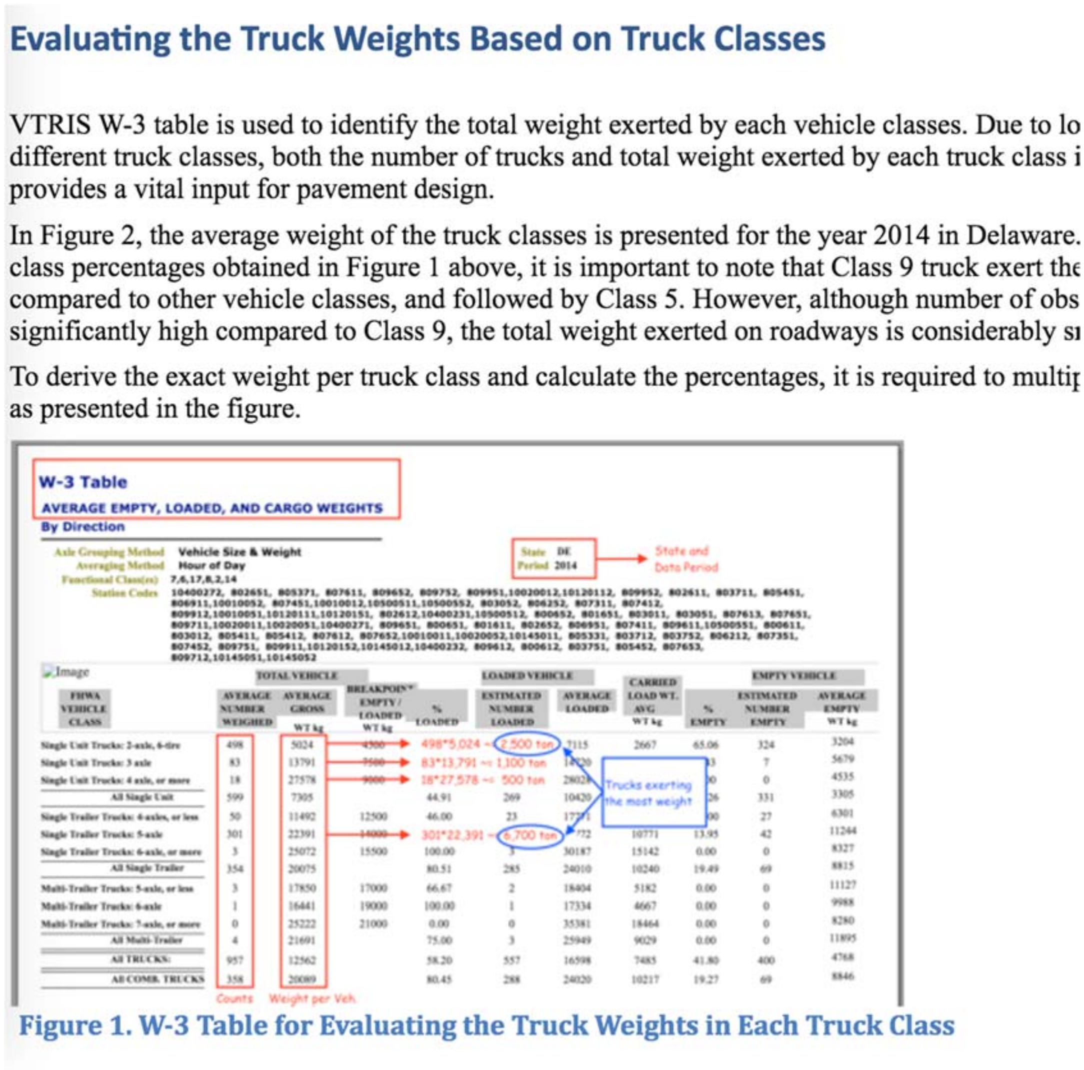
5.4.1 Class/Weight Trend Module

Different vehicle classes can have significantly different spatial and temporal distributions in a roadway network. These variations in terms of how many and what type of vehicles are traveling on which roads affect the planning and operation of the roadways in addition to policy and roadway design processes. Therefore, it is vital to assess the seasonal and geographic variation of the truck traffic and the weight exerted on roadways in a state. In Class/Weight Trend Module, the user will be guided to identify the most common truck types and trucks that exert the most weight to be considered in establishing vehicle classification and truck weight groups.

FHWA's VTRIS W-Tables *(27)* are created with the vehicle classification and weight data provided by states to present an overall representation of truck traffic in each state based on FHWA's 13-vehicle classification category. In TMDEST, the user will be directed to use the VTRIS W-tables to identify the most common truck types seen on the roadways, and the truck types exert the most weight. If the user already has knowledge on this variation, then the Class/Weight Trend Module will help to decide if one or more vehicle classification groups should be used to establish the necessary groups. The module will provide necessary links to an explanatory web page and an extenal MS Excel file to further the analysis.

The external web page is designed to provide a detailed explanation of VTRIS website as well as the possible information to obtain from different W-Tables. The user will be guided through this web page regarding how to read and obtain the necessary information, the most common truck types and weight trends in our case.

Figure 42 and Figure 43 present an overview of prepared web page and how the user is guided through graphical explanations.



Evaluating the Truck Weights Based on Truck Classes

VTRIS W-3 table is used to identify the total weight exerted by each vehicle classes. Due to lo
different truck classes, both the number of trucks and total weight exerted by each truck class i
provides a vital input for pavement design.

In Figure 2, the average weight of the truck classes is presented for the year 2014 in Delaware.
class percentages obtained in Figure 1 above, it is important to note that Class 9 truck exert the
compared to other vehicle classes, and followed by Class 5. However, although number of obs
significantly high compared to Class 9, the total weight exerted on roadways is considerably sı

To derive the exact weight per truck class and calculate the percentages, it is required to multiр
as presented in the figure.

W-3 Table

AVERAGE EMPTY, LOADED, AND CARGO WEIGHTS

By Direction

Axle Grouping Method: Vehicle Size & Weight
Averaging Method: Hour of Day
Functional Class(es): 7,6,17,8,2,14
Station Codes: 10400272, 802651, 805371, 807611, 809652, 809752, 809951,10020012,10120112, 809952, 802611, 803711, 805451, 806911,10010052, 807451,10010012,10500511,10500552, 803052, 806252, 807311, 807412, 809912,10010051,10120111,10120151, 802612,10400231,10500512, 800652, 801651, 803011, 803051, 807613, 807651, 809711,10020011,10020051,10400271, 809651, 800651, 801611, 802652, 806951, 807411, 809611,10500551, 800611, 803012, 805411, 805412, 807612, 807652,10010011,10020052,10145011, 805331, 803712, 803752, 806212, 807351, 807452, 809751, 809911,10120152,10145012,10400232, 809612, 800612, 803751, 805452, 807653, 809712,10145051,10145052

State: DE
Period: 2014

Image

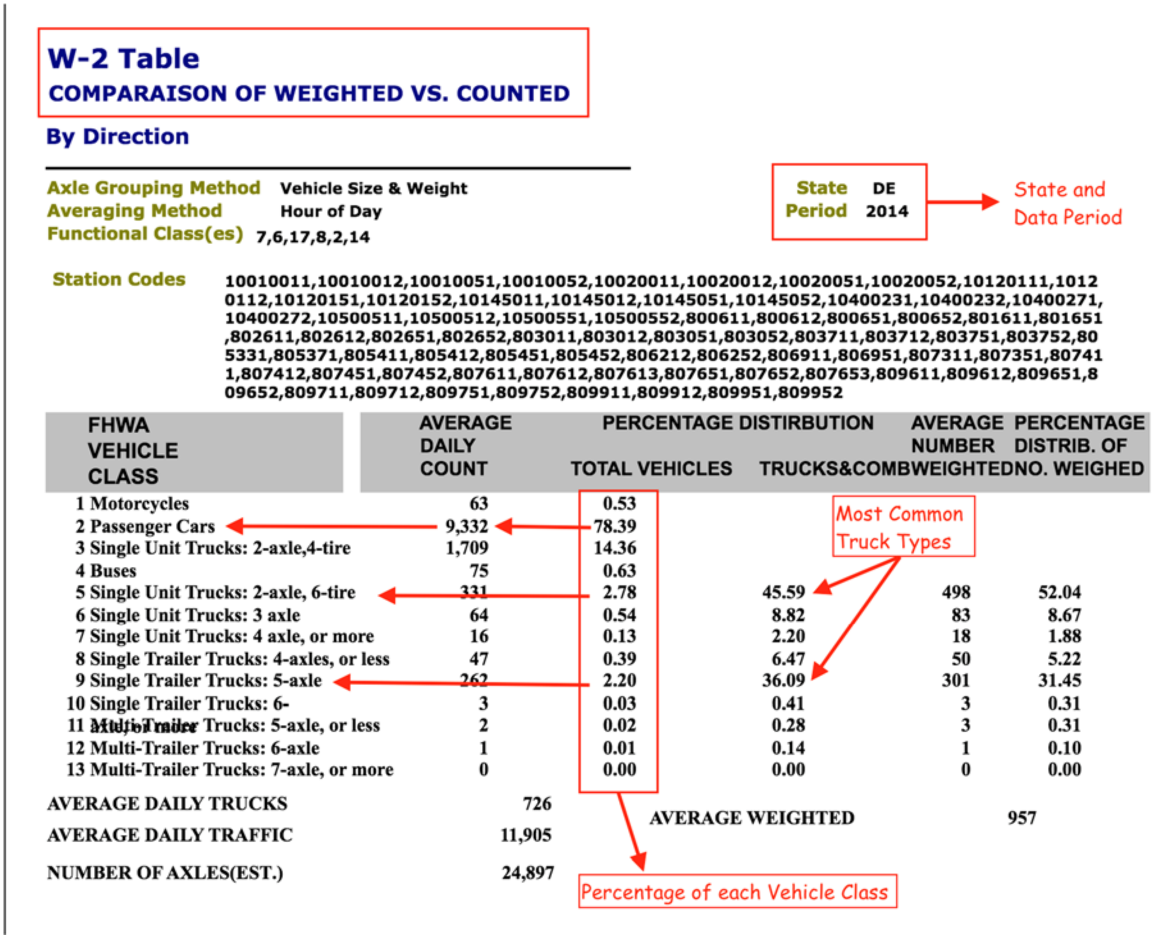
FHWA VEHICLE CLASS	TOTAL VEHICLE AVERAGE NUMBER WEIGHED	AVERAGE GROSS WT kg	BREAKPOINT EMPTY / LOADED WT kg	% LOADED	LOADED VEHICLE ESTIMATED NUMBER LOADED	AVERAGE LOADED	CARRIED LOAD WT. AVG WT kg	% EMPTY	EMPTY VEHICLE ESTIMATED NUMBER EMPTY	AVERAGE EMPTY WT kg
Single Unit Trucks: 2-axle, 6-tire	498	5024	~~4500~~	498*5,024 ~ 2,500 ton		7115	2667	65.06	324	3204
Single Unit Trucks: 3 axle	83	13791	~~7500~~	83*13,791 ~ 1,100 ton		[illegible]	[illegible]	[illegible]	7	5679
Single Unit Trucks: 4 axle, or more	18	27578	~~9000~~	18*27,578 ~ 500 ton		[illegible]	[illegible]	[illegible]	0	4535
All Single Unit	599	7305		44.91	269	10420	[illegible]	[illegible]	331	3305
Single Trailer Trucks: 4-axles, or less	50	11492	12500	46.00	23	[illegible]	[illegible]	[illegible]	27	6301
Single Trailer Trucks: 5-axle	301	22391	~~14000~~	301*22,391 ~ 6,700 ton		[illegible]	10771	13.95	42	11244
Single Trailer Trucks: 6-axle, or more	3	25072	15500	100.00	3	30187	15142	0.00	0	8327
All Single Trailer	354	20075		80.51	285	24010	10240	19.49	69	8815
Multi-Trailer Trucks: 5-axle, or less	3	17850	17000	66.67	2	18404	5182	0.00	0	11127
Multi-Trailer Trucks: 6-axle	1	16441	19000	100.00	1	17334	4667	0.00	0	9988
Multi-Trailer Trucks: 7-axle, or more	0	25222	21000	0.00	0	35381	18464	0.00	0	8280
All Multi-Trailer	4	21691		75.00	3	25949	9029	0.00	0	11895
All TRUCKS:	957	12562		58.20	557	16598	7485	41.80	400	4768
All COMB. TRUCKS	358	20089		80.45	288	24020	10217	19.27	69	8846

Figure 1. W-3 Table for Evaluating the Truck Weights in Each Truck Class

Figure 42. Class/Weight Module Web Page designed to guide reading the VTRIS W-Tables

VTRIS W-2 table is primarily used to identify the percentage of trucks in total volume and percentage of each truck class among vehicle classification groups 5 to 13. This information can be filtered based on roadway functional classification, WIM stations, and even for the direction of the traffic. The percentage of each truck class reveals the most commonly seen truck type(s) to be considered for establishing vehicle classification groups. For instance, 2014 Delaware W-2 table provided in Figure 43 presents that Class 5 Vehicles (Single Unit Truck, 2-axle, 6 tire) contain 45.59% of the truck traffic and Class 9 vehicles (Single Trailer Truck - 5-axle) contain 36.09% of the truck traffic. It is clearly visible that Class 5 and Class 9 trucks contain more than 80% of the truck traffic in Delaware. Therefore, these two truck classes can be used for establishing vehicle classification groups.

Similarly, VTRIS W-3 table is used to identify the total weight exerted by each vehicle class. Due to the fact that loads can vary in different truck classes, both the number of trucks and total weight exerted by each truck class is critical.



W-2 Table

COMPARAISON OF WEIGHTED VS. COUNTED

By Direction

Axle Grouping Method: Vehicle Size & Weight
Averaging Method: Hour of Day
Functional Class(es): 7,6,17,8,2,14

State: DE
Period: 2014

State and Data Period

Station Codes: 10010011,10010012,10010051,10010052,10020011,10020012,10020051,10020052,10120111,10120112,10120151,10120152,10145011,10145012,10145051,10145052,10400231,10400232,10400271,10400272,10500511,10500512,10500551,10500552,800611,800612,800651,800652,801611,801651,802611,802612,802651,802652,803011,803012,803051,803052,803711,803712,803751,803752,805331,805371,805411,805412,805451,805452,806212,806252,806911,806951,807311,807351,807411,807412,807451,807452,807611,807612,807613,807651,807652,807653,809611,809612,809651,809652,809711,809712,809751,809752,809911,809912,809951,809952

FHWA VEHICLE CLASS	AVERAGE DAILY COUNT	PERCENTAGE DISTRIBUTION TOTAL VEHICLES	PERCENTAGE DISTRIBUTION TRUCKS&COMB	AVERAGE NUMBER WEIGHTED	PERCENTAGE DISTRIB. OF NO. WEIGHED
1 Motorcycles	63	0.53			
2 Passenger Cars	9,332	78.39			
3 Single Unit Trucks: 2-axle,4-tire	1,709	14.36			
4 Buses	75	0.63			
5 Single Unit Trucks: 2-axle, 6-tire	331	2.78	45.59	498	52.04
6 Single Unit Trucks: 3 axle	64	0.54	8.82	83	8.67
7 Single Unit Trucks: 4 axle, or more	16	0.13	2.20	18	1.88
8 Single Trailer Trucks: 4-axles, or less	47	0.39	6.47	50	5.22
9 Single Trailer Trucks: 5-axle	262	2.20	36.09	301	31.45
10 Single Trailer Trucks: 6-axle or more	3	0.03	0.41	3	0.31
11 Multi-Trailer Trucks: 5-axle, or less	2	0.02	0.28	3	0.31
12 Multi-Trailer Trucks: 6-axle	1	0.01	0.14	1	0.10
13 Multi-Trailer Trucks: 7-axle, or more	0	0.00	0.00	0	0.00

Most Common Truck Types

AVERAGE DAILY TRUCKS 726
AVERAGE DAILY TRAFFIC 11,905
NUMBER OF AXLES(EST.) 24,897

AVERAGE WEIGHTED 957

Percentage of each Vehicle Class

Figure 43. VTRIS W-2 Table for Evaluating the Vehicle Classification Distribution by Vehicle Classification Groups

The user is then guided to provide some information obtained from VTRIS W-Tables to evaluate if one or more truck classes should be used to establish the vehicle classification groups. In general, the user will be recommended to focus on truck classes that contain at least 70%-80% of the total truck traffic and exert the majority of the weight. For instance, in Delaware, Class 5 and Class 9 trucks contain approximately 80% of the total truck traffic and nearly 80% of the total truck weight exerted on roadways. Therefore, temporal and spatial variation of Class 5 and 9 trucks are primarily used to establish the vehicle classification groups.

5.4.2 MADT/AADT Methods Module

Estimation of MADT and AADT measures are two of the critical tasks in states' traffic monitoring program. It is simply because the vast majority (>95%) of the roadway segments are covered with short-duration (coverage) data programs that require deriving and utilizing necessary adjustment factors for the estimation of these measures. Therefore, using an appropriate model to meet the needs and priorities of the transportation agency is vital.

MADT/AADT Estimation Module aims at improving the decision of evaluating and selecting the proper methods to perform the necessary calculation. The module not only improves the decision but also provides information regarding the factors affecting the decision such as the effect of missing data.

Among many approaches developed and used over the years, three methods are included in the development of the TMDEST – MADT/AADT Estimation Module. These methods are selected based on the complexity of the method and the representation of missing data to increase the reliability. These methods are:

1. Simple average of all days
2. AASHTO Method – Day-of-week and month specific factors
3. HPSJB Method – hourly data combined with day-of-week and month specific factors

Among these three methods, the simple average of all days was chosen to represent the simplicity of the calculations. AASHTO method was chosen due to the fact that it incorporated temporal variation well and widely used by state highway agencies. Additionally, research indicated that there was no significant difference perceived between AASHTO method and other methods incorporating temporal variations *(7, 8, 21)*. The last method included here, HPSJB method, was considered since this new methods incorporates hourly data from missing days and provides a slight improvement in the estimations *(9)*.

