Data Collection and Annual Average Daily Traffic (AADT) Estimation for Non-Federal Aid System (NFAS) Roads

Safe Roads for a Safer Future

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U.S. Department of Transportation

Federal Highway Administration

FHWA Safety Program

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NOTICE

QUALITY ASSURANCE STATEMENT

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TECHNICAL DOCUMENTATION PAGE

<table>
<tr><td colspan="2">1. Report No.
FHWA-SA-20-064</td><td colspan="2">2. Government Accession No.</td><td>3. Recipient's Catalog No.</td></tr>
<tr><td colspan="4" rowspan="2">4. Title and Subtitle
Informational Guide on Data Collection and Annual Average Daily Traffic (AADT) Estimation for Non-Federal Aid-System (NFAS) Roads</td><td>5. Report Date
March 2020</td></tr>
<tr><td>6. Performing Organization Code</td></tr>
<tr><td colspan="4">7.Author(s)
Ioannis Tsapakis, William Holik, Subasish Das, Edgar Kraus, and Paul Anderson</td><td>8. Performing Organization Report No.</td></tr>
<tr><td colspan="4" rowspan="2">9. Performing Organization Name and Address
Texas A&M Transportation Institute (TTI)
3135 TAMU
College Station, TX 77843</td><td>10. Work Unit No.</td></tr>
<tr><td>11. Contract or Grant No.
DTFH61-16-D-00004L</td></tr>
<tr><td colspan="4" rowspan="2">12. Sponsoring Agency Name and Address
Federal Highway Administration Office of Safety
1200 New Jersey Ave., SE
Washington, DC 20590</td><td>13. Type of Report and Period
August 2016 – April 2020</td></tr>
<tr><td>14. Sponsoring Agency Code
FHWA</td></tr>
<tr><td colspan="5">15. Supplementary Notes
The contract manager for this report was Marc Starnes.</td></tr>
<tr><td colspan="5">16. Abstract
This is an Informational Guide on traffic data collection and estimation of annual average daily traffic (AADT) for non-Federal aid-system (NFAS) roads. NFAS roads refer to rural minor collectors (6R) and both rural and urban local roads (7R and 7U). This Informational Guide describes four preparation steps for safety data integration and an eight-step process for developing a random stratified sampling scheme and AADT estimates for NFAS roads. The intent of the Informational Guide is to assist both experienced traffic monitoring personnel and those who are new to traffic data collection and AADT estimation. The Informational Guide includes methods suitable for agencies that do not collect data nor estimate AADT for NFAS roads, as well as for those desiring to improve their practices and the accuracy of their AADT estimates. Readers are encouraged to take those portions most relevant to their needs to develop a stratification scheme and AADT estimates. Agencies do not have to adopt all the activities described in the Informational Guide.</td></tr>
<tr><td colspan="2">17. Key Words:
annual average daily traffic, AADT, traffic count, random stratified sampling, decision tree, traffic data, low-volume roads, non-federal aid-system roads</td><td colspan="3">18. Distribution Statement
No restrictions.</td></tr>
<tr><td>19. Security Classif. (of this report)
Unclassified</td><td colspan="2">20. Security Classif. (of this page) Unclassified</td><td>21. No. of Pages
146</td><td>22. Price</td></tr>
</table>