Each method is given a score between 0 and 300 (either 0, 100, 200 or 300) based on selected criteria such as complexity level of the processing, the presence of missing data, and the amount of missing data. These criteria will be prompted to the user to assign a score to each method based on how well they meet the criteria (well, moderate, poor). Table 15 presents the scores assigned to each method based on the user's responses.

Table 17. Score Table for MADT/AADT Estimation Methods

<table>
<tr><th colspan="2">Evaluation Criteria</th><th>Simple Average</th><th>AASHTO</th><th>HPSJB</th></tr>
<tr><td colspan="2">Level of Processing</td><td>300</td><td>200</td><td>100</td></tr>
<tr><td rowspan="2">Have Missing Data</td><td>Yes</td><td colspan="3">*Included in the following criteria</td></tr>
<tr><td>No</td><td>300</td><td>300</td><td>300</td></tr>
<tr><td rowspan="4">Amount of Missing Data (days/month)</td><td>< 3 days</td><td>200</td><td>300</td><td>300</td></tr>
<tr><td>< 7 days</td><td>100</td><td>300</td><td>300</td></tr>
<tr><td>< 15 days</td><td>0</td><td>300</td><td>300</td></tr>
<tr><td>> 15 days</td><td>0</td><td>300</td><td>300</td></tr>
<tr><td rowspan="2">Hourly Missing Data</td><td>Yes</td><td>0</td><td>0</td><td>300</td></tr>
<tr><td>No</td><td>100</td><td>300</td><td>300</td></tr>
<tr><td rowspan="2">Temporal Variation</td><td>Yes</td><td>0</td><td>300</td><td>300</td></tr>
<tr><td>No</td><td>300</td><td>0</td><td>0</td></tr>
</table>

It is important to note that simple average of all days and HPSJB methods represent the least and most complex methods. Similarly, AASHTO method represents the method that incorporate temporal variation excluding the hourly missing data. Therefore, agencies can easily replace the AASHTO method with other methods using day-of-week and monthly adjustment factors in the final recommendation list to see how well they fit in the sorted list of recommended methods.

5.4.2.1 Key Variables

"Have_missing" list variable is designed to ask if the continuous count data includes missing data with a prompt to user "Do you have a considerable amount of missing data from your continuous count stations?" The user must respond with "Yes", "No" or "Don't Know" to this prompt. As similar to other rules created, "Don't Know" response will be treated as the worst possible scenario, as similar to "Yes" response in this case.

The variable *"Amount_missing"* asks the user "Please select the amount of missing data in your continuous count stations:" The choices for user response are "1 days/Month", "4 days/Month", "7 days/Month", "15 days/Month" and "more than 15 days/Month". The increase in the amount of missing data will reduce the score assigned to "Simple_Average" method and increase the score assigned to other three methods that reduce the effect of missing data in the MADT/AADT estimations.

The variable *"Dist_of_missing"* is intended to obtain information regarding the distribution of the missing data. The user is prompted "Do you know if the distribution of missing data is random or not." with additional explanation "e.g. There might be issues with old sensors for reporting accurate data in winter months, sensors in urban streets might be producing volume data with a high error rate, etc." The purpose of asking about the distribution of missing data is to alert the user regarding the reliability of the data and further estimations if the non-random missing data is present.

The variable *"Missing_hourly"* list variable is designed to ask the user if the data set includes a considerable amount of missing hourly data. If the user indicates the presence of missing hourly data, then the HPSJB method will be given a high score since this method improves the MADT/AADT estimations in data sets with missing hourly data.

"Temporal_variation" variable is used for asking if the user wants to include the week-of-day and/or monthly variation in the estimation of MADT/AADT measures in case the data set does not include missing data. The reason for this question is to make sure that the module can recommend proper methods if the user plans using day-of-week and monthly adjustment factors to expand the short-duration counts.

"Simple_Average", *"AASHTO"* and *"HPSJB"* confidence variables are assigned to represent the four selected MADT/AADT estimation methods in this module. Each question prompted to the user will assign a score between 0 and 300 to these three confidence variables as explained previously. Then, the summation of all scores assigned to each variable will indicate a final score that will be used for ranking the methods. Confidence variable with the highest score will be indicating the most recommended MADT/AADT estimation method to the user.

"Note" collection variable is used for displaying specific information to the user in a certain node based on the user's selection. For instance, if the user selects that the distribution of data is not random in certain locations, the variable will display the following note:

> **"Please note that regularity in missing data can be caused by variety of factors such as heavy volume, poor maintenance, communication infrastructure problems, environmental factors, etc. Regularity in missing data should be monitored and addressed to increase the accuracy and reliability of the collected data and estimated summary statistics."**

5.4.2.2 Logic Blocks

A single logic block is used to construct the rules in the MADT/AADT Estimation Module. This logic block prompts list variable questions to the user and assigns a score to each confidence variable based on the user's response. The primary focus of the rules constructed in the logic block is evaluating the presence, distribution, and amount of missing data. Then, predetermined three methods are evaluated based on the final scores they received. Figure 44 presents a sample portion of the logic block in the MADT/AADT Estimation Module.

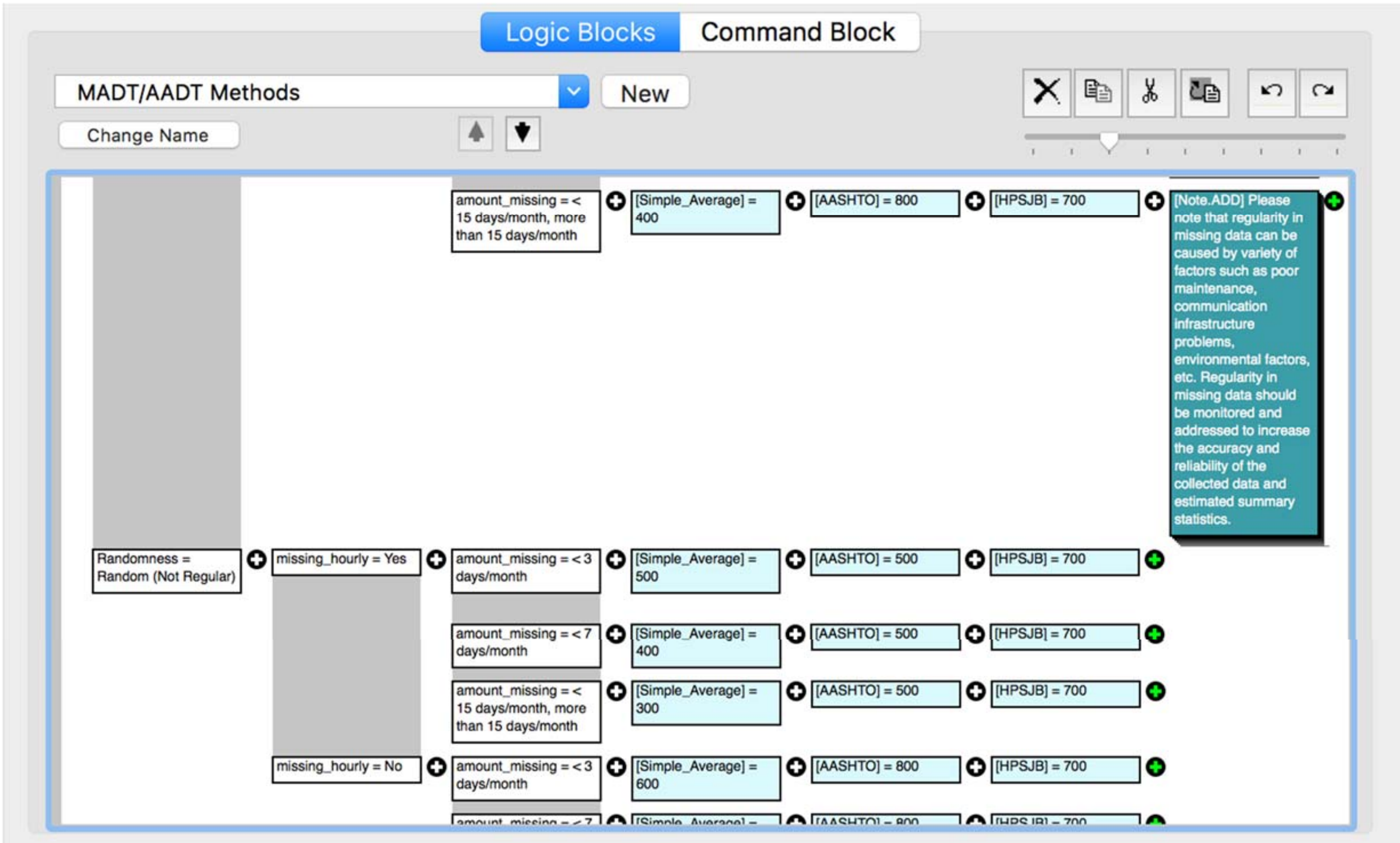


Figure 44. MADT/AADT Estimation Module - Logic Block

5.4.2.3 Command Block

The command block in this module starts with a welcome page to inform the user about the purpose of the module, evaluation procedure and possible MADT/AADT estimations methods recommended to the users. This page will be displayed to the user at the beginning of the module before prompting the questions. Then the command block derives all confidence and collection variables by using the backward chaining method. However, since each rule will be assigning a score to each confidence variable based on the rule structure presented in the logic block, there is no difference between using forward or backward chaining in this module, because each confidence variable will require firing the same set of rules.

After deriving the confidence and collection variables, the command block is also used to present the necessary information to the user. This information includes presenting the user's answers to the prompted questions, and list of estimation methods sorted by the final score. Additionally, if there is a "note" derived after user selecting specific rules, this note will also be displayed in the final recommendation page (Figure 45).

Based on Your input of:

Do you have a considerable amount of missing data from your continuous count stations? Yes

Du you know if the distribution of missing data is regular or not. (i.e. There might be issues with old sensors for reporting accurate data in winter months, sensors in urban streets might be producing volume data with high error rate, etc.) Regular

Please select the amount of missing data in your continuous count stations: < 3 days/month

Do you have considerable amount of hourly data missing each days? (If you have considerable amount of missing data - possibly few hours per day, you can increase the reliability of the results by using the methots that incorporates hourly data for MADT/AADT estimations.) Yes

Recommended MADT/AADT Estimation Methods:

Please note that recommended methods are sorted based on the final score they received based on your selections.

HPSJB (Highway Policy Steven Jessberger Battelle) Method Conf=700.0

Simple Average Method Conf=500.0

AASHTO Method Conf=500.0

Note: Please note that regularity in missing data can be caused by variety of factors such as poor maintenance, communication infrastructure problems, environmental factors, etc. Regularity in missing data should be monitored and addressed to increase the accuracy and reliability of the collected data and estimated summary statistics.

OK

Figure 45. MADT/AADT Estimation Module - Final Results Page

5.4.3 TPG Methods Module

Traffic Pattern Group analysis is one of the crucial tasks in states' traffic monitoring programs. This task enables creating groups that are statistically sound and easily applicable to derive necessary adjustment factors and summary statistics from expanding the short-duration counts. Among different approaches presented in Chapter 2, four selected methods are included in designing TPG Methods Module. These four methods are traditional approach, cluster analysis method, cluster analysis with functional classification, and volume-based grouping. The only method that is not covered previously is cluster analysis with functional classification method evaluates the seasonal variation within each roadway functional class and determines the number of groups should that be established.

These 4 methods are assessed based on seasonal variation, volume trends, and geographic coverage. Similar to MADT/AADT estimation module design, each TPG method will be assigned a score based on the user's answers and how well they meet the given criteria. Then, all scores will be accumulated to obtain a final score for each method to make a recommendation to the user.

This module only performs a quick evaluation of TPG analysis methods and leaves the establishment of TPGs to the user. It is because that establishing TPG require a large amount of data (MADT and AADT measures, location, and functional classification of each CCS) and performing needed mathematical and statistical procedures. However, TPG Module that is presented in the next section provides an approximate method for establishing TPGs by using the cluster analysis with functional classification method.

Table 18. Score Table for TPG Analysis Methods

<table>
<tr><th colspan="2">Evaluation Criteria</th><th>Traditional Approach</th><th>Cluster Analysis</th><th>Cluster with Roadway Func. Class.</th><th>Volume Groupings</th></tr>
<tr><td colspan="2">Level of Processing</td><td>300</td><td>100</td><td>100</td><td>200</td></tr>
<tr><td rowspan="2">Seasonal Variation</td><td>Yes</td><td>0</td><td>300</td><td>300</td><td>0</td></tr>
<tr><td>No</td><td>300</td><td>200</td><td>200</td><td>300</td></tr>
<tr><td rowspan="2">Seasonal Variation in Same Urban/Rural Typology</td><td>Yes</td><td>0</td><td>300</td><td>300</td><td>0</td></tr>
<tr><td>No</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td rowspan="2">Functional Classification</td><td>Yes</td><td>300</td><td>100</td><td>300</td><td>100</td></tr>
<tr><td>No</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
</table>

5.4.3.1 Key Variables

In TPG Methods Module, list and confidence variables are primarily used for the selection of appropriate methods. The *“Seasonal_Var”* variable asks the user “Do you want to incorporate seasonal variation as a factor while establishing TPGs?” The user can select either “yes” or “no”. If the user selects “yes”, the inference engine will assign a high score to the methods that incorporate seasonal variation such as cluster analysis, and a low score that does not contain seasonal variation such as volume-based grouping.

The variable *“SeasVar_FunctionalClass”* prompts to user “Do you have noticeable seasonal variation within same roadway functional classes in the same Urban/Rural typology. (e.g. some rural major collectors present high seasonal variations and some not = Yes, or All urban major arterials present similar seasonal variation = No)” If the user indicates the presence of seasonal variation within the same roadway functional classification, then the method of cluster analysis with functional classification will be assigned a higher score than the cluster analysis and traditional methods.

The variable *"Geographic_Coverage"* is used for asking the spatial extent of the roadway network in the state or study area. If the user states the existence of wide geographic coverage with distinctive traffic characteristics, then the TPG analysis can be applied regionally.

The variable *"Functional_Classification"* is designed to ask the user if the TPG method should consider the use of roadway functional classification. The prompt for this variable is " Do you want to include roadway functional classification as a factor while establishing TPGs?" The choices for user response are "Yes" and "No."

The confidence variables *"TPG_Traditional"*, *"TPG_Cluster"*, *"TPG_Cluster_Func"*, and *"TPG_Volume"* are designed to represent the determinaed 4 TPG analysis methods. Based on the user selection and defined criteria regarding how well the answer is meeting the criteria, the confidence variables will be assigned a score between 0 and 300 (either 0, 100, 200 or 300). A Higher score will be representing that the method well addresses the user's selection.

5.4.3.2 Logic Blocks

Three logic blocks are constructed to set the rules for different subjects. With the backward chaining method, this approach significantly reduces the number of nodes required if the system is constructed in a single logic block. The "Seasonal

Variation" logic block controls the rules related to seasonal variation and derives the confidence variables.

The logic block "Functional Classification" uses the two variables (*SeasVar_FunctionalClass"* and *"Functional_Classification"*) to fire the necessary rules to evaluate the inclusion of roadway functional classification to establish TPGs. The logic block "Seasonal Variation" is designed to fire the rules related to asking if the user wants to include the seasonal variation, and if so to what extent. Following Figure 46 presents the screenshot of the logic blocks in the TPG Methods Module.

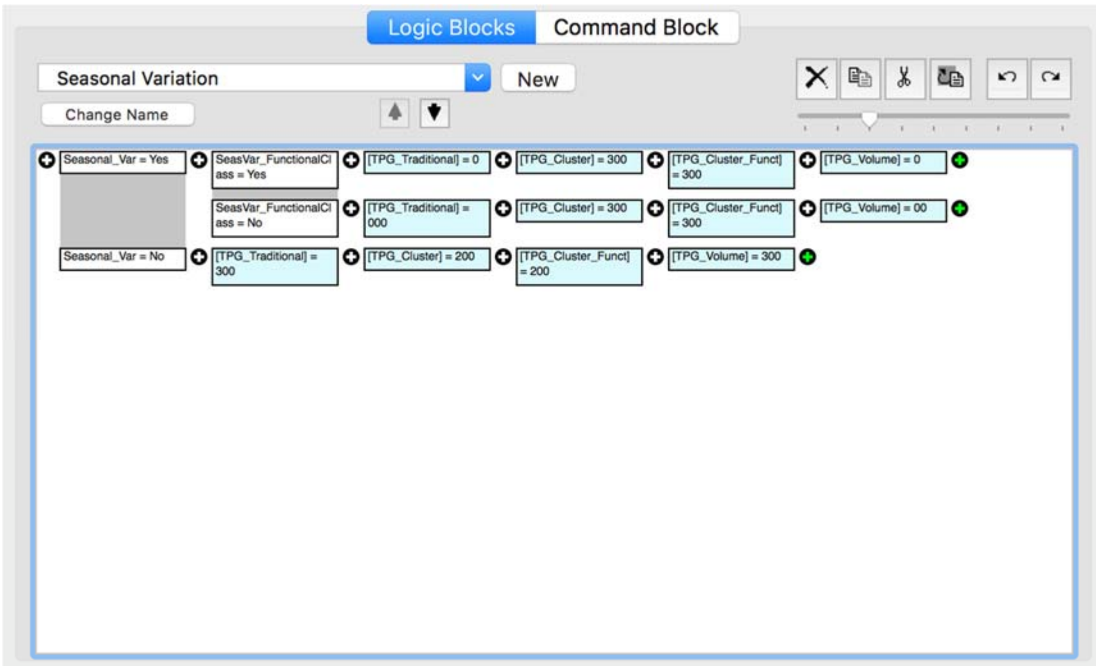


Figure 46. Logic Blocks in TPG Methods Module

5.4.3.3 Command Block

The command block in TPG Methods Module is structured similarly to MADT/AADT Estimation Module. The command block displays the purpose of the module along with the TPG methods that are evaluated in a welcome page. The user is also informed about the evaluation criteria. Then, the command block defines the inference engine processing method as backward chaining to derive all necessary confidence and collection variables. The command block also controls the final results page and its design features. In the final page, the recommended TPG methods will be listed in addition to the informative notes regarding the reasoning behind the decision. If necessary, any note derived with collection variable in response to certain conditions will be displayed to the user.

5.4.4 TPG Groups Module (Establishing the Traffic Pattern Groups with Seasonal Variation)

In TPG Groups Module of the TMDEST, the user is offered to establish the traffic pattern groups with an approximate cluster analysis and functional classification method. This approximate method will specifically be helpful for a quick evaluation of current traffic pattern groups and/or testing the current total number of groups. The module will ask seasonal variation and urban/rural typology questions for each roadway functional class to decide how many groups are needed to represent each roadway functional class. TPG Groups Module starts with FHWA's roadway functional classification categories *(49)* and HPMS data reporting categories. The following primary categories in both urban and rural typology are used to evaluate the seasonality in TPG Groups Module:

1. Interstates, Freeways & Expressways
2. Other Principal Arterials
3. Minor Arterials
4. Collectors

5. Local Roads

Then, with the responses of the user, each roadway functional classification will be assessed individually to decide if there is a need to represent the class with more than one group due to seasonality. Afterward, the groups will be evaluated to see if there is an opportunity to merge groups across different functional classification groups such as merging the major and minor collectors in rural areas into a single group. This is performed by using the seasonality responses of the user for each roadway functional classification.

Roadway functional classification is considered representing the volume of the roadways in addition to creating identifiable groups. On the other hand, seasonal variation is used for the detection of recreational roadways within roadway functional classification. This approach represents the third TPG method evaluated in the previous section, cluster analysis with roadway functional classification method. Therefore, asking the seasonality of each class to the user and defining the TPGs in this way is considered a simple representation of the cluster analysis with functional classification method, which is used in DelDOT TPG establishment study and can easily be applied to other states.

The number of stations in each group is evaluated based on a rule of thumb suggested by TMG and data analysis results of DelDOT case study. For instance, TMG states that urban arterial presents less than 10% CV, and DelDOT data reveals 5% CV for urban principal arterials. As a result, 5% CV value is used to define an approximate minimum number of stations. Then, the current number of stations in this category is asked to the user and tested if there is a need for additional new stations.

5.4.4.1 Key Variables

Three primary variable types (list, confidence, and collection) were used in the TPG Groups Module. List variables are used to lessen the complexity of the logic blocks by asking simple questions that require a single answer. These questions are mainly employed to describe the seasonality of the traffic volume in each roadway functional classification. For instance, *"Do you think there is variation among roadways within Urban Minor Arterials in terms of monthly variations?"* is prompted to evaluate whether urban minor arterials should consist of one or more groups.

Confidence variables are used to describe the possible outcomes (TPGs) in this module. Each possible TPG is labeled with one confidence variable such as urban minor arterials, urban collectors, rural arterials – seasonal, rural recreational roads, etc. Based on the user selection of the presence and extent of seasonality, the confidence variable will be assigned non-seasonal, seasonal or recreational for each roadway functional classification. Additionally, as similar to the use in other modules, collection variables are used to inform the user regarding a specific situation.

Each roadway functional classification in each urban/rural typology consists of at least two list and two confidence variables. The list variable *"U_OPA_S"* is labeled to represent the seasonality question for Urban Other Principal Arterials (OPA), and prompts *"Do you think there is variation among roadways within Urban Other Principal Arterials in terms of monthly variations?"* to the user. The choices for user response are "*Yes (Some roads present different seasonal variation)"* or *"No (All roads present similar seasonal variation)"*. In some cases where there is a possibility that certain roadway functional classification may not be present, a third option will be provided such as *“Don't have Rural Interstates, Freeways and Expressways.*

The list variable *“U_OPA_SL”* is used to determine the level of seasonality if the user indicated the seasonality in the previous question. The user will be provided a simple statement to compare the variation in MADT in addition to a graphical representation. The user will first be noted about the previous response regarding the seasonality. Then, the user will be prompted *“Which of the following best represents the seasonal Urban Other Principal Arterials?”* to determine the level of seasonality in each roadway functional class. Two graphs are used to assess the level of seasonality in urban and rural typology (Figure 47 and Figure 48). The following choices for user response include a brief description to guide the user.

- Response choices for the urban typology:
    - Urban A: MADT stays within 10% of the AADT
    - Urban B: MADT stays within 20% of the AADT
    - Urban C: MADT can be present beyond the 20% of the AADT
- Response choices for the rural typology:
    - Rural A: MADT stays within 25% of the AADT
    - Rural B: MADT stays within 50% of the AADT
    - Rural C: MADT can be present beyond the 50% of the AADT

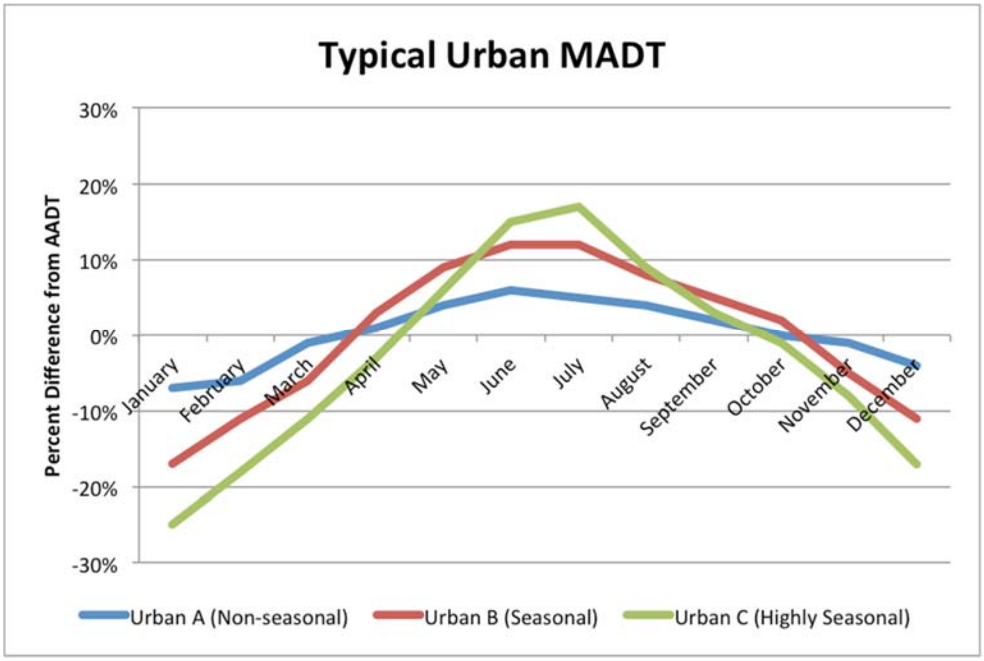


Figure 47. Typical Urban MADTs with Percent Changes

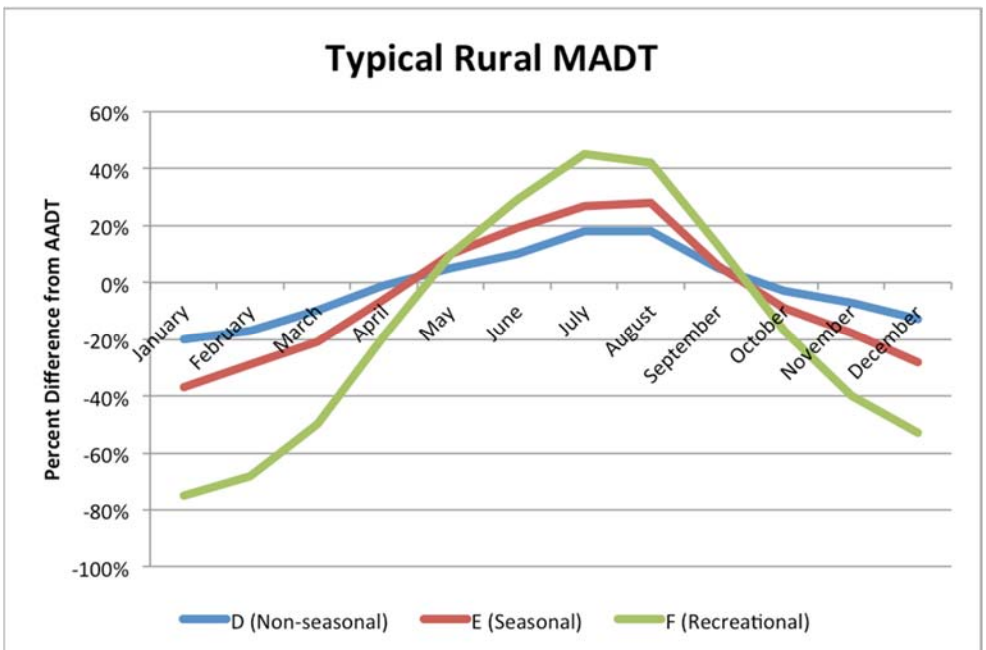


Figure 48. Typical Rural MADTs with Percent Changes

The confidence variables *"Urban_OPA_S"* and *"Urban_OPA"* are used to represent the seasonal and non-seasonal urban other principal arterials respectively. If the user does not indicate any seasonality, then only *"Urban_OPA"* confidence variable will be assigned to the urban OPAs. On the other hand, if the user indicates the seasonality, *"Urban_OPA_S"* and/or *"Urban_OPA"* will be assigned.

Similar variable types and notations are used for all roadway functional classes listed in Table 19 and the rules are structured in separate logic blocks. Furthermore, additional list and confidence variables are used to evaluate the merging opportunities across classes within the same urban and rural typology. This evaluation is performed in arterials and collectors while excluding the local roads and Interstates, Freeways and Expressways. These two groups can present significantly different traffic patterns. These variables are named *"Urban_Arterials"*,*"Rural_Collectors"*, and *"Rural_Collectors_S"*. For instance, the level of seasonality and confidence variables in urban OPAs and urban minor arterials will be evaluated to see if these groups show similar seasonality. If so, the confidence variables *"Urban_Arterials"* and *"Urban_Arterials_S"* can replace the *"Urban_OPA"*, *"Urban_OPA_S"*, *"Urban_MA"*, and *"Urban_MA_S"*. Therefore, two groups will be formed instead of four to represent the urban arterials.

Additionally, the list of variables used in TPG Groups Module along with variable types is listed in Table 20.

Table 19. Roadway Functional Classes Used in TPG Groups Module

Urban	Rural	Abbreviation used in variables
Interstates, Freeways, and Expressways	Interstates, Freeways, and Expressways	Int
Other Principal Arterials	Other Principal Arterials	OPA
Minor Arterials	Minor Arterials	MA
Major Collectors	Major Collectors	MC
Minor Collectors	Minor Collectors	MiC
Local Roads	Local Roads	Local

Table 20. List of Variables in TPG Groups Module

Variable Type	Variable Names
List Variables	U_Int_S, U_Int_SL, U_OPA_S, U_OPA_SL, U_MA_S, U_MA_SL, U_MC_S, U_MC_SL, U_MiC_S, U_MiC_SL, U_Local_S, U_Local_SL, R_Int_S, R_Int_SL, R_OPA_S, R_OPA_SL, R_MA_S, R_MA_SL, R_MC_S, R_MC_SL, R_MiC_S, R_MiC_SL, R_Local_S, R_Local_SL, U_Art_NS, U_Col_NS, R_Art_NS, R_Col_NS
Confidence Variables	Urban_Int, Urban_Int_S, Urban_OPA, Urban_OPA_S, Urban_MA, Urban_MA_S, Urban_MC, Urban_MC_S, Urban_MiC, Urban_MiC_S, Urban_Local, Urban_Local_S, Urban_Arterials, Urban_Arterials_S, Urban_Collectors, Urban_Collectors_S, Urban_Recreational, Rural_Int, Rural_Int_S, Rural_OPA, Rural_OPA_S, Rural_MA, Rural_MA_S, Rural_MC, Rural_MC_S, Rural_MiC, Rural_MiC_S, Rural_Local, Rural_Local_S, Rural_Arterials, Rural_Arterials_S, Rural_Collectors, Rural_Collectors_S, Rural_Recreational
Collection Variables	Note_Urban, Note_Rural, Note

5.4.4.2 Logic Blocks

TPG Groups Module consists of 19 logic blocks to structure the rules for the determination of approximate TPGs. Table 21 presents the list of the logic blocks and their primary objectives in this module. The majority of the logic blocks (12 out of 19) are designed similarly to evaluate the seasonality of the roadways within each roadway functional class in both urban and rural typology. Each of these logic blocks starts with asking the presence of seasonality in roadway functional class. Then, if the user indicates the seasonality, the inference engine will fire the second rule to determine the extent of the seasonality.

Table 21. Logic Blocks in TPG Groups Module

Logic Block	Purpose of the Logic Block
Urban/Rural Interstate, F&E	Evaluation of presence and extent of seasonality in Urban/Rural Interstate, F&E
Urban/Rural OPA	Evaluation of presence and extent of seasonality in Urban/Rural OPA
Urban/Rural Minor Arterials	Evaluation of presence and extent of seasonality in Urban/Rural Minor Arterials
Urban/Rural Major Collectors	Evaluation of presence and extent of seasonality in Urban/Rural Major Collectors
Urban/Rural Minor Collectors	Evaluation of presence and extent of seasonality in Urban/Rural Minor Collectors
Urban/Rural Local Roads	Evaluation of presence and extent of seasonality in Urban/Rural Local Roads
Urban/Rural Arterials	Testing the possibility of merging Urban/Rural Arterials
Urban/Rural Collectors	Testing the possibility of merging Urban/Rural Collectors
Urban/Rural Seasonal	Evaluation of seasonal routes
Recreational Roads	Evaluation of recreational routes

Afterward, the inference engine will assign a score to selected confidence variables to identify the possible TPGs (Figure 49). The value of the score given to each confidence variable does not reflect a weighted score since the final outcome will only be the list of the TPGs. Therefore, the confidence variables will not be sorted based on the assigned scores. However, a simple strategy is used for selecting or eliminating the confidence variables from the final list. Initially, each confidence variable (group candidate) is assigned a value of "2" based on the rule structure in each logic blocks. Afterward, when the module assesses and agrees to merge any two groups, the inference engine will assign "2" to the new confidence variable and "-1" to the merged confidence variables. For instance, based on the user inputs, seasonal urban major and minor collectors are assigned a score of "2". Then, due to the similarity in seasonal variation, these two groups are merged and constituted the group "seasonal urban collectors". Therefore, *"Urban_Collectors_S"* will be assigned "2" and *"Urban_MC_S"* and *"Urban_MiC_S"* will be assigned "-1". This score reduction will result in final scores of "1" for seasonal urban major and minor collectors. At the final recommendation to the user, only the confidence variables that receive a score of "2" will be displayed to the user as recommended TPGs.

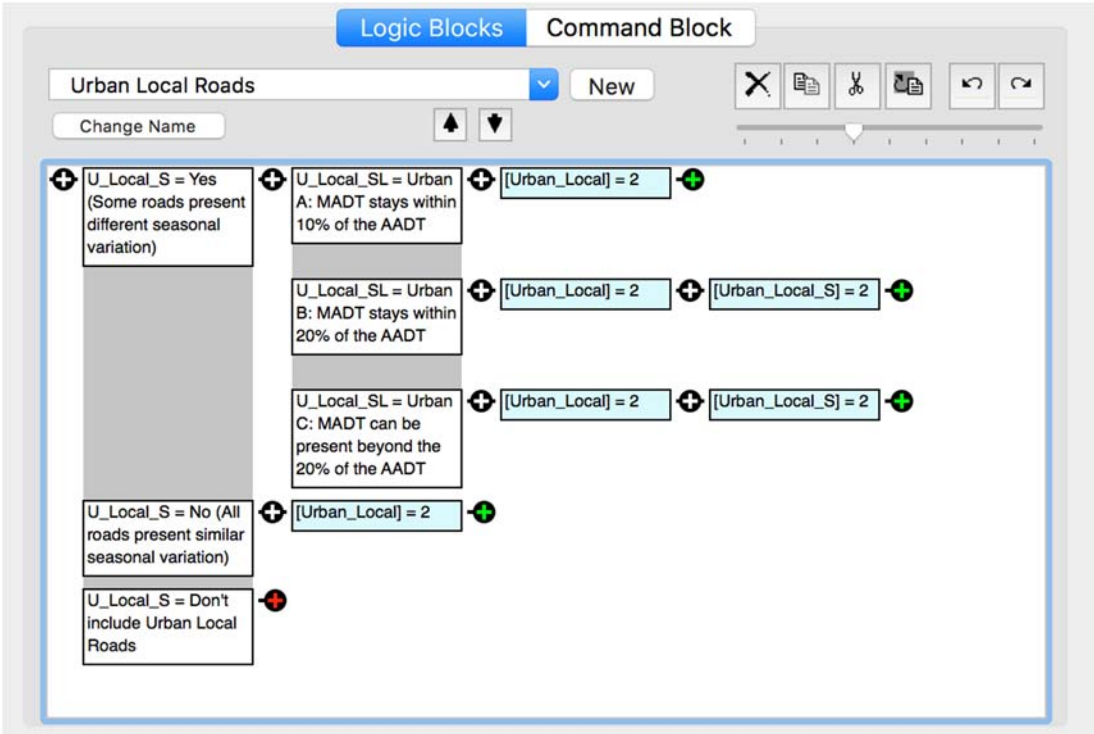


Figure 49. Urban Local Roads Logic Block in TPG Groups Module

The logic blocks “Urban Seasonal” and “Rural Seasonal” are designed to identify if the extent of the seasonality is similar across the groups to yield a merge. Simple Boolean test expressions are used to control the similarity between groups. For instance, the following expression is used to test if the seasonal urban other principal arterials and seasonal urban minor arterials present parallel variation (Urban B type: MADT stays within 20% of the AADT). If so, these two groups will be merged and a new confidence variable will be introduced to the group list.