Form DOT F 1700.7 (8-72) Reproduction of completed pages authorized

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

TABLE OF CONTENTS

List of Tables

List of Figures

ACRONYMS

AADT	Annual average daily traffic
AASHTO	American Association of State Highway and Transportation Officials
ACS	American community survey
ADT	Average daily traffic
AEGIST	Applications of Enterprise GIS for Transportation
ARNOLD	All road network of linear referenced data
CART	Classification and regression trees
CCS	Continuous count station
CFR	Code of Federal Regulations
CMF	Crash modification factor
DOT	Department of Transportation
DVRPC	Delaware Valley Regional Planning Commission
FDE	Fundamental data elements
FHWA	Federal Highway Administration
GIS	Geographic information systems
HPMS	Highway Performance Monitoring System
HSIP	Highway Safety Improvement Program
IT	Information technology
LEHD	Longitudinal Employer-Household Dynamics
LRS	Linear referencing system
MAP-21	Moving Ahead for Progress in the 21st Century Act
MIRE	Model inventory of roadway elements
MOA	Memorandum of agreement
MOU	Memorandum of understanding
MPO	Metropolitan Planning Organization
NYSDOT	New York State DOT
NFAS	Non-Federal aid-system
PTR	Portable traffic recorder
QA	Quality assurance
QC	Quality control
SEMCOG	Southeast Michigan Council of Governments
SPF	Safety performance function
TMG	Traffic Monitoring Guide
TRCC	Traffic Records Coordinating Committee
VDOT	Virginia DOT
WIM	Weigh-in-motion

EXECUTIVE SUMMARY

The purpose of this Informational Guide is to provide transportation agencies with information about collecting data and developing annual average daily traffic (AADT) estimates for non-Federal aid-system (NFAS) roads. NFAS roads refer to roadway functional classifications rural minor collectors, and both rural and urban local roads. The expectation is to use the AADT estimates in data-driven safety analysis, as defined by the Highway Safety Improvement Program (HSIP) Final Rule. The Guide presents a framework (Figure 1) that consists of two major parts: *Preparation* and *AADT Estimation*.

The first part includes four basic steps that are necessary to prepare for effective data collection and sharing of traffic volume data among agencies. These steps are part of a larger safety data integration process that FHWA published in 2016. The second part, called *AADT Estimation*, includes eight steps that describe how to improve an existing stratification scheme, develop new schemes, collect traffic volume data, and estimate AADT for NFAS roads.

The intent of this framework is to assist both experienced traffic monitoring personnel and those who are new to traffic data collection and AADT estimation. The Informational Guide includes methods suitable for agencies that a) do not collect data nor estimate AADT for NFAS roads, and b) desire to improve their practices and the accuracy of their AADT estimates. For this reason, the framework incorporates both traditional (manual) stratification approaches, as well as more advanced non-traditional classification methods such as decision trees.

The target agencies of this Informational Guide are Metropolitan Planning Organizations (MPOs), Federal, State, Tribal, and local governments that own NFAS roads. The primary audience within the target agencies are traffic monitoring officials who typically collect, process, analyze, integrate, archive, publish, or report traffic data and AADT estimates. A secondary audience is traffic safety managers, analysts, and researchers who use AADT in data-driven safety analysis such as performing system-wide network screening analysis, developing crash modification factors (CMFs), calibrating and developing safety performance functions (SPFs), and evaluating the effectiveness of highway safety improvement projects and countermeasures.

The Guidebook includes relevant noteworthy practices, lessons learned, and computational examples from six pilot studies with various transportation agencies. The two appendices describe the impact of AADT estimation errors on data-driven safety analysis and present an inexpensive trip generation method that estimates traffic volumes on residential roads. Agencies do not have to conduct all the activities described in the Informational Guide. Readers are encouraged to adopt those elements most relevant to their needs given their available resources.