([[U_OPA_SL]] = 2) & ([[U_MA_SL]] = 2)

5.4.4.3 Command Block

The command block in TPG Groups Module is designed similar to other modules: a welcome page, processing methods, and presenting final results. The welcome page clearly states the purpose of the model and describes the adopted approach, followed procedure and necessary information/data to perform the procedure. The user is also informed about the other modules that can help retrieving the necessary information or improving the obtained results such as estimating the sample size for each TPG.

Then, the command block defines the inference engine processing method as forward chaining in cooperation with backward chaining to derive all necessary confidence and collection variables. Forward chaining is selected because logic blocks are structured in a sequential order. Additionally, use of the same confidence variables in different places can force to derive the final value of the confidence variable before moving the second confidence variable in backward chaining. This can result in jumping to a rule that does not make any sense to the user at that point.

The command block also controls the design of the final results page. It is critical to present the results in a simple but effective way to the user. In the final results page, the recommended TPG groups are listed to the user. Additionally, the user is notified that the recommended groups are based on the user inputs and an approximate method. If there is a specific note derived from a collection variable that is fired during the execution of the rules, then this note is also presented to the user (Figure 50).

Figure 50. Final Results Page of TPG Groups Module

5.4.5 Adjustment Factors Module

Adjustment Factor Module aims at improving the decision on which adjustment factors are necessary to be used to expand the collected short-duration counts. Proper use of adjustment factors is significantly important for an accurate estimation of the MADT and AADTs. Improper use of adjustment factors may result in overestimating or underestimating the summary statistics. For instance, an inconsistency between collected short-duration data and estimated AADT was detected while conducting the DelDOT case study. A short duration data is collected in the month of July on a highly recreational roadway section with an average daily traffic of approximately 29,000 veh/day. Then, the estimated AADT is stated as 29,591, which seems inaccurate considering the monthly adjustment factor is approximately 0.60 in these recreational roadways. Therefore, AADT is expected to be around 18,000 veh/day. This illustration provides a great example for an improper use of adjustment factors and the necessity for a tool such as TMDEST Adjustment Factor Module to aid in selecting the proper adjustment factors to be used.

In the Adjustment Factor Module, the user will be prompted with specific questions regarding when, how long and in what format the short-duration data was collected. The inference engine will then select the appropriate adjustment factors that need to be used and presented to the user with necessary explanation. Following sections describe the necessary variables, logic blocks and command blocks to perform this task in Corvid Core® environment.

5.4.5.1 Key Variables

The multiple-choice list, confidence, and collection variables are used to construct the logic block in the Adjustment Factor Module. *"Data_Type"* list variable is used for asking the user whether the collected short-duration data is for volume or vehicle classification. Then, the user will be prompted to select the Traffic Pattern Group (TPG) or Vehicle Classification Group (VCG) that the short-duration data segment is assigned into in the variable *"TPG_vol"* or *"VCG_class"*. DelDOT's TPG and VCG groups are used for building the logic block in this case study. However, it can be modified based on the particular agencies' group assignments or designed to be entered by the user.

The list variable *"Axle_Vehicle"* is designed to ask if the collected short-duration data is axle-based or vehicle-based to determine if the axle correction factor (ACF) is necessary to be used in the calculation.

The *"Month"* variable is used to ask the month the short-duration data was collected in. Similarly, *"day_of_week"* variable is used to ask the day(s) the short-duration data was collected in. Then, these variables are used to recommend if and what monthly adjustment factors (MAF) and day-of-week adjustment factors (DAF) will be used in the estimation of AADT.

The variable *"duration_of_data"* list variable is used to obtain information regarding the duration of the short-duration data. The user will be prompted, "Please select the duration of short-duration (coverage) data" and "24-hour, 48-hour, 72-hour, 5-day and weeklong" options will be provided.

"Same_year" list variable is designed to ask the user if the short-duration data is collected in the current or previous years to determine if the growth factor (GF) should be used.

The inference engine utilizes the previously explained list variables to determine which confidence variables should be recommended to the users. Four primary confidence variables are evaluated and used for the recommendation to the user. Axle correction factor (ACF), monthly adjustment factor (MAF), day-of-week adjustment factor (DAF), and growth factor (GF) are assigned either '0' or '1' based on the rules fired. Then, all values will be multiplied to assign a final score to the confidence variables, where all confidence variables assigned a final score of '1' will be recommended for the AADT estimations.

The *“note”* collection variable is used to display the certain type of information to the end user such as *“You should include the growth factor (GF) for all the years since the data collection in your AADT estimation. (Please note that you indicated the data is collected more the six years ago. Traffic Monitoring Guide recommends covering all roads with a minimum of six-year cycle.).”* The collection variable is also designed to incorporate the prompt values and derived confidence variables so that the note can dynamically change based on the user’s selections and confidence variable values.

5.4.5.2 Logic Blocks

Multiple Logic blocks are used to simplify design and reduce the number of nodes to be built in the decision tree. By using the backward chaining method, the inference engine will choose the necessary logic blocks and rules to fire and drive the confidence and collection variables for a final goal.

Logic block “type” is the first logic block to introduce and explains the purpose of the Adjustment Factor Module to the user. Then, the user will be prompted to obtain the information for *“data_type”*, *“TPG_Vol”*, *“VCG_Class”* and *“axle-vehicle”* variables.

Logic blocks “month” and “day-of-week” is used for obtaining the information regarding the day(s)-of-week and the month of the year the short-duration data is collected in.

“Growth Factor” logic block is designed to ask if the short-duration data collected in the current year or in the previous years. If the user selects that it was collected in a previous year, then the inference engine will fire another rule to identify how long ago the data was collected. This logic block displays if and how many growth factor values should be used in AADT estimations. Following Figure 51 presents the variables in the Growth Factor logic block.

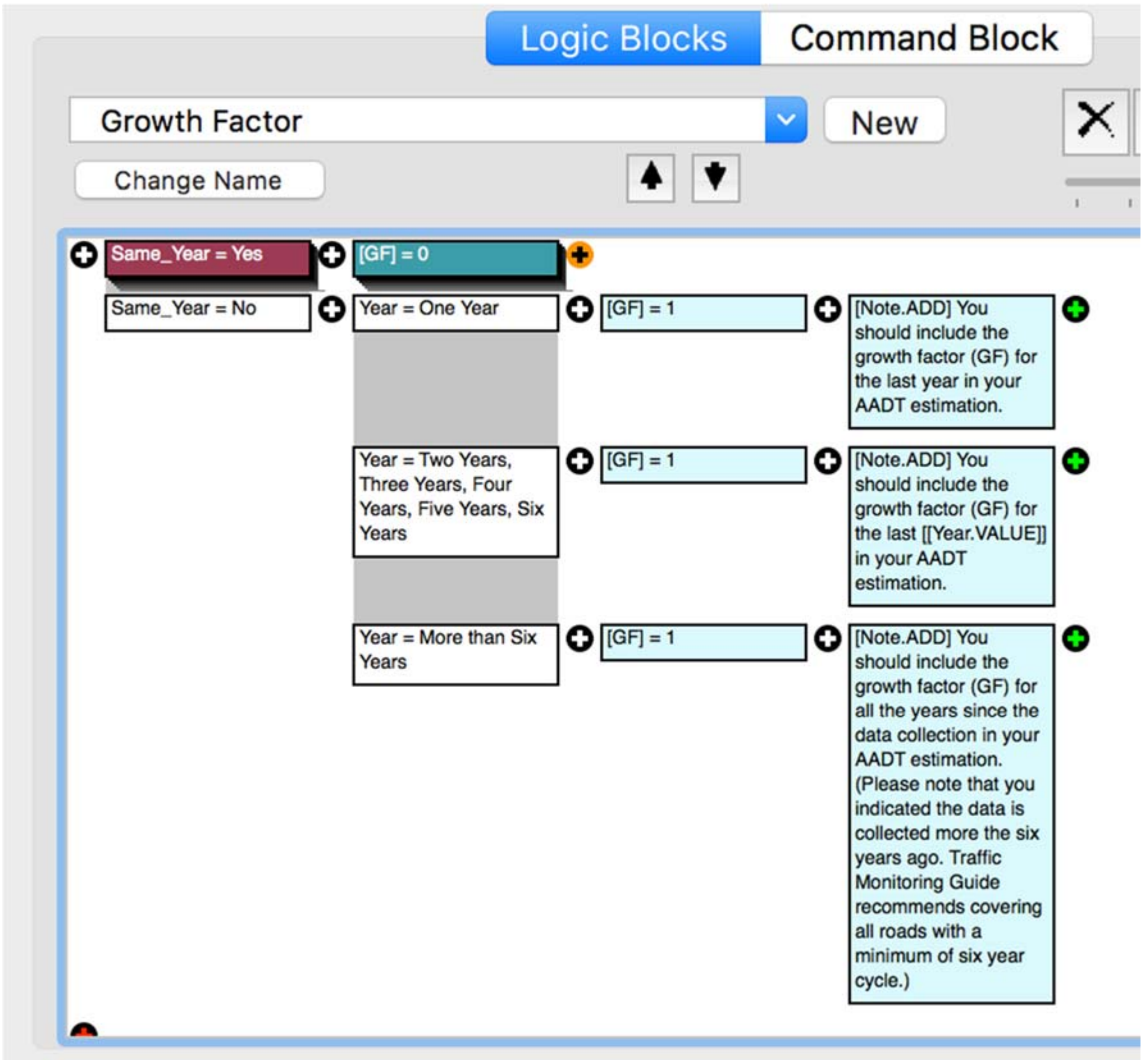


Figure 51. Growth Factor Logic Block in Adjustment Factor Module

The logic block “Duration” is used for asking the duration of short-duration (coverage) data for deciding if the DAF is necessary to use. If so, which days of the week adjustment factors should be used in the estimation of AADT. This logic block will help to obtain the necessary value for *“duration_of_data”* variable and to decide if the *“day_of_week”* rule should be fired.

5.4.5.3 Command Block

The command block in the Adjustment Factor Module is designed to derive all confidence and collection variables, and present the results to the end user. All confidence variables will be derived to assign a final score to each. Then, only the variables with a final score of 1 (they can get either ‘0’ or ‘1’ where ‘1’ means use the specified adjustment factor) will be displayed to the user. Additionally, the only collection variable *“note”* will also be displayed on the final results page to inform the user with additional note(s) regarding the selections the user previously made. Figure 52 presents the design settings of the module to plan where, how and in what format the results will be displayed to the end user.

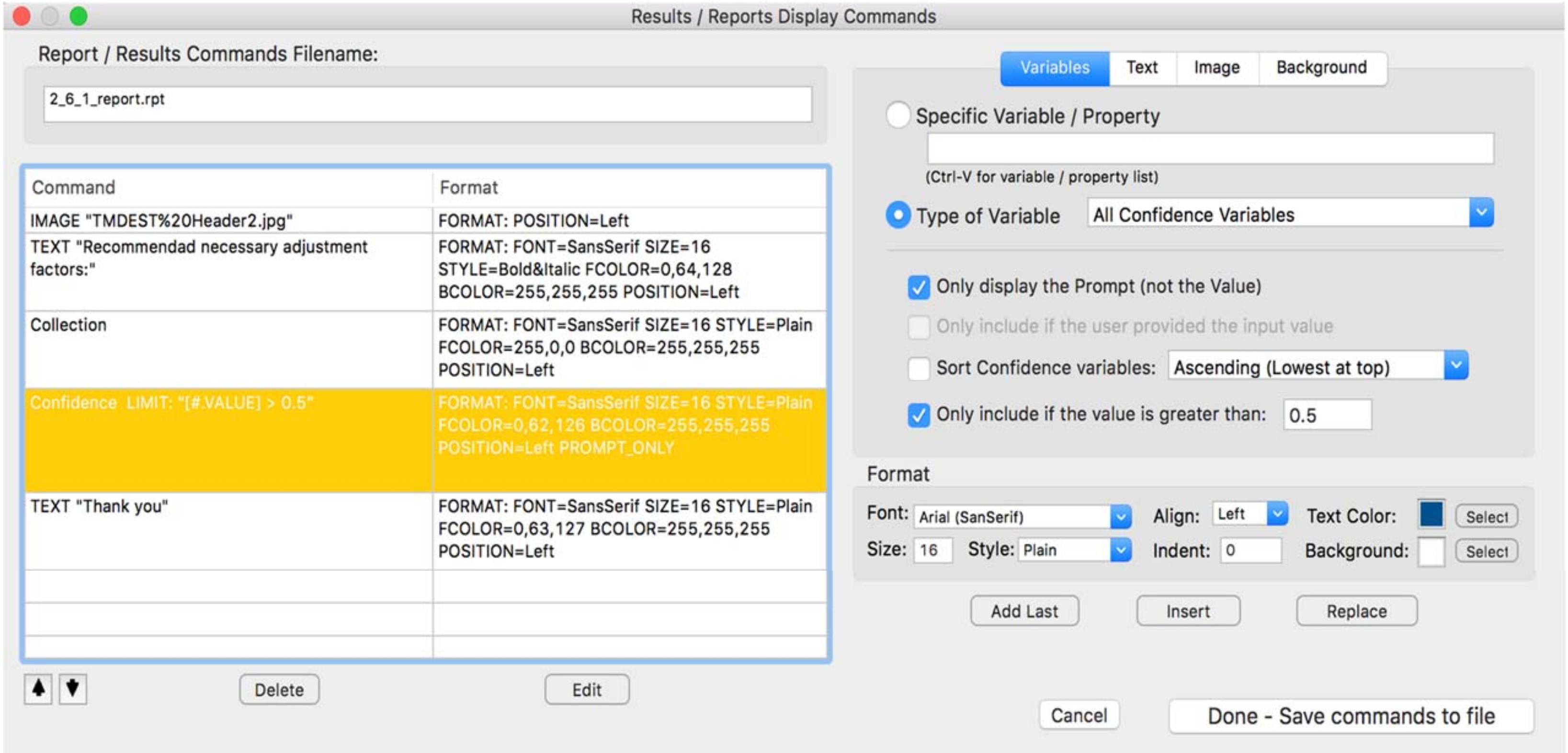


Figure 52. Report Page Design of the Adjustment Factor Module

5.5 Case Study Two: Sample Size Estimation for Traffic Pattern Groups by Using TMDEST Interactive Tool (Sample Size Estimation Module)

In this demonstration, TMDEST interactive tool is used for estimating the sample size for Traffic Pattern Groups (TPG) by following the procedure recommended in TMG *(2)*. The interactive tool requires several inputs from users in the form of simple entry to execute the necessary calculations. These inputs are the number of TPGs, the number of continuous count stations (CCS), and coefficient of variation (CV) values for continuous count stations in selected TPGs. Other necessary inputs such as desired confidence level and precision interval could be requested in the form of multiple-choice selection. For instance, users will be asked to choose one of the three confidence level presented: 90%, 95% or 99%.

Users are guided with on-screen instructions (e.g. *"Please enter the total number of …")* to initiate the data input process. Since the requested input only contains numerical or string values, data input is performed within the user interface. In case the user is not familiar with the requested input, the simple explanation of the requested input (such as *"X is calculated by…"),* and examples and external links are provided if necessary. Therefore, users are able to perform the necessary prerequisite calculations to continue the process. The primary calculation for this case study is the determination of CVs for each TPG. Considering the possibility that the user does not know or is not able to calculate the CV values, users are also provided an approximate method for choosing the seasonality of the continuous count stations in each group. In this approach, MADT graphs that were used in TPG Methods Module (Figure 47 and Figure 48) were used to derive the level of seasonality in each group. These three graphs were determined based on TMG's rule of thumb: urban seasonal variation is under 10%, rural variation is 10%-25%, and recreational 25+% CV. Based on the user selection, an additional question will be directed to determine whether the TPG is close to the lower or upper limit of the intervals. In this question, a very simple expression will be used such as *“Does traffic volume nearly doubles in 7summer months? (Yes/No/Don’t Know).”* In a case of the user selecting the *“Don’t Know”* option, the logic interface is constructed to assign it to the worse scenario. With the selection of MADT graph and answering a simple traffic volume question, the approximate CV value will be assigned to the specific TPG. Then, final calculations of sample size and provided decision will be approximate. Figure 53 presents a simple process flow of sample size estimation for TPGs.