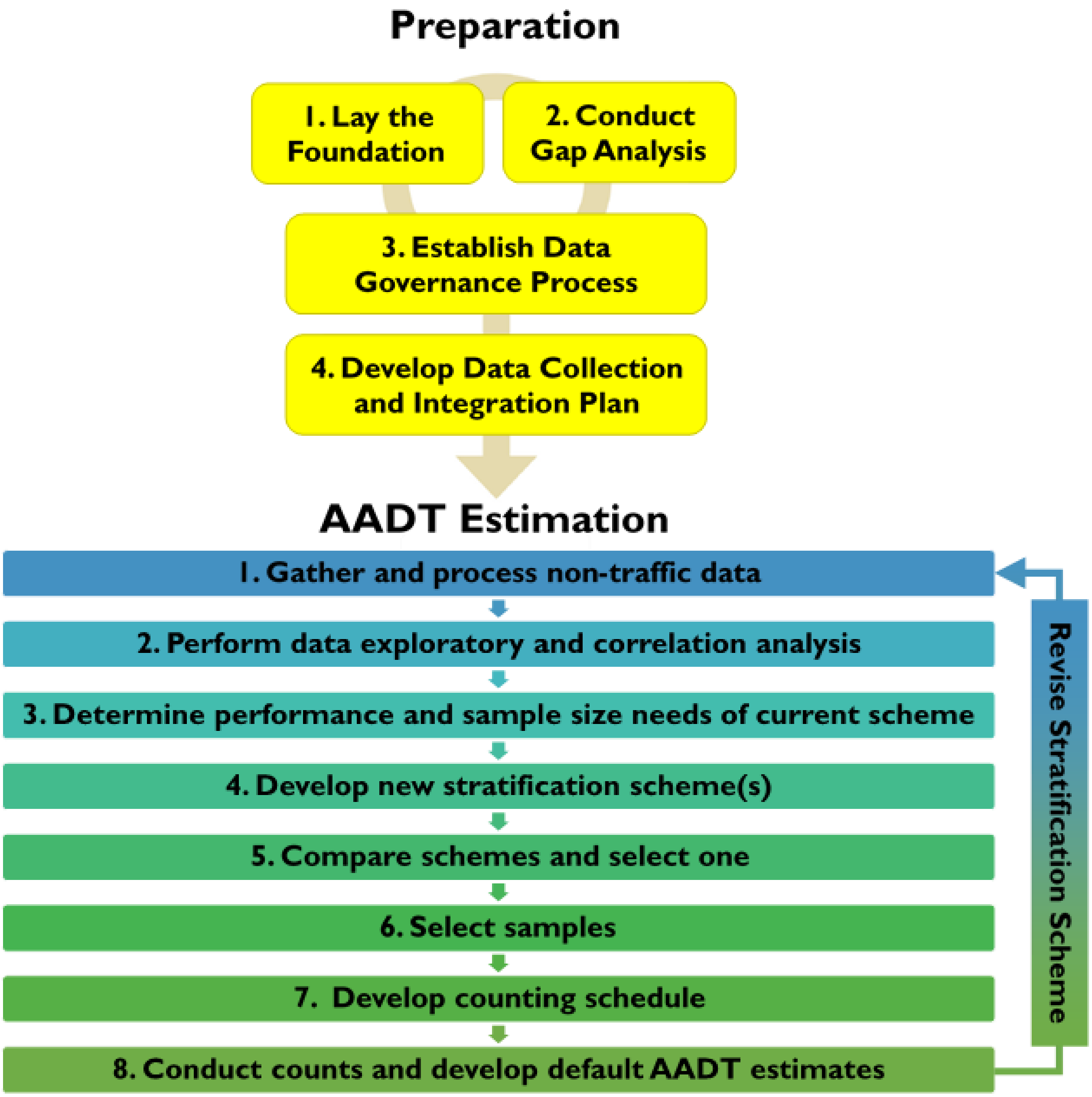


Figure 1. Flowchart. Process to Collect Data and Estimate AADT for NFAS Roads.

CHAPTER 1 — INTRODUCTION

1.1 BACKGROUND

Chapter 1 at a Glance

- 1.1 Background
- 1.2 Scope
- 1.3 Framework
- 1.4 Audience
- 1.5 AADT estimation
- 1.6 Requirements
- 1.7 Organization

Annual average daily traffic (AADT) is one of the most widely used data elements in transportation engineering. The FHWA *Traffic Monitoring Guide* (TMG)—the main reference for transportation agencies on traffic data collection, processing, analysis, and reporting—defines AADT as the "total volume of vehicle traffic of a highway or road for a year divided by 365 days".[1] Transportation agencies use AADT to meet data reporting requirements, better inform decision-making, and support various agency functions related to planning, design, operations, safety, maintenance, environmental analysis, etc.

State Departments of Transportation (DOTs) are required to report AADT every year to the Highway Performance Monitoring System (HPMS) for the full extent of mainlines, samples, and ramps on all Federal-aid facilities.[2] In addition, the 2016 Highway Safety Improvement Program (HSIP) Final Rule requires States to have access to AADT along with other Model Inventory of Roadway Elements (MIRE) Fundamental Data Elements (FDE) for all public paved roads, including non-Federal aid-system (NFAS) roads, by year 2026.[3] According to the HSIP Final Rule:

> *The MIRE FDE are beneficial because collecting this roadway and traffic data and integrating those data into the safety analysis process would improve an agency's ability to locate problem areas and apply appropriate countermeasures, hence improving safety.*

The NFAS includes roads that are functionally classified as:

- Minor collectors in rural areas (6R).
- Local roads in rural areas (7R).
- Local roads in urban areas (7U).

According to 2016 Federal Highway Administration (FHWA) *Highway Statistics*, these functional classes together account for more than 75 percent of the total roadway mileage in the United States.[4] Table 1 shows the total roadway length by functional classification and rural/urban designation.

Table 1. Total Road Length by Functional Class and Rural/Urban Designation.[(4)]

Federal Aid	Functional Classification and Rural/Urban Code	Road Length (Miles)	Percent
Yes	1R - Rural Interstates	29,133	0.7%
Yes	2R - Rural Other Freeways and Expressways	6,378	0.2%
Yes	3R - Rural Other Principal Arterials	89,728	2.2%
Yes	4R - Rural Minor Arterials	133,809	3.2%
Yes	5R - Rural Major Collectors	407,650	9.8%
No	6R - Rural Minor Collectors	258,477	6.2%
No	7R - Rural Local Roads	2,002,878	48.4%
—	**Subtotal**	2,928,054	70.7%
Yes	1U - Urban Interstates	19,058	0.5%
Yes	2U - Urban Other Freeways and Expressways	12,255	0.3%
Yes	3U - Urban Other Principal Arterials	66,137	1.6%
Yes	4U - Urban Minor Arterials	112,384	2.7%
Yes	5U - Urban Major Collectors	129,173	3.1%
Yes	6U - Urban Minor Collectors	16,961	0.4%
No	7U - Urban Local Roads	856,085	20.7%
—	**Subtotal**	1,212,054	29.3%
—	**Total**	**4,140,108**	**100.0%**

A dash denotes not applicable.

Existing Federal guidance does not fully address (as of the publication of this document) how States should collect data and estimate AADT for NFAS roads to meet the new requirements of the HSIP Final Rule. Similarly, the 2016 FHWA *HPMS Field Manual* does not provide information on AADT volume group ranges, precision levels, and sampling procedures for NFAS roads.[(2)] The HSIP Final Rule asks States to collect additional MIRE FDEs as needed to support system-wide or site-specific safety analysis.[(3)]

1.2 SCOPE

The purpose of this Informational Guide is to provide transportation agencies with information about collecting data on NFAS roads and developing AADT estimates for use in data-driven safety analysis, as defined in the HSIP Final Rule. Considering that many transportation agencies perform stratified sampling to develop default AADT estimates for NFAS roads, this Informational Guide focuses on the improvement of potentially existing stratification schemes and development of new random stratified sampling schemes. The Guide will help readers to:

- Understand basic traffic monitoring concepts.
- Understand the importance and need for producing AADT estimates for NFAS roads.
- Conduct a self-assessment on existing resources and data.

- Establish data sharing practices with other agencies.
- Validate existing stratification scheme and quantify the accuracy of current AADT estimates, if any.
- Develop new stratification schemes manually as well as by applying the classification method decision trees.
- Compare effectiveness and data needs of different stratification schemes.
- Collect traffic volume data and develop new AADT estimates.