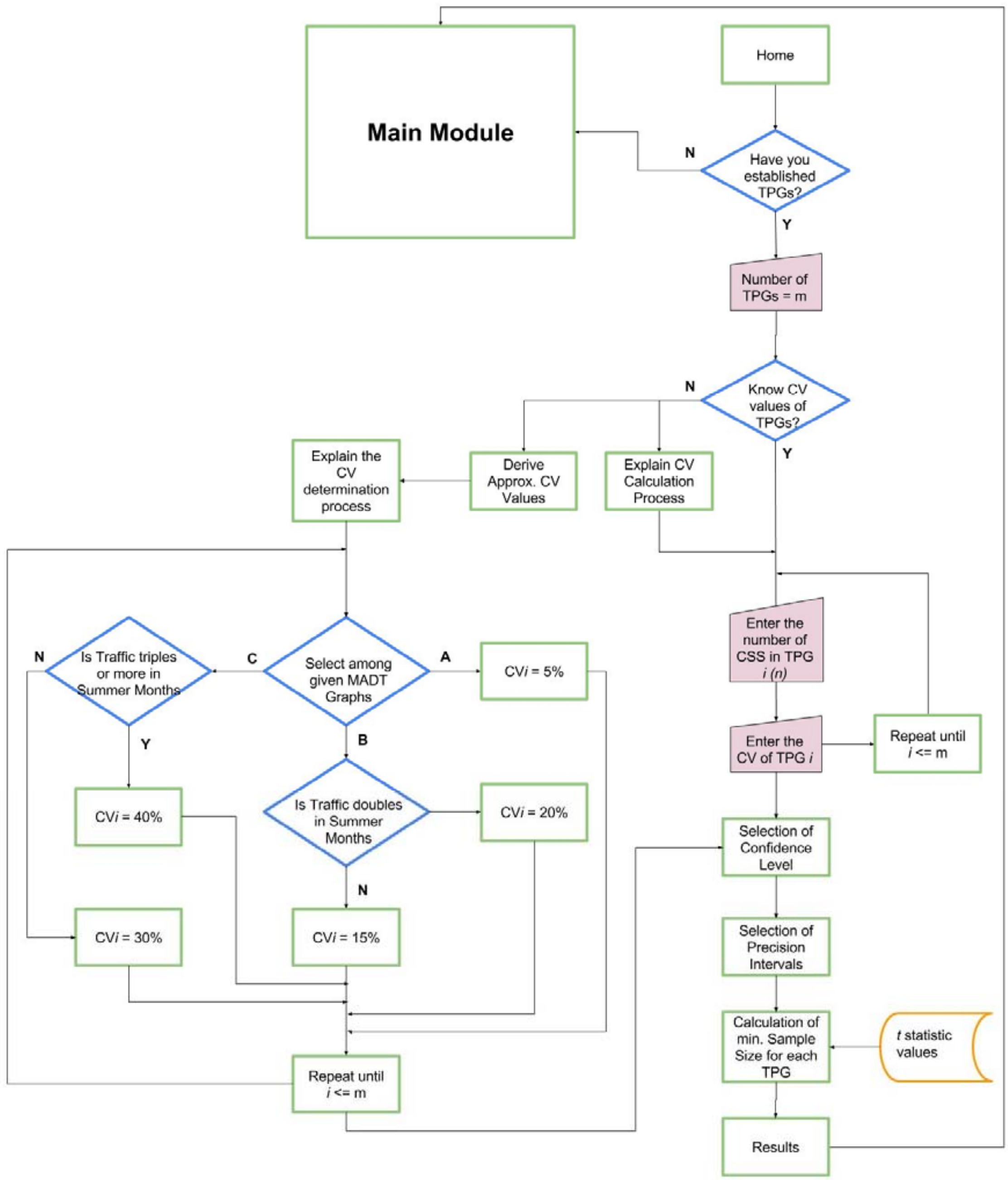


Figure 53. Process Flow for Determination of Sample Size for Each TPG

5.5.1 Variables Used in Sample Size Estimation Module

Four types of variables are primarily used in building the Sample Size Estimation Module. These variables are: list variables, numeric variables, confidence variables, and collection/report variables. Key variables that are used for interacting with the end users are presented here in detail and a list of all variables are presented later at the en of this section in

Table 22.

The sample size estimation module starts with a welcome page explaining the purpose of the module and, data and information required to perform the necessary calculations. Since the overall purpose and use of the TMDEST framework is provided to the user in the main module, only a brief introduction will be given specifically for the sample size estimation module. For instance, the user is informed that he/she will need to input the number of TPGs, the number of continuous count stations in each group, and respective Coefficient of Variation (CV) values. Additionally, since the CV values may not be available or easy to obtain, a statement will be added to inform the user that an approximate CV calculation method will be provided and explained.

5.5.1.1 Multiple Choice List Variables

There are several multiple choice list variables used to enable the user to select among provided on-screen options. This approach also helped to keep the logic blocks as simple as possible for processing the decision flow.

There are few list variables used to make sure the user understands the purpose of the sample size estimation module and following the correct steps for testing the sample size. In this regard,*“TPG_Established”* list variable is used for asking if the user already established TPGs with the following prompt: *“Have you established Traffic Pattern Groups (TPGs)? (TPG can also be named "volume groups" or "seasonal groups". TPGs are usually established to group continuous count stations (sometimes named as ATRs) based on seasonal variation, volume, and roadway functional classification characteristics.)”* The user is provided with simple Yes/No options to continue. If a user has not established TPGs, then a link will be provided to direct the user to the main module.

The variable *“CL”* provides three confidence level options (90%, 95%, and 99%) to the user and the variable *“PI”* provides three precision interval options (5%, 10%, and 20%) for selecting the desired confidence level and precision intervals respectively. These selections are then used for testing if the current numbers of continuous count stations (CCS) meet the selected precision intervals with given confidence level. Additionally, 95% confidence level and 10% precision interval will be presented with a note indicating that FHWA’s Traffic Monitoring Guide recommends these values. Figure 54 presents the prompt and provided on-screen options for the selection of *“CL”* and *“PI”* variables.

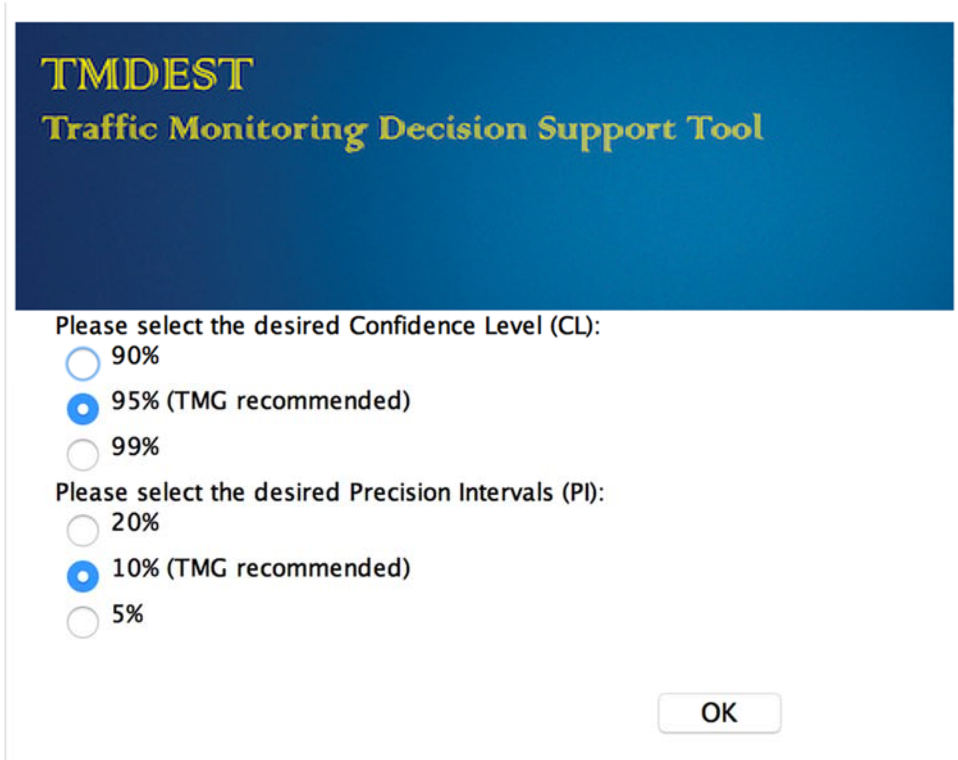


Figure 54. Confidence Level and Precision Interval Prompt in TMDEST

Another key list variable *"Know_CV"* is used for asking if the user knows the CV values of each TPG or needs assistance for this task. The user is prompted *"Please select the appropriate method for the Coefficient of Variation (CV) input. If you do not have the CV values, you can either use Excel for the CV calculation or use graphical method for an approximate calculation. (After this step, you will be directed to enter the number of continuous count stations for TPGs, and to select desired Confidence Level and Precision Intervals)."* Three options provided for this selection, where each option will direct the user to the appropriate node for on-screen selections and data input.

- I have CV values
- I can derive CV values in MS Excel with provided instructions
- I want to use graphical approximate calculation method

If the user selects *"I have CV values"* option, then the inference engine will move on to the logic block where the user provides the number of continuous count stations, CV values and select confidence level and precision intervals for the calculation.

On the other hand, the user can select *"I can derive CV values in MS Excel with provided instructions"* and follow the instructions in a separate MS Excel file provided with a separate link. However, the user will also be prompted another list variable, "Excel_Proficiency", to make sure the user can perform certain specific tasks in MS Excel such as opening a file, entering values into designated cells, and copy/paste, etc. Figure 55 presents the provided MS Excel file for assisting the user for the calculation of CV values.

*If you would like to calculate the Coefficient of Variation (CV) for a single continuous count station (CCS), place the MADT values in corresponding cells in the first row below.
*If you would like to calculate the Coefficient of Variation (CV) for a group of continuous count stations (CCS) place the MADT values in corresponding cells starting from the first row below.
***Use the red highlighted CV value and input into the TMDEST module**

CV: 21%

Station #	MADT (veh/day)												AADT	CV
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec		
1	2221	3226	2934	2209	2434	2258	2525	2142	2743	2672	2899	3103	2614	14%
2	372	211	221	244	299	479	308	373	312	481	407	201	326	29%
3	2467	2028	2669	2821	3373	2054	2742	2843	2493	2374	2762	2786	2618	13%
4	210	207	491	488	408	376	314	452	316	400	236	259	346	29%
5	220	240	260	265	266	266	270	290	280	250	240	220	256	8%
6	370	339	484	268	490	266	445	342	405	371	268	490	378	22%
7	224	339	261	249	344	217	235	237	209	411	302	231	272	22%
8	363	281	348	218	267	487	471	369	327	417	411	297	355	22%
9	223	346	345	485	429	246	480	390	293	290	278	414	352	24%
10	256	234	346	275	364	410	346	300	365	340	284	246	314	17%
11	396	246	268	361	423	314	349	339	381	383	448	462	364	17%
12	288	277	454	485	235	256	489	308	333	248	371	269	334	27%
13	364	243	339	451	204	321	322	286	217	436	416	254	321	25%
14	475	413	323	389	356	419	213	446	267	494	230	417	370	24%
15	290	406	330	445	298	437	374	389	245	281	376	407	357	18%
16	290	248	468	349	427	319	275	375	238	428	282	302	333	22%
17	483	282	409	210	267	346	324	212	334	337	238	439	323	26%
18	256	220	352	252	301	427	261	304	404	479	375	278	326	24%
19	257	314	248	470	448	261	214	347	382	293	484	238	330	28%
20	437	369	362	440	278	285	307	359	338	393	268	321	346	16%

Figure 55. MS Excel File for the Calculation of CV Values

The variable *"Approximate_CV"* is used in the determination of approximate CV values by using a graphical method. One graph with three MADT data plots where each one is demonstrating different CV ranges, is presented to the user and asked to select one of them based on the monthly variation of continuous count stations in a specific TPG (Figure 56). A detailed explanation of the graphs is also provided to assist the user (e.g. MADT graph includes three types of curves A, B and C where A-5%: Monthly Average Daily Traffic Volume (MADT) does not change significantly throughout the year). If the user selects *"A"*, then CV values assigned as 5%. This value is obtained considering the rule of thumb range provided by TMG (urban roads 0%-10% CV) and DelDOT data analysis results, where two urban groups produce 4.5% and 4.6% CVs.

On the other hand, if the user selects *"B"*, where CV values are represented between 10%-25%, the user will be prompted another list variable "*Range_CV*" to determine if the CV values are close to the lower or upper limits of the range. For this purpose, a simple expression is used and the user is prompted, *"Please select the most appropriate from following options"* where the options are: *"monthly average daily traffic volume increase 50% or less in summer months"* and *"monthly average daily traffic volume nearly doubles in summer months"*. Therefore, based on user selection, either 15% or 20% CV value will be assigned to *"Enter_CV"* variable for further calculation. Similar procedure is applied to selection of "C" to ask if the traffic volume nearly triples in summer months for assigning one of the predetermined CV values of 30% and 40%. Moreover, the user will be informed that MADT data plot "C" represents the recreational roadways, which is not required to meet the defined precision intervals.

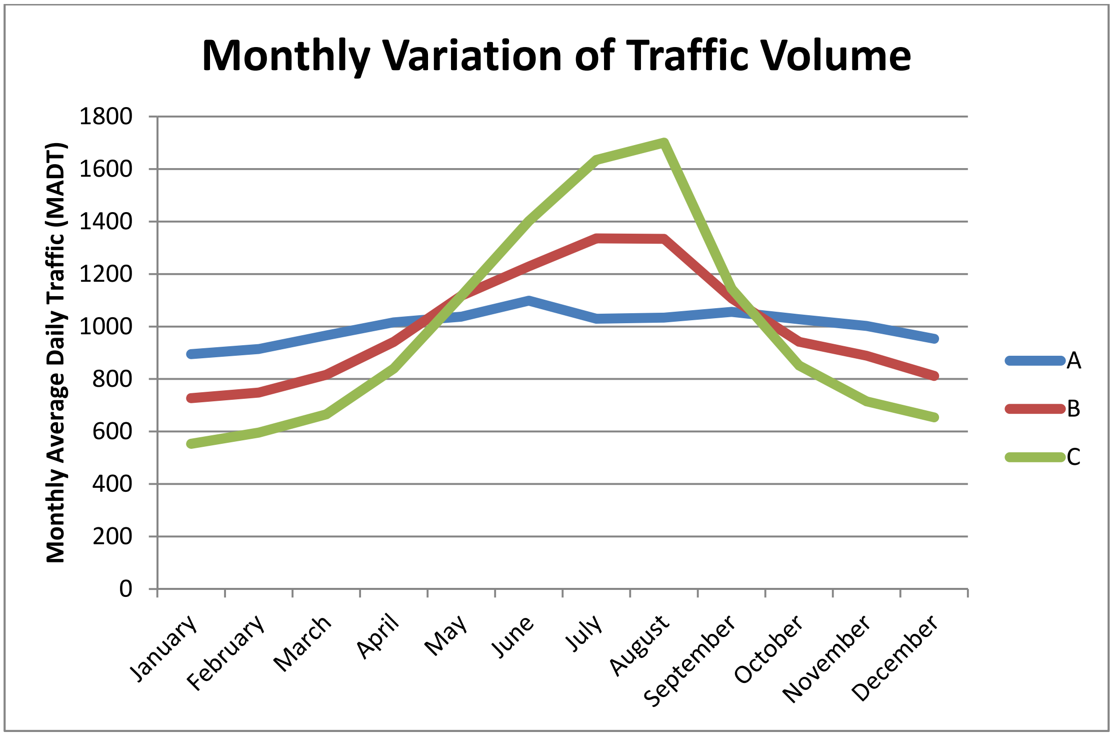


Figure 56. Monthly Variation of Traffic in Three Different CV Range

5.5.1.2 Numerical Variables

"N_TPG" numeric variable is used for controlling the number of TPGs for the purpose of calculation and reporting. "N_TPG" asks the user *"How many TPGs do you have in your Traffic Monitoring Vehicle Classification Data Program? (Please enter a value between 2-20)"*. Most volume and vehicle classification data programs establish TPGs between four and ten (e.g. DelDOT has 8 volume and 4 vehicle classification groups). Additionally, N_TPG value is limited to 20 to reduce the processing time for this case study. The primary purpose for asking N_TPG is creating loops for performing the necessary calculation for each TPG.

The variable *“N_CCS”* prompts the user: “*Please enter the number of continuous count stations (CCS) in this specific TPG?”* The variable for the number of CCS is restricted to an integer value between 1 and 100. The user can enter a numerical value for the space provided by the prompt. This numeric variable is used for acquiring proper *t*-statistics value from the file (using n-1 degrees of freedom and given confidence level) and calculating the precision level percentage. Moreover, if the calculated precision interval percentage does not meet the given criteria, N_CCS value will be used in an “IF” loop to increase the number of CCS with one increment and calculate the precision intervals again until meeting the given criteria.

“*Enter_CV*” numeric variables are used for asking CV value in a TPG. These variables are primarily used in “I have CV Values” option asked in “*Know_CV*” variable. The prompt asks the user *“Please enter the Coefficient Variation (CV) of the Traffic Pattern Group. (Please, enter only the numbers without % indicator. e.g. in CV 12.35%, enter 12.35)”* The value assigned to *“Enter_CV*” variable is used for calculating the precision interval for the given number of CCS and confidence level. Besides, if the user enters a CV value larger than 25%, the user will be immediately prompted with a note: *“You entered a Coefficient of Variation (CV) larger than 25% in this Traffic Pattern Group (TPG). Most roads assigned into this TPG should be recreational/highly seasonal. Please note that FHWA's Traffic Monitoring Guide DOES NOT require meeting the 10% Precision Interval for recreational roads. Do you still want to calculate PI for this TPG or want to move to the next TPG?”* This note will be prompted in *“Rec_CV*” list variable with two options: *“I want to calculate the PI”* and *“I want to move to the next TPG*”. Based on user’s selection, the process will continue to the next step.

5.5.1.3 Confidence and Collection/Report Variables

"Calculated_PI" confidence variable is used for representing the calculated precision interval to test if the calculated value is less than the desired precision interval. A mathematical expression will be used to calculate the precision interval by using t-statistics, CV and number of CCS in a group. If the calculated value is equal to or less than the desired PI, then the number of continuous count stations in given TPG is enough, and there is no need to install more CCS. However, if calculated value is larger than the PI, then N_CCS variables will be increased one increment and the process will be repeated until calculated value become smaller than desired PI level.

The collection variable "note_to_user" is used for displaying a specific note to the user at certain points throughout the process. For instance, if the user enters CV value larger than 25%, then the note *"You entered a Coefficient of Variation (CV) larger than 25% in this Traffic Pattern Group (TPG). Most roads assigned into this TPG should be recreational/highly seasonal. Please note that FHWA's Traffic Monitoring Guide DOES NOT require meeting the 10% Precision Interval for recreational roads."* will be displayed to inform the user.

Another collection variable *"final_results"* is used for building a final results note to the end user. This collection variable is supported with some selected user inputs that are embedded in the final note. The "final_results" collection variable is used in the final page to summarize the user inputs and display the final recommendation. Fir instance, if the number of continuous count stations satisfies the selected precision interval requirement with given CV value and confidence level, the "final_results" variable will display the following note to the user: "You indicated that you have “6” number of continuous count stations in this TPG with CV value of “4.2%”. With desired CL of 95% and PI of 10%, you have enough CCS in this group.”

The values that are presented in quotation marks will be obtained from the respective variables that were selected or inputted by the user. Based on the results/decision reached at the end of the process, the note will be displayed in the *“results”* variable will vary such as “ … you need ‘two’ more continuous count stations to meet the desired precision interval in this TPG.”

The list of all variables used in Sample Size Estimation Module is listed in Table 22.

Table 22. Variables Used in Sample Size Estimation Module

Multiple Choice List Variables	TPG_Established, PI, CL, Know_CV, Approximate_CV, Excel_Based_CV, Go_to_Excel_Based_Calc**, Go_to_CCS_Test_Module**, Go_to_PI_Calc_Module**, Go_to_Approx._CV_Calc_Md**
Numeric Variables	N_TPG, N_CCS, asPI, asCI, Enter_CV, 95*x1*
Confidence Variables	Go_to_establish_TPG, Calculated_PI,
Collection/Report Variables	Final_Results, note_to_user

**t*-statistic values change based on CL and N_CCS,
** Go_to_... variables are used for performing the different tasks in different modules

5.5.2 Logic Blocks Used in Sample Size Estimation Module

Multiple logic blocks are used for a variety of tasks in sample size estimation module to offer an efficient and robust expert system. Logic blocks aim at reaching the conclusions in the THEN parts of the rules by using the IF parts of the rules. By using the backward chaining method, the inference engine selects and fires appropriate rules to reach a given ‘goal’, which is calculated PI statistics and testing if the given sample size satisfies the selected PI statistics in this example. While approaching to a final goal, the inference engine can also assign ‘immediate goals’ to obtain a specific value or solution to be able to reach a final goal (e.g. selecting a method for CV input and deriving the CV value).

Logic blocks sometimes are used for deriving a single factor such as “CL” or “PI”, or combining several factors such as requesting “N_CCS” and “CV” values from the user and performing necessary calculations. The purpose of each logic block and tasks performed in it is explained in this section.

“SampleSize_Intro” logic block initiates the module and provides necessary information regarding the purpose of the module, the type of inputs it requires, and how the results will be delivered. Then, this logic block asks if the user has already established TPGs and is ready for performing the sample size estimation. Afterward, the number of TPGs will be asked and assigned to “N_TPG” variable for creating a “loop” to perform the necessary calculations multiple times. In the final question of this logic block, the user is asked to select one of the provided methods for providing CV input to the system. Based on user’s selection, the inference engine will move forward to another logic block.

If the user selects the “I have CV Values” in the previous section, the inference engine will move to the “EnterCV_Module” logic block, to enable data entry and calculations. In “EnterCV_Module” logic block, the user will be asked to enter the number of CCS in first TPG and respective CV value for this specific group.

Then, this module will perform a simple test to check if the given CV value is larger than 25%. If so, an informative note will be delivered to the user stating, *"You entered a Coefficient of Variation (CV) larger than 25% in this Traffic Pattern Group (TPG). Most roads assigned into this TPG should be recreational/highly seasonal. Please note that FHWA's Traffic Monitoring Guide DOES NOT require meeting the 10% Precision Interval for recreational roads*." Based on user's selection, the inference engine will move forward to another logic block.

CL and PI modules are designed to ask the user to select the proper confidence level and precision interval for the calculation. In this module, TMG recommended values are emphasized if the user is not familiar with the values. Figure 43 presents the user interface of the TMDEST for obtaining the CL and PI values. The CL selection is than used for incorporating appropriate *t*-statistics value for the calculation. PI value is then used to test if the current sample size is statistically significant at the given confidence level.

The logic block "Excel_Based_Calc" is designed to inform the user about the excel file which is provided externally with the hyperlink embedded into the user interface. The necessary steps are provided with a brief explanation in the "Excel_Based_Calc" logic block and detailed explanation is provided in the excel spreadsheet. The user will be directed to the "EnterCV_Module" logic block to enter the necessary CV values to further the process.

"Approx._CV_Calc_Md" logic block is designed to help the end user for assigning CV values for TPGs with the graphical approximate method. The user will be asked to select among given three MADT graphs based on the seasonal variation (see Figure 45) of a specific TPG to assign a CV value to the *"Approximate_CV "* variable.

"PI_Calc_Module" logic block is used for performing the necessary calculations to derive PI value for a given confidence level and CCS. This logic block also obtains proper *t*-statistics value from a data file. Once the number of CCS, CL and PI selections, and CV values are derived, the inference engine will execute the "PI_Calc_Module" logic block.

The logic block "CCS_Test_Module" is designed to test if the calculated PI is lower than the selected PI. If so, the inference engine displays the final results to the user with a collection variable to summarize the user specified/entered necessary values and explanation of the results. If the calculated PI is greater than the selected PI, then the number of continuous count stations given by the user will be increased with one increment until the criteria are met.

5.5.3 Command Block Used in Sample Size Estimation Module

Command blocks are used for controlling the inference engine regarding "what to do" with variables and rules provided in logic blocks. Additionally, command blocks also enable integrating with external data sources and provide designing the results and recommendations that will be presented to the user. One limitation with Corvid Core® is that the knowledge engineer can only build one command block compared to Exsys Corvid®. Knowledge engineer is forced to combine all the necessary regulations due to this limitation, which makes the process a bit complicated. However, the inference engine can perform the required steps to execute the sample size estimation module.

The first command in the command block initiates the integration of external file for the *t*-statistic values. A simple text file is created to include the *t*-statistic values for the confidence levels of 90, 95 and 99 and degrees of freedom from 1-50. Based on the user input for the number of continuous count stations (*N_CCS*) and selected confidence level, the appropriate *t*-statistic values will be included in the calculation of the *"Calculated_PI"* variable. This process is managed with the "READ" tab in the command block (Figure 57).

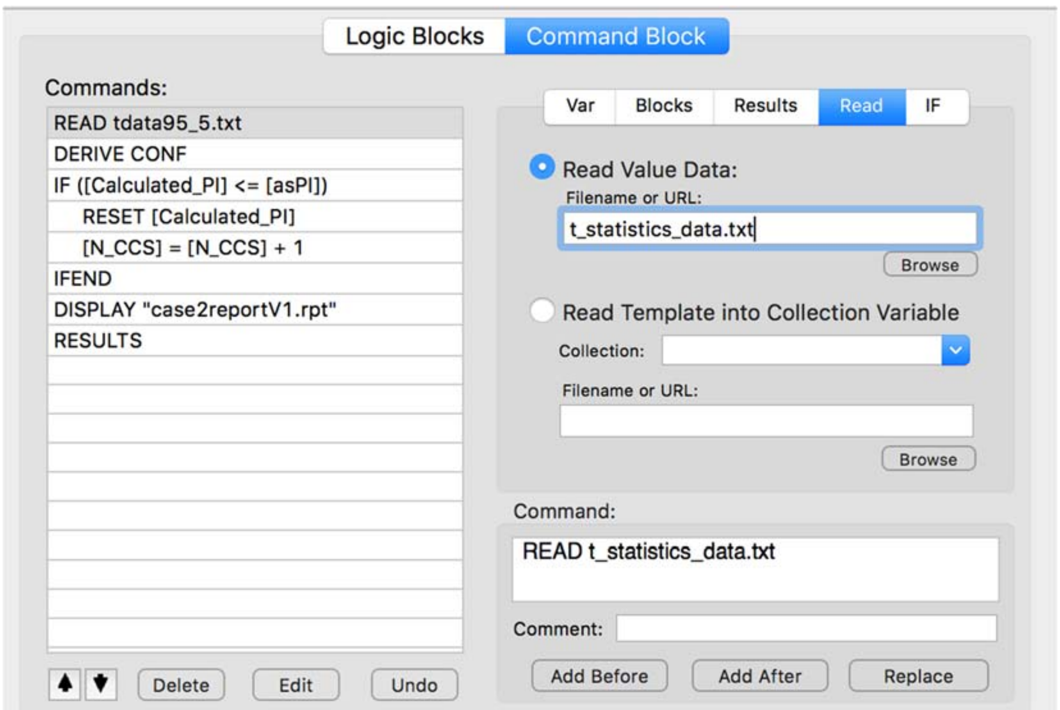


Figure 57. Reading from an External File in Corvid Core

Another key feature in the command block is an "IF/WHILE" loop that helps to iterate the calculation procedure to see if the *"Calculated_PI"* is greater than the desired PI. If so, the IF module will increase the number of continuous count stations

(*N_CCS*) and reset the “Calculated_PI” to enable inference engine to perform the analysis again (Figure 58). This process is required to find the minimum required number of continuous count stations to meet the desired confidence level and precision interval. Therefore, if there is a need for additional station(s), the user will be informed regarding the number of additional CCS needed.

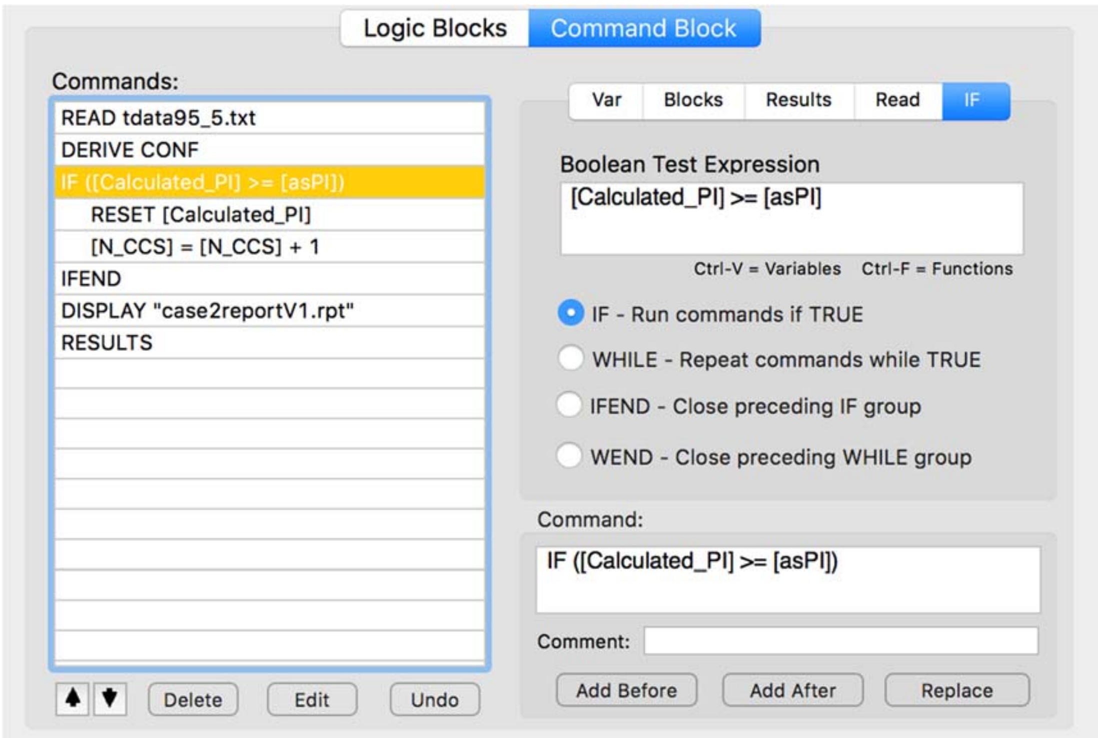


Figure 58. "IF/WHILE" Logics in Corvid Core

The primary setting in the command block is deciding “how” and “when” the rules for variables/logic blocks will be executed. The knowledge engineer can use forward chaining, backward chaining or combination of these two methods to derive the necessary confidence variables as explained in Chapter 3 of this dissertation. In sample size estimation module, backward chaining method is more suitable to perform the necessary calculation because the final goal (*calculated_PI*) can be obtained in different ways (Enter_CV and Graphical Approximate CV). The inference engine sets the "*calculated_PI*" as final goal and "*CV*" as immediate goals to help calculating the "*calculated_PI*" confidence variable. Similarly "*CL*", "*PI*", and "*N_CCS*" are also treated as immediate goals for the calculation of the "*calculated_PI*".

The final setting used in command block is designing the results page to present the results/recommendations and to inform the user regarding the reasoning behind the decisions. Corvid Core® enables creating a results page to be displayed to the user with advanced design features such as integrating with external web page templates. On the other hand, Exsys Corvid® offers more advanced features such as writing the results into a report template in a database to automate the execution of rules and collection of reports, specifically in automated systems such as expert system based diagnostic applications.

In the sample size estimation module, the final results page will display all the necessary user inputs and expert systems decisions and recommendations. Although the content and provided variables can change based on the calculations and results, the common content will include:

- Number of CCS provided by the user,
- CV value provided by the user or obtained from graphical approximate method,
- Desired confidence level and precision intervals,

- If the current number of CCSs are statistically significant
- Required additional number of stations, if necessary.

The final page will also incorporate some design features such as TMDEST header and a title. Additional design features are also included (e.g. highlighting if there is a need for additional stations) to emphasize the important results and recommendations.

5.6 Verification, Validation and Evaluation of the TMDEST Modules

Verification, validation and evaluation (VV&E) of an expert system is a critical task to ensure the reliability and usefulness of the built system. Without performing these important tasks, the system may be malfunctioning, misleading or totally useless. Miskell et al. *(50)* simply describes these tasks as:

- Verification: to show the **system is built right**
- Validation: to show **the right system was built**
- Evaluation: to show **the usefulness of the system**

Size and complexity of an expert system are the primary factors for the selection of appropriate methods for the VV&E process. Wentworth et al. *(43)* summarizes the well-known verification and validation methods and explains them in detail. In building TMDEST, the basic proof method is used for the VV&E process. The basic proof method partitions the large systems into small pieces and assesses each system separately before the overall evaluation of the whole system. Therefore, issues and inconsistencies can be detected and treated easily. Since the TMDEST is built in small sub-systems to reduce the complexity and to simplify the VV&E, the basic proof method is found to be an appropriate way to perform the VV&E procedures. Wentworth et al. *(43)*present the VV&E process in Figure 59 for both small and large systems.

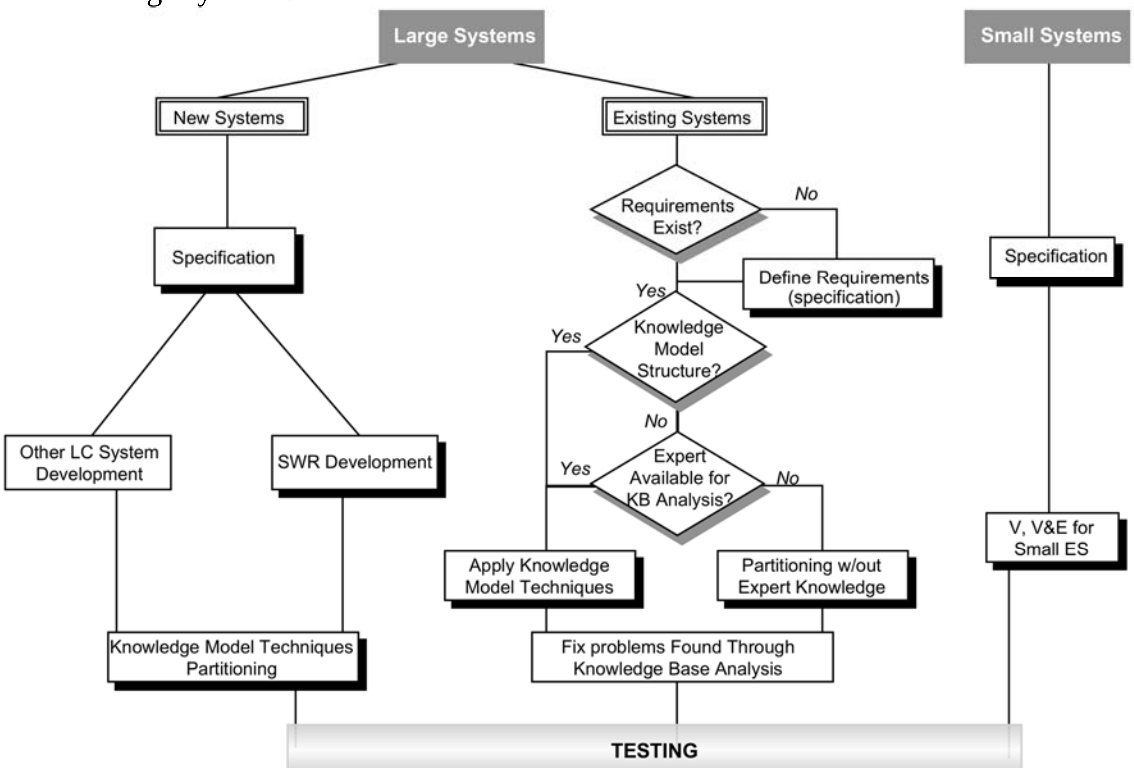


Figure 59. Verification and Validation Process ***(43)***

It is important to note that the use of an expert system development tool significantly improves the verification and validation process specifically for end-user developers compared to programming language based expert system development such as LISP or CLIPS. Corvid Core® guides the developer to build correct and consistent rules and Boolean expressions, and displays the rule structure to the developer to present all the conditions to reach a specific conclusion. In Figure 60, the left side of the screen presents the rule structure while the right side displaying all the conditions and reached conclusions to a highlighted path in the Rule View Panel. Additionally, Corvid Core® displays a warning message if the developer uses an incorrect Boolean expression, or "IF" rules. On top of that, the Corvid Core® has a 'trace' option where the developer can follow the processing steps of the inference engine while the expert system is running. Therefore, the developer can see the sequence of the rules fired and the assigned True/False conditions to each rule. This feature can have a significant contribution on following the path of the rules specifically where multiple logic blocks are used. Following lines are provided as an example of the information displayed in the trace feature in TPG Groups Module:

> Testing node: Urban Major Collectors : 9
>
> Node False: Urban Major Collectors : 9
>
> Testing node: Urban Major Collectors : 11
>
> Node TRUE: Urban Major Collectors : 11
>
> Assigning: [Urban_MC] = 2
>
> Assigning Confidence Variable [Urban_MC] : 2.0
>
> Testing node: Urban Minor Collectors : 3
>
> Attempting to get value for [U_MiC_S]

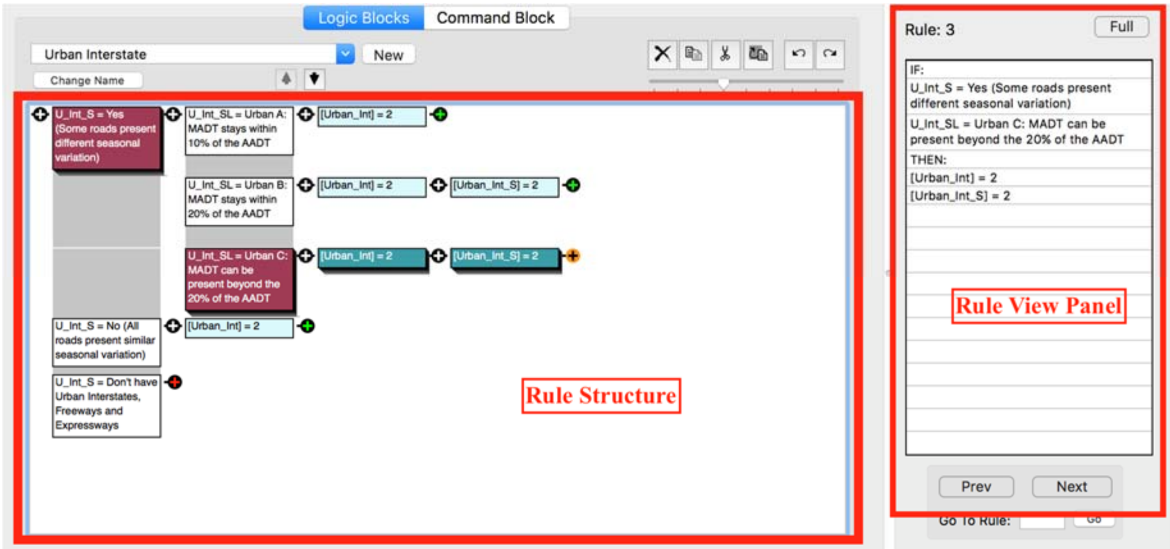


Figure 60. Rule View Panel in Corvid Core

The TMDEST and containing modules are evaluated based on defining system specifications, testing the completeness, consistency, and correctness, and validating the knowledge base. Completeness is used to ensure that there is output for all possible inputs in the system. On the other hand, consistency ensures that expert system produces consistent results for all the possible inputs. Correctness evaluates the design of an expert system for a given set of specifications. Finally, validation of knowledge base ensures the quality of the knowledge constructing the expert system.