The intent of this Informational Guide is to assist both experienced traffic monitoring personnel and those who are new to traffic data collection and AADT estimation. The Informational Guide includes methods suitable for agencies that do not collect data nor estimate AADT for NFAS roads, as well as for those desiring to improve their practices and the accuracy of their AADT estimates.

1.3 FRAMEWORK

This Informational Guide presents a framework (Figure 2) that consists of two major parts. The first part, called *Preparation*, includes four basic steps that are necessary to prepare for effective data collection and sharing of traffic volume data among target agencies. These steps are part of a larger safety data integration process that FHWA published in 2016 (*Informational Guide for State, Tribal, and Local Safety Data Integration*).[(5)] The second part, called *AADT Estimation*, includes eight steps that describe how to improve an existing stratification scheme, develop new random stratified sampling schemes, collect data, and estimate AADT for NFAS roads.

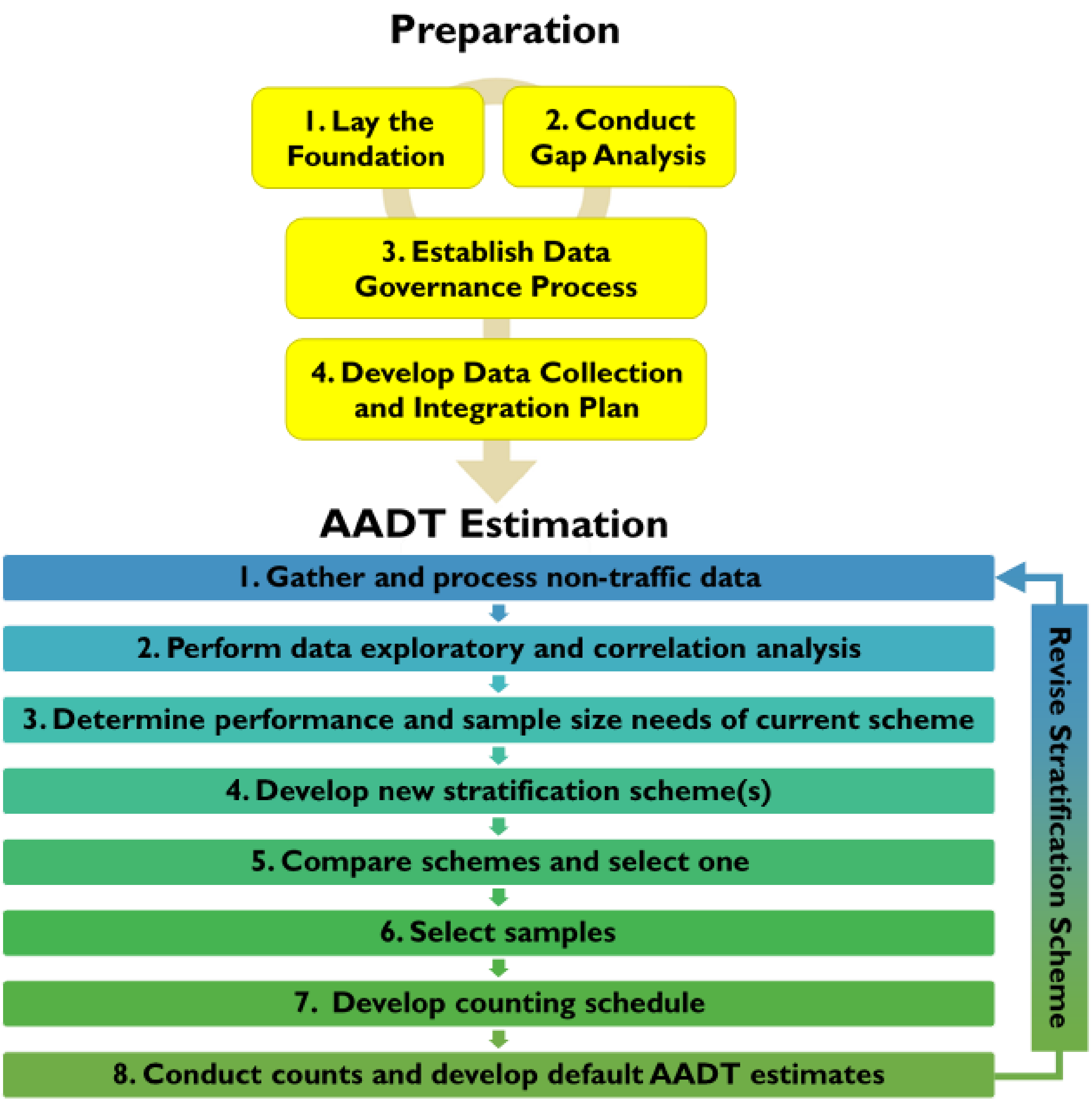


Figure 2. Flowchart. Process to Collect Data and Estimate AADT for NFAS Roads.

1.4 AUDIENCE

The target agencies of this Informational Guide are Metropolitan Planning Organizations (MPOs), Federal, State, Tribal, and local governments that own NFAS roads. Table 2 shows the total length of NFAS roads in the United States by roadway functional classification, rural/urban designation, and roadway ownership.[(4)]

Table 2. Total Roadway Length (Miles) by Functional Classification, Rural/Urban Designation, and Ownership.[(4)]

Agency - Roadway Owner	Rural Minor Collectors (6R)	Rural Local (7R)	Urban Local (7U)	Total	Percent
County	175,471	1,184,588	181,047	**1,541,106**	49.4%
Town, Township, Municipal[1]	12,757	532,539	631,302	**1,176,598**	37.7%
State Highway Agency	60,015	121,994	32,393	**214,402**	6.9%
Federal Agency[2]	7,632	119,767	7,901	**135,301**	4.3%
Other Jurisdictions[3]	2,602	43,990	3,442	**50,034**	1.6%
Total	**258,477**	**2,002,878**	**856,085**	**3,117,441**	100.0%
Percent	8.3%	64.2%	27.5%	100.0%	NA[4]

[1] Prior to 1999, municipal was included with other jurisdictions. Some States may have incomplete and missing ownership data.

[2] Roadways in Federal parks, forest, and reservations that are not a part of the State and local highway systems.

[3] Includes State park, State toll, other State agency, other local agency, and roadways not identified by ownership.

[4] Not applicable.

Counties own around 50 percent of all NFAS roads in the United States, followed by towns that own approximately 38 percent. The remaining 12 percent belongs to Federal, State, and other agencies. Rural local roads account for the majority (64 percent) of all NFAS roads, followed by urban local roads (28 percent) and rural minor collectors (8 percent).

The primary audience within the target agencies are traffic monitoring officials (e.g., managers, planners, data analysts, database administrators, Geographic Information Systems [GIS] analysts, information technology [IT] staff, and data technicians) who typically collect, process, analyze, integrate, archive, publish, or report traffic data and AADT estimates. A secondary audience is traffic safety managers, analysts, and researchers who use AADT in data-driven safety analysis such as performing system-wide network screening analysis, developing crash modification factors (CMFs), developing and calibrating safety performance functions (SPFs), and evaluating the effectiveness of highway safety improvement projects and countermeasures.[(6)]

1.5 AADT ESTIMATION

Many agencies estimate AADT using variations of a traditional method that Drusch first introduced in 1966[7] and is recommended by FHWA's TMG.[1] The traditional approach combines traffic data from permanent and portable traffic counting equipment. Permanent stations, known as continuous count sites (CCSs), collect traffic data 24 hours a day, seven days a week for either all days of the year or extended periods of time.[1] Although CCSs capture actual traffic volumes at a specific site, the purchase, installation, operation, and maintenance cost of these counters is high. Due to budgetary constraints, agencies tend to install them at select locations. For many segments where CCS do not exist, agencies collect short-duration (e.g., 24, 48, 72 hours, one week) or seasonal data using portable traffic recorders (PTRs). The goal is to accurately adjust and expand the short-duration counts to AADT estimates. The main steps of the traditional AADT estimation method are:

- Gather traffic volume data from CCSs and calculate several adjustment factors (e.g., monthly, day-of-week, axle correction factors, etc.) for each CCS. Chapter 2 provides more information about calculating basic traffic parameters and adjustment factors.
- Establish temporal (monthly or others) pattern groups that are reasonably homogenous. Create groups of CCSs or factor groups based on traditional grouping approaches (i.e., roadway functional classification and geographical stratification), cluster analysis, volume factor groups, by roadway, by area of influence, or a combination of these methods.
- Compute adjustment factors for each group of CCSs. The group adjustment factors are computed from the individual factors of the sites contained in each group.
- Assign short-duration counts to the previously determined factor groups.
- Multiply the average daily traffic (ADT) of a short-duration count with the appropriate group adjustment factor(s) to generate an AADT estimate for the counted segment.[1]

Unlike higher roadway functional classifications that agencies routinely count for various purposes including meeting HPMS requirements, NFAS roads typically have significantly lower count coverage. Further, conducting a high number of counts on the extensive NFAS road network can be financially difficult. To reduce data collection costs, many agencies combine the traditional AADT estimation approach with stratified sampling techniques that include the following general steps:

- Stratify NFAS road network to create as homogenous groups of roads (or strata) as possible in terms of AADT. The stratification is often based on one or multiple attributes (e.g., roadway functional class, rural/urban designation, etc.).

- Select and count a sample of roads from each group (or stratum). The goal of the counted samples is to provide similar traffic volumes that are representative of all the roads within each stratum.

- Calculate a default AADT estimate for each stratum using the counts collected in the previous step. The default AADT value of each stratum is assigned to every segment (within the stratum) where traffic volume data are not available – these segments are widely known as *uncounted* segments. On the other hand, *counted* segments are those for which traffic volume data exist.

While most agencies use traditional stratified sampling approaches to develop default AADT estimates for NFAS roads, there are other types of AADT estimation methods that can be broadly divided into three major groups, as shown in Figure 3.