5.6.1 System Specifications

The first step involves defining the system specifications. This step enables identifying the purpose of the expert system to be built and resources required in this process. Therefore, VV&E will use the defined system specifications to assess if and how well the expert system does the job that it intended to do. For this reason, each TMDEST module is listed in

Table 23 along with the purpose to for the VV&E process.

Table 23. Defining the Purposes of the TMDEST Modules

TMDEST Module	Purpose of the Module
Class/Weight Trend Module	Guide the user to identify the most common truck types and trucks that exert the most weight to be considered in establishing vehicle classification and truck weight groups.
MADT/AADT Methods Module	Evaluate different MADT and AADT estimation methods based on presence and extent of the missing data, and inclusion of temporal variations to recommend the most appropriate methods to the user.
TPG Methods Module	Evaluate four TPG analysis methods (Traditional Approach, Cluster Analysis, Cluster Analysis with Roadway Functional Classification, Volume-based Groupings) based on seasonal variation, volume trends and geographic coverage to recommend the most appropriate methods to the user.
TPG Groups Module	Establish the TPGs with an approximate cluster analysis and functional classification method by asking the seasonal variation and urban/rural typology questions to the user for each roadway functional class.
Adjustment Factor Module	Improve the decision on which adjustment factors are necessary to be used to expand the collected short-duration counts for the estimation of AADTs.
Sample Size Estimation Module	Evaluate the number of continuous count stations (CCS) in each TPG for statistical significance and suggest the required additional number of stations if necessary.

When defining the specifications, the primary focus is placed on “What is to be produced” and “What are the required inputs and data?” Thus, each module can be evaluated if the required data and/or input are obtained and a satisfactory result is produced.

5.6.2 Completeness

Completeness was checked for each logic block in each module by following the rule view panel. This evaluation ensures that all rules in a path have a conclusion. In some cases, a logic block is designed to derive only one confidence variable that will be used in another logic block. In these situations, combinations of rules in different logic blocks are used for testing the completeness of the path. Each of the six modules and corresponding rules in the TMDEST checked for completeness. There is no rule observed that does not produce a conclusion to the user or a confidence variable that is used in another logic block. Following example provides the rules and derived conclusions for the Adjustment Factors Module:

Logic Block: Type - Rule 2:

If "Data_Type" = Volume

OR "Axle_vehicle" = Vehicle

then "ACF" = yes.

Logic Block: Growth Factor - Rule 1:

If "Same_Year" = Yes

then "GF" = 0.

Logic Block: Month - Rule 1:

If "Month " = January

OR "Month" = February

…

OR … "Month" = December

then "MAF" = 1

then NOTE: [[Month.VALUE]].

Logic Block: Duration - Rule 5:

If "Duration_of_Data " = Weeklong (Consecutive seven days)

then "Duration" = 7

then "DAF" = 0

then NOTE: Note to the user.

Another important verification step is to find the mutually inconsistent conclusions within the rules. This evaluation eliminates identifying the holes in a rule where the IF part of the rule is not defined. For instance in Sample Size Estimation Module, a numerical value (number of CCS) is required from the user. Although the logical options are positive integer values, the expert system should be designed to cover all possible options to eliminate a non-defined value. This issue can be overcome in two ways: adding nodes to the rule to cover other options (e.g. negative values), or using variable settings to limit the user input to positive integer values. In the “number of CCS” variable, the user is limited to positive integer values between 2 and 20 in any group. Additionally, a similar procedure was applied to all rules where the rule is structured to cover a range of possibilities. Few examples are presented below:

TPG Groups Module - Logic Block: Urban Arterials:

- Urban A: MADT stays within 10% of the AADT
- Urban B: MADT stays within 20% of the AADT
- Urban C: MADT can be present beyond the 20% of the AADT

MADT/AADT Methods Module - Logic Block: MADT/AADT:

Variable: Amount_Missing (limited to positive integer values)

- < 3 days/month
- < 7 days/month
- < 15 days/month
- >15 days/month

One issue was detected in the above rule to derive a value to *"Amount_Missing"* variable in the trace feature. Initially, it is assumed that the inference engine will not test the < 7 days/month option and other options if the < 3 days/month is met. However, it was noticed that the inference engine tests all the options before moving the next rule. Although this wasn't a significant issue in our case, the options in the rule are replaced with the following list variable to force the inference engine to fire the appropriate rule based on the user selection.

- < 3 days/month
- 4 to 7 days/month
- 8 to 15 days/month
- >15 days/month

The result of the correctness evaluation revealed that all rules provide either a conclusion to the end user or a confidence variable that can be used in another rule. Additionally, the rules in each module cover all options, specifically for numerical values, to eliminate any non-defined range.

5.6.3 Consistency of Results

The consistency of the results is checked for each TMDEST module to ensure that the inference engine does not produce inconsistent results. This evaluation is specifically crucial for the modules that use backward chaining method. In that, the inference engine fires the appropriate rules to satisfy a given goal rather than following a structured path. Therefore, the inference engine can fire a rule that contradicts with a previous selection of the user's.

In checking the consistency of the results, the inconsistent conclusions are evaluated separately in each module. This was done by testing that these inconsistent results do not occur at the same time at any point. For instance, in TPG Groups Module, there are two options for urban minor arterials regarding how many groups can be recommended. If there is a considerable seasonality among urban minor arterials then two groups will be used. However, it is important to check that one group recommendation should not be a conclusion in the presence on seasonality. Similarly, a two-group recommendation should not be a conclusion if there is no seasonality. Following expressions present testing the inconsistent results in this rule.

Logic Block: Urban Minor Arterial:

{"Seasonal Variation" = Yes

AND

("Seasonality Level" = within 20%

OR

"Seasonality Level" = beyond 20%)}

= FALSE

Logic Block: Urban Minor Arterial:

{"Seasonal Variation" = No

OR

(Seasonal Variation" = Yes

AND

“Seasonality Level" = within 10%)}

= FALSE

Checking the consistency of the results is also simplified in expert system development tools, in Corvid Core® specifically since the rules are structured in similar to tree diagrams. Therefore, designing the rules systematically with confirming the completeness eliminates the possibility of inconsistent results.

Consistency evaluation carried out in all six modules specifically in TPG Methods Module and Sample Size Estimation Module due to a large number of rules and the high possibility of inconsistency in results. Evaluation of seasonality in each roadway functional classification was checked individually to ensure the correctness and consistency. The result of the evaluation showed that there are no inconsistent results produced in the TMDEST modules.

5.6.4 Correctness/Specification Satisfaction

The overall result of the correctness evaluation presents if the design meets the specifications set at the beginning of the development process. In some cases, the expert system may not meet all the criteria specified due to the complexity of the problems, the amount of user input required, consequences of failure, and possibly high cost. Therefore, an overall evaluation is required.

Each TMDEST module is evaluated if the module can meet the design specifications and evaluation results presented below:

Class/Weight Trend Module is designed to guide the user to identify the most important vehicle classes and the trucks that exert the most weight. The module meets the design specifications with one limitation. The necessity of using an external website for the FHWA's VTRIS W-Tables may increase the complexity of finding the necessary information on the website. For this reason, an informative page is provided to the user regarding how to obtain the necessary inputs. This page and containing information was presented and discussed in detail in Figure 42 and Figure 43 in Chapter 5 section 5.4.1.

MADT/AADT Methods Module is designed to inform the user regarding the major MADT and AADT estimation methods and recommends the most appropriate methods based on the presence and amount of missing data, and the inclusion of temporal variations. The only weak side of this module is that the evaluated methods are limited to three to simplify the process. However, these three methods are selected among the widely used methods to represent the different complexity levels and incorporation of missing data. Therefore, these three methods well represent the variety of the methods for the estimation of MADT and AADT measures.

The design specifications of the TPG Methods Module include the evaluation of four TPG analysis methods with multiple-choice questions. Seasonal variation, volume characteristics and geographic coverage are used as evaluation criteria. Multiple-choice questions are used to minimize the user input. It is considered that the module well meets the design specifications regarding evaluating the TPG analysis methods and recommending the most appropriate ones based on the user's response to the prompted questions.

TPG Groups Module satisfied the design specifications well by providing an approximate estimation of TPGs based on roadway functional classification and seasonal variation. One limitation in this module is the representation of the seasonal variation. Both urban and rural roadway functional classes are represented by three levels of seasonality (non-seasonal, seasonal, and highly seasonal or recreational) for an approximate determination of seasonality. Although this assumption is considered a good representation, it still does not reflect the actual variation between groups that require a large amount of data to be processed.

Adjustment Factors Module also meets the design specifications. The module incorporates all possible adjustment factors and evaluates the necessity of the use. Multiple-choice questions are used to make the prompted questions to the end user as simple as possible.

Sample Size Estimation Module is designed to test the number of continuous count stations in each TPG for statistical significance. This module requires a considerable amount of numerical input (number of CCS and CV values) from the user, which makes the module slightly complex. However, the module satisfies the design specifications and evaluates the necessity and quantity of the required new stations.

Overall evaluation of the TMDEST can yield that each module well satisfies the design specifications. However, there is a lack of coordination between modules due to limitations in the development tool Corvid® Core. For instance, TPG Groups

Module does not transfer the recommended TPGs to the Sample Size Estimation Module for the evaluation of sample sizes. If it was possible, which main platform Exsys® Corvid is capable of doing so, the Sample Size Estimation Module could simply use the number of recommended groups to structure the rules to estimate the required new stations when necessary. However, an external page is designed to provide detailed information regarding the TMDEST and containing modules to the end user to follow the sequence of the modules of select the appropriate module from the menu.

5.6.5 Validation of Knowledge Base

The knowledge base contains all the necessary knowledge that the expert system is built on. Any missing or incomplete knowledge can produce errors and affect the performance of the expert system. This missing or incomplete knowledge can be raised from expert(s) incomplete/incorrect knowledge, knowledge engineer's failure to understand the expert, or not including all conditions (holes in the condition). In the concept of end user developers, where a single person can be both expert and knowledge engineer, the knowledge base can sometimes contain only the limited knowledge to solve an individual problem. However, it is critical to ensure that this limited knowledge is correct and complete within its problem domain and produce valuable results.

Wentworth et al. *(43)* discuss two types of validation: logical validation and semantic validation. Logical validation more assesses the completeness and consistency of the expert systems. Logical validity is required but not sufficient for the accuracy and reliability of the results. On the other hand, semantic validation deals with the extent of the knowledge base to ensure that it contains all the necessary knowledge and information. In another word, “it must base its decisions on all information considered to be relevant by the expert.”

There are two types of resources used to construct the knowledge base in the TMDEST. The first one contains information from published standard documents such as Traffic Monitoring Guide, AASHTO Guidebook, and published articles. Knowledge and information related to TPG analysis and respective mathematical and statistical procedures were used as explained in these documents. On the other hand, the second type of resource contains expertise knowledge to perform the approximate evaluation methods. Thus, the validation of this part of the knowledge base is performed by using a True/False test.

In the True/False test, randomly selected rules are expressed in a simple sentence. Some of these rules are intentionally structured to produce false statements. Then, the sentences are presented to the expert and tested if the expert can give true and consistent responses. Following the same procedure, few sentences were produced from MADT/AADT Estimation, TPG Methods, and TPG Groups Modules and checked if the statement in these sentences makes sense.

MADT/AADT Estimation Module:

- If there is no or insignificant amount of missing data, it is better to use the simple average method for the estimation of MADTs and AADTs. - TRUE
- There is no significant difference between simple average and AASHTO Methods. - FALSE

- There is no significant difference between methods, which incorporates weekday-weekend, Monday to Friday or Monday to Thursday, midnight-to-midnight or noon-to-noon daily traffic data. - TRUE
- If there are considerable amounts of missing hourly data, HPSJB method produces slightly better results. - TRUE

TPG Groups Module - Logic Block: Urban Arterials:

- MADT in non-seasonal urban roads can usually stay with 10% of the AADT – TRUE
- Traffic volume is three times higher in summer months compared to winter months in rural roads. – FALSE
- It is better to combine the Interstates with principal arterials if both presents similar monthly variations – FALSE

The vast majority of the knowledge and information is originated from already published and verified materials. Therefore, there is no need to validate the accuracy and reliability of the incoming knowledge. However, it is critical perform the semantic validation to ensure that all primary factors are included in the decision making process. This evaluation was performed on all six modules, and satisfactory results were obtained. The MADT/AADT Methods Module incorporates two major factors: 1. amount and extent of missing data and 2. the complexity of the calculation. Similarly, TPG Methods Module covers the most known and applied TPG analysis methods that incorporate temporal variation and roadway functional classification.

Additionally, the True/False test fulfilled the need for validating the knowledge base specifically, where the knowledge was not coming from a standard document. The randomly selected rules were tested with True/False test. The results revealed that the rules produce correct and consistent conclusions/recommendations to the user.

5.7 Summary of Chapter 5

Chapter 5 introduced the concept of Traffic Monitoring Decision Support Tool (TMDEST) and its components. This knowledge-based expert system application is developed to assist the transportation professionals for the states' traffic monitoring programs, specifically for establishing traffic pattern groups (TPGs). The TMDEST and containing six modules were explained in detail. Corvid Core® expert system development tool is used for building the TMDEST and corresponding subsystems.

The TMDEST is designed to cover a variety of tasks within traffic monitoring program's TPG establishment process. Starting with the determination of vehicle classification and truck weight trends, it continues to evaluate different methods for the estimation of MADT/AADT and TPG analysis. TPG Groups Module offers an approximate approach to establishing TPGs by incorporating roadway functional classification and seasonal variation. Then, two other modules provide support to test the sample size for the each TPG and determine the appropriate adjustment factors to be used in expanding short-duration counts. Using multiple modules that focus on different tasks gives flexibility to the user. In this way, the user can to perform the whole process by following the sequence of the modules or only selected task(s).

Among the six modules, TPG Groups Module is the primary focus of this study in order to facilitate the quick and easy evaluation of the TPGs. In this module, TPGs are established based on the roadway functional classification and seasonal variation. Roadway functional classification is integrated to form identifiable groups and to enable the data integration with HPMS. Seasonal variation is used to simulate the cluster analysis in a simple way for each roadway functional class. Three levels of seasonality are included in this evaluation to represents the non-seasonal, seasonal and highly seasonal/recreational roadways. Urban and rural typology is also considered in the module. The output of this module recommends a list of roadway functional classes (either combined or separated due to seasonality) for the TPGs.

Verification, Validation and Evaluation (VV&E) is performed on each module and the whole system to ensure that the expert system was built right and does the job that it intends to do. Utilization of an expert system development tool significantly contributed to the verification and validation process. The simple proof method was used to evaluate each module for completeness, consistency, and correctness. Although the majority of the content in the knowledge base was obtained from FHWA’s traffic monitoring guide, simple true/false test was applied to some modules where the content was partially generated to validate the knowledge base. TMDEST and each module are considered as valid and applicable tool in states traffic monitoring program with room for improvements.

Chapter 6

SUMMARY, CONCLUSIONS AND RECOMMNEDATIONS

6.1 Summary

This dissertation documents a research effort to contribute to the traffic monitoring program in states by using an expert system based tool, called Traffic Monitoring Decision Support Tool (TMDEST). The proposed tool can be used to check the current traffic pattern groups (TPGs) and the number of continuous count stations (CCS) in each group, or offer an approximate approach for establishing TPGs and evaluating the sample size in each group. Additionally, the TMDEST can be used to identify the most common truck types and trucks that exert the most weight to be considered in establishing vehicle classification and truck weight groups; evaluate MADT and AADT estimation methods based on presence and extent of the missing data; and evaluate TPG analysis methods based on seasonal variation and volume trends to recommend the most appropriate methods to the user. The primary focus of the TMDEST is the TPG analysis and its internal components to improve the accuracy and reliability of the collected and processed data to meet the state and federal needs. However, it has the potential to expand the coverage to improve the short-duration data collection and evaluation of emerging technologies where the expert system based applications can have a significant contribution.