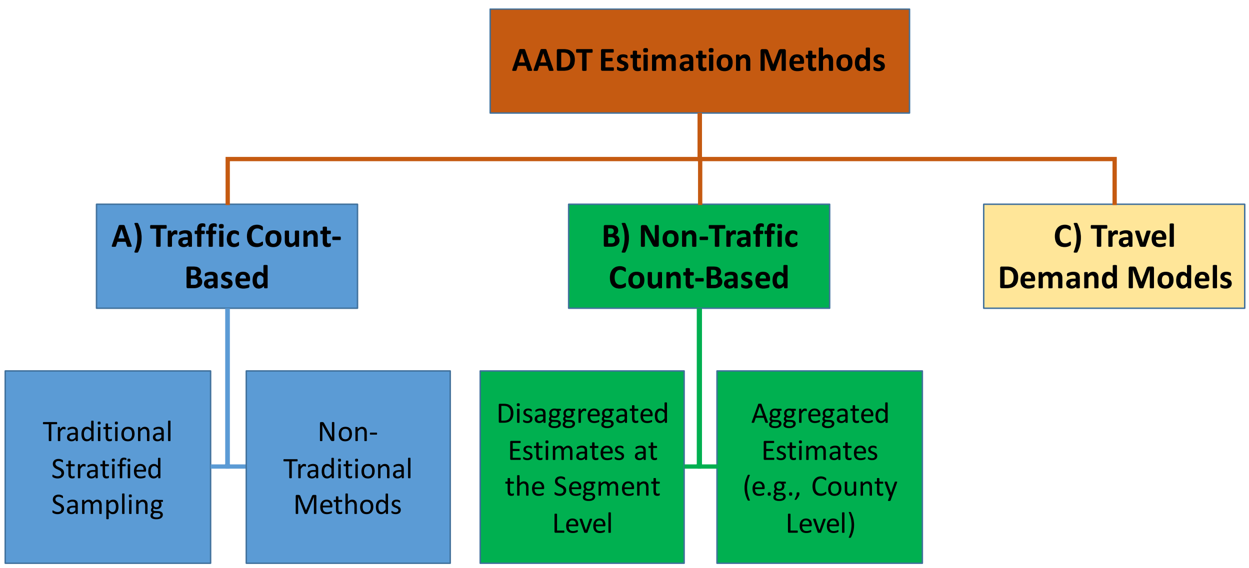


Figure 3. Chart. Types of AADT Estimation Methods for NFAS Roads.

The traffic count-based methods or simply count-based methods require traffic volume data that agencies typically obtain from continuous and short-duration traffic counters, as described above. The count-based methods mainly include traditional stratified sampling methods that most agencies use to develop default AADT estimates;[8, 9, 10, 11, 12, 13, 14, 15, 16] and non-traditional approaches such as statistical and machine/deep learning methods that directly estimate AADT by avoiding the errors inherent in each step of the traditional approach described above.[17, 18, 19, 20, 21] Estimating AADT using a combination of traffic, passively collected data (e.g., from cell phone and navigation devices), and other types of data (e.g., demographic and socioeconomic data) has attracted some attention over the last few years. Ongoing FHWA pooled-fund study *Exploring Non-Traditional Methods to Obtain Vehicle Volume and Class Data* is currently examining the accuracy of AADT estimates developed from non-traditional data sources and methods.[22]

The non-traffic count-based methods or non-count-based methods allow the direct estimation of AADT using alternative types of data such as traffic, roadway, demographic, socioeconomic, passively collected (e.g., GPS and location-based services data from mobile devices), land use, area of influence (e.g., distance from permanent sites and distance from major roads), temporal variables (e.g., hour of day, day of week, weekday, weekend, month, season), and administrative data (e.g., county boundaries and city limits). These methods can produce a) disaggregated AADT estimates at the roadway segment level,[23, 24, 25, 26, 27, 28] and b) AADT estimates aggregated by functional class, county, ZIP code, U.S. Census geographical units (e.g., block groups and tracts), area, region, and other geographical levels.[29, 30, 31, 32, 33, 34, 35]

Travel Demand Models (TDMs) incorporate mathematical equations to capture travelers' decisions and allocate trips to roads.[28, 36, 37, 38, 39] MPOs and local agencies typically develop and use TMDs to model primarily small- to medium-size areas and regions.[40] The traditional travel demand modeling process consists of four steps: trip generation, trip distribution, mode choice, and trip assignment. The main data inputs in travel demand modeling are AADT, transportation network, land use, survey, and socioeconomic data.

Among the various AADT estimation methods that exist in the literature, this Informational Guide focuses on stratified sampling that many agencies use to estimate AADT for NFAS roads.

1.6 REQUIREMENTS

The HSIP is legislated under Section 148 of Title 23, United States Code (23 U.S.C. 148) and regulated under Part 924 of Title 23, Code of Federal Regulations (23 CFR Part 924).[41, 42] The purpose of the HSIP is to achieve a significant reduction in fatalities and serious injuries on all public roads. The HSIP requires a data-driven, strategic approach to improving highway safety with a focus on performance. The Moving Ahead for Progress in the 21st Century Act (MAP-21) and the Fixing America's Surface Transportation Act continue the HSIP as a core Federal-aid program. The MAP-21 requires States to collect a subset of MIRE FDE [23 U.S.C. 148(e)(2)(A)] that are necessary to perform system-wide network screening, locate problem areas, and implement appropriate countermeasures to improve safety.

Federal requirements that govern the collection of MIRE FDE, including AADT, are:

- 23 CFR Part 924.11(b) requires States to incorporate