The primary target audience of the TMDEST is the states' DOT personnel who are responsible for collecting, analyzing and reporting traffic monitoring data.

However, the proposed tool can be utilized by any state or federal agency, private companies and research community that are interested in traffic monitoring data, their spatial and temporal patterns and data collection and analysis methods.

The State Departments of Transportation have been collecting, summarizing and reporting traffic data for decades for the planning and operational purposes in national and state level. FHWA initiated the Traffic Monitoring Program to bring standardization in data types and formats, and to create a national level road inventory database. Traffic monitoring is measured at various spatial and temporal levels to collect a variety of data types depending on the intended use and the expected outcome of the collected traffic information. Primarily, a small number of continuous count stations are used for monitoring the temporal variations and extensive short-duration counts are used for ensuring the spatial coverage. Therefore, state roadways are comprehensively assessed through the continuous count stations to establish traffic pattern groups to be used in expanding extensive short-duration counts. Consequently, it becomes critical to forming the TPGs correctly and to use the most appropriate MADT and AADT estimation methods.

In the first part of this study, data from 84 continuous count stations were used for evaluating the spatial and temporal variation of traffic patterns in Delaware. The entire dataset includes volume data from 84 stations, classification data from 24 stations and weight data from 22 stations for the years 2012, 2013 and 2014. The primary focus of this part was to evaluate the seasonal variation of the traffic and to determine the TPGs. The study was performed in three stages for estimating the volume, vehicle classification and truck weight traffic patterns. Mathematical and statistical procedures are used for determination of seasonal variation and assignment of TPGs. Evaluation of vehicle classification and WIM stations increased our understanding of the composition of the vehicles in Delaware. Prior knowledge on truck traffic patterns and individual evaluation of sites revealed that few locations present significantly different truck traffic patterns compared to others, and were discussed in Chapter 4.

Then, a traffic monitoring survey was designed to investigate the issues and challenges in other states' traffic monitoring programs, specifically in volume, vehicle classification and truck weight programs focusing on continuous and short-duration data collection and data processing. Survey results were then evaluated to see if the problems identified by survey respondents coincide with the experiences during the evaluation of DelDOT traffic monitoring program study.

In the second part of the study, the concept of the TMDEST is presented. The TMDEST framework covers a variety of tasks for the TPG establishment process. Starting with the determination of vehicle classification and truck weight trends, it continues to establish the TPGs and test the sample size for each group. Using multiple modules that focus on different tasks gives flexibility to the user to perform only selected task(s) if necessary. The TMDEST and corresponding six modules were developed in Corvid Core® expert system development tool. Corvid Core® was selected due to its powerful design features and user friendly interface compared to other development tools.

6.2 Conclusions

Conclusions of this study are presented in two parts. The evaluation and updating of the DelDOT traffic monitoring program is presented in the first part along with the national level survey to identify the issues and challenges in states' traffic monitoring programs. Then, the development of TMDEST framework and containing modules are presented in the second part.

6.2.1 Conclusions of DelDOT Traffic Monitoring Program Evaluation

Evaluation of volume data program within DELDOT traffic monitoring program revealed that traffic characteristics have shifted on Kent and Sussex County roadways from recreational to commuter/recreational. It is observed that Kent and Sussex Counties currently carry high traffic volumes during non-summer months. Therefore, TPGs have been revised to accommodate these changes. Proposed TPGs satisfy the required minimum number of station criteria, and no new sites are needed for statistical accuracy and reliability. However, it is observed that major roadways in NCC are under-represented in the determination of TPGs and respective adjustment factors. Therefore, it is recommended to increase the coverage in NCC for volume data by either installing new ATR sites, or incorporating TMC resources that also produce continuous volume data.

Interstates I-95, I-295, and I-495 are not extensively covered with continuous count stations. Three stations are located on Northern part of I-95 and I-495 near PA line and do not reflect the traffic characteristics on the entire 40.6 miles of Interstates in Delaware. Therefore, it is suggested to further evaluate whether the Interstates can be monitored with conventional ATR stations or new technologies (or current TMC resources) should be incorporated.

DE 1 has been increasingly changing from a principal arterial to a limited access freeway/expressway over the last two decades. The northern part of DE 1 (north of CD Canal) is included in TPG 1 with Urban Interstates and Freeways/Expressways. Other three stations (8037, 8046 and 8047) that are located on DE 1 (between CD Canal and Dover) show very similar characteristics with recreational rural arterials and are included in TPG 5. It is suggested to re-evaluate the traffic pattern on these three stations in the near future, possibly in five years, to see if these stations present different traffic patterns and require a separate rural freeways/expressways traffic pattern group.

The truck weight data program evaluated the truck weights in Delaware by using 22 WIM stations across the state. It is observed that class 5 (single unit, 2-axle trucks) and class 9 (single trailer, 5-axle trucks) trucks compose 80% of the total truck traffic in Delaware. Similarly, class 5 and class 9 trucks apply 79.6% of the total weight exerted on roads. Thus, these two truck classes are primarily used for establishing truck weight groups. Both class 5 and class 9 trucks did not reveal noticeable seasonal variations for truck weights.

Evaluation of truck weight data shows that class 5 and class 9 trucks present different characteristics in urban and rural typology. Class 5 trucks present higher average truck weights in urban areas than rural. Conversely, class 9 trucks show higher average truck weights in rural areas than urban. One of the critical conclusions of the study is that the Interstates are not well monitored with WIM stations related to the evaluation of truck traffic. Considering the complexity of installing and maintaining WIM station on interstates, it is recommended that DelDOT investigate other non-intrusive technologies that can be useful in determining vehicle types and truck weights on interstates. Also, coordinating with neighboring states of MD and PA and using available truck weight data near borderlines can help understand the truck weight patterns on Delaware interstates. Additionally, the current numbers of WIM stations are found to be adequate for non-interstate roads for monitoring the seasonal changes in Delaware.

The short-duration data program in DelDOT covers approximately 3,460 roadway segments with a maximum of a six-year cycle. Weeklong volume counts help eliminate the day-of-week variation and provides higher accuracy. Moreover, vehicle classification short-duration counts are performed in a 48-hour duration. One major issue is detected at the percentage of classification counts within the total short-duration counts. TMG recommends that 25-30 percent of the short-duration count should be performed as classification counts. However, DelDOT performs nearly 100 classification counts and 800 volume counts, which is between 10%-15%. Therefore, an increase in the number of short-duration classification counts is recommended to ensure that different vehicle classes, specifically trucks are accurately estimated.

6.2.2 Conclusions of TMDEST Framework Development

After the DelDOT traffic monitoring program evaluation, a national level survey was designed to identify the common issues and challenges that states are facing in traffic monitoring programs across the U.S. The eight-question survey (two demographics and six traffic monitoring related) was sent out to 50 State Departments of Transportation traffic monitoring related offices and 13 responses received. The results revealed that traffic monitoring programs are under the pressure of budgetary constraints to renew/update the data collection technologies and improving data analysis methods. Additionally, lack of /inefficient QC/QA procedures, increasing data requests from federal agencies, lack of/insufficient quality staff are some of the issues highlighted by state agencies.

Experiences from DelDOT case study and survey results revealed that there is a need to improve the analysis of collected traffic monitoring data and establish better QC/QA procedures. Additionally, considering the increased data requests from FHWA and budget constraints, any possible improvement should reduce (or at least not significantly increase) the time and resources spending on the data analysis to improve the overall quality of the traffic monitoring program. Therefore, an expert system based application has been developed to contribute to the establishment and control of the TPGs, which is a key factor for the accuracy and reliability of the traffic monitoring data.

The expert system based decision support tool TMDEST is developed to improve the knowledge and decision making capability of transportation professionals who are responsible for collecting, analyzing and reporting of traffic monitoring data. The TMDEST and corresponding six modules were developed for facilitating the establishment of TPGs within states traffic monitoring programs. However, it has the potential to expand the coverage to short-duration data collection and evaluation of emerging technologies where the expert system based applications can have a significant contribution.

Each TMDEST module focuses on a single task that can also be integrated with other modules. The Class/Weight Trend Module assists to identify the most common truck types and trucks that exert the most weight to be considered in establishing vehicle classification and truck weight groups. This module answers the question of whether one (or few) vehicle classification categories should be considered when establishing the vehicle classification groups. In many states, majority of truck traffic consists of few types of trucks and heavy vehicles that are less commonly observed may have unusual travel patterns. Therefore, this module helps the user to identify these truck types (vehicle classification categories) by using the FHWA VTRIS W-Tables. These truck types are then used in other modules while establishing the TPGs.

MADT/AADT Methods Module evaluates different MADT and AADT estimation methods based on presence and extent of the missing data, complexity of method implementation and the inclusion of temporal variations to recommend the most appropriate methods to the user. This module can be used to distinguish the most appropriate methods for the estimation of MADT and AADT measures and test if the agency's current estimation method coincides with it. Moreover, implementation of each method is explained in an external web page that is also linked to the results.

Similarly, TPG Methods Module evaluates four TPG analysis methods (Traditional Approach, Cluster Analysis, Cluster Analysis with Roadway Functional Classification, Volume-based Groupings) based on seasonal variation, volume trends and geographic coverage to recommend the most appropriate methods to the user. This module is successfully used to provide an insight and guidance in cases when the user wants to perform the TPG analysis by using other data analysis means such as cluster analysis.

TPG Groups Module is designed to be one of the primary focuses of this study. This module helps to establish the TPGs with an approximate cluster analysis and functional classification method by asking the seasonal variation and urban/rural typology questions to the user for each roadway functional class. Seasonal variation is used to simulate the cluster analysis in a simple way for each roadway functional class. Three levels of seasonality are included in this evaluation to represent the non-seasonal, seasonal and highly seasonal/recreational roadways. On the other hand, roadway functional classification is included to form identifiable groups and to enable the data integration with HPMS. Therefore, users are provided a simple way to establish TPGs or to check the TPGs that are already in use.

Sample Size Estimation Module evaluates the number of CCS for statistical significance and suggests the required additional number of stations if necessary. This module has proven to be useful for testing if each TPG have enough number of CCS. Although this task can also be performed with a spreadsheet based document and required formulas, the expert system based application enables integrating with other modules. Moreover, this module presented an example to read data from external sources (reading corresponding t/statistics values from an external file), which proves the Corvid Core® expert system's capability of interacting with external sources.

Adjustment Factor Module helps to identify which adjustment factors are necessary to be used to expand the collected short-duration counts for the estimation of AADTs. Considering the amount of short-duration data collected daily, this module can have a significant contribution towards the accuracy of the estimations based on collected data. Additionally, since most states outsource the short-duration data collection, this module can also be used as a quality control tool. In previous modules, to focus was on continuous count data to form the TPGs and to derive the necessary adjustment factors. In this module, the derived adjustment factors are implemented to expand the short-duration counts. The Adjustment Factors Module is considered one of the highly used and easily practical parts of the TMDEST in traffic monitoring programs. Moreover, TMDEST and containing modules do not require a separate software package or a special setting and simply work on a web browser. Therefore, it is very practical to be used by both transportation agencies and contractors in short-duration data collection.

Verification, Validation, and Evaluation (VV&E) was performed on TMDEST and each module to make sure that the modules are designed properly and meet the design specifications. Few factors affected the VV&E process. The first one is the utilization of an expert system development tool, which provides significant advantages over programming language based expert system development, specifically for end-user developers. The graphical user interface and guidance provided by Corvid Core® reduced the possibility of making errors and eliminated building incorrect expressions. Additionally, the ‘trace’ feature enabled following the inference engine’s rule execution for an easy detection of problems. The second effect is building the TMDEST in small pieces (modules) to simplify both design and VV&E process. Each module was individually assessed before an overall evaluation of the TMDEST.

The simple proof method was used in each module for checking the completeness, consistency, and correctness. The evaluation of each module resulted that rules are complete and correct, and the results are consistent and meet the design specifications. Additionally, a simple true/false test was applied to the modules to ensure the accuracy and quality of the knowledge constructing the expert system’s knowledge base. Since FHWA’s Traffic Monitoring Guide and some other well accepted and published documents were used while constructing the vast majority of the knowledge base, true/false test produced positive results, as expected. The test was applied more extensively to the modules where the content and the procedure were not fully obtained from a documented knowledge. The results revealed that the knowledge base contains comprehensive and accurate knowledge and information to produce reliable results.

6.2.3 Merits and Demerits

The major contribution of the TMDEST is knowledge structuring. Collected facts and knowledge in different levels were integrated in TMDEST to provide a synthesized information to the user. These different levels of information are composed of federal guidelines, well accepted research methods, mathematical and statistical procedures, and state level facts and limitations. Therefore, users are able to perform the selected tasks by following the guidance provided.

One of the most important merits of the TMDEST is that it does not require any software packages and works on a web browser. So, users with a computer with the Internet connection can utilize the TMDEST and answer a few questions to get a specific recommendation. Considering the possible applications in short-duration data collections, it may become very useful for both agency and contractors.

Another key advantage of the TMDEST is its ease of operation. The user only needs to answer a few questions and input simple numerical data in some cases to reach a conclusion. Although the user should have background knowledge regarding the terminology, data inputs, etc., the questions are designed to be as simple as possible. Moreover, considering the possibility of the user not being able to answer some questions or obtain required numerical inputs, an external web page and MS

Excel Spreadsheets are provided so that the user can have explanation about the concept and guided to derive the necessary values.

Building the TMDEST in small expert systems that are focused on different tasks gives flexibility to update or revise each module without much effort. This approach provides a great opportunity to work closely with the users to improve the tool. Similarly, addition of a new partition (e.g. location determination for short-duration data collection) also becomes easier and requires a VV&E process for the new module.

The tool presents demerits as well. First, the primary target audience of the tool is transportation agencies that are involved with traffic monitoring data. Therefore, the user needs to be knowledgeable on continuous count stations and their spatial and temporal patterns. Without having such knowledge and information, the tool does not provide any recommendations to the user. Another critical point is that if the user does not have the necessary data, information and/or knowledge, the external resources can explain and guide the user to obtain the required values. However, in that case, the user should have an extensive data to perform the required tasks. For instance, TPG establishment process requires a substantial amount of data. This data includes at least MADT and AADT values from each continuous count stations for the establishment of the volume groupings. Moreover, vehicle classification and truck weight data require both MADT and AADT values for the each vehicle classification category (26 times larger than volume data need).

6.3 Recommendations

The primary factors that have been considered in TMDEST and the TPGs are seasonal variation, urban/rural typology, and roadway functional classification, where roadway functional classes can also represent the volume trends. There might be additional factors that affect the formation of groups such as proximity to attraction centers or major truck traffic generating facilities, etc. Inclusion of these factors may improve the creation of TPGs and recommended groups.

Additionally, the developed tool should integrate a user feedback system for the testing the usefulness of the tool. This feature can have two contributions: (1) eliminating the limitations/difficulties to improve the performance of the system, (2) enabling the use of the tool by different state highway agencies. Each agency can have different needs and priorities in their traffic monitoring programs. Therefore, a user feedback system creates an opportunity to identify the differences and improve the tool. Additionally, such information can be helpful to identify the differences between state highway agencies regarding the traffic monitoring programs.

It is believed that a "location determination for a short-duration count tool" can be highly beneficial. The TMDEST with its current modules aims to improve the accuracy and reliability of the TPGs and derived adjustment factors to be used in expanding short-duration counts. Moreover, it is also critical to ensure the accuracy and reliability of short-duration count data. Therefore, a possible module can be designed to incorporate different factors to suggest a possible location for the count. Some of these factors are proximity to intersections, number of lanes, posted speed limit, proximity to driveways/entrances, if it is in a waving zone, etc. Such tool can be highly practical to be utilized both at the office for the determination of optimum locations and at the field to make sure the count location meets the pre-determined specifications.

A similar approach can be used in the evaluation of data collection tools. This can be treated as QC/QA tool for evaluating and even ranking the data collection tools for a given set of features among themselves. For instance, DelDOT has been integrating length-based vehicle classification technologies for the collection volume and vehicle classification data. This non-intrusive technology can have a significant contribution specifically for the locations where the in-pavement sensors are hard to maintain or not practical. Therefore, length-based classification technologies can be evaluated based on a set of criteria with possibly different weights given each criterion by using KBES. This approach can provide a reliability index for the length-based vehicle classification data collected in states' traffic monitoring programs.

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Appendix A

SURVEY QUESTIONNAIRE

Survey Title: Traffic Monitoring Program in State DOTs

Q1 Please specify your state Department of Transportation (DOT).

Q2 Please specify your position in your state DOT.

Q3 Please describe how the state DOT is organized to handle the traffic monitoring program in your state.

Q4 Please list the significant challenges that the state DOT faces during the continuous data collection, specifically for the collection of volume, vehicle classification and weight data.

Q5 Please list the significant challenges that the state DOT faces during the short-term data collection, specifically for the collection of volume, vehicle classification and weight data.

Q6 Please list the significant challenges that the state DOT faces during the data processing of volume, vehicle classification and weight data.

Q7 Please describe the leading causes of inefficient traffic monitoring program in the state DOT from your experience.

Q8 Please describe the effective measures for improving the traffic monitoring program in the state DOT from your experience.

Appendix B

IRB EXEMPTION LETTER

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

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DATE:	July 11, 2016
TO:	Abdulkadir Ozden
FROM:	University of Delaware IRB
STUDY TITLE:	[925359-1] Traffic Monitoring in State DOTs
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	July 11, 2016
REVIEW CATEGORY:	Exemption category # *(2)*

Thank you for your submission of New Project materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Nicole Farnese-McFarlane at (302) 831-1119 or nicolefm@udel.edu. Please include your study title and reference number in all correspondence with this office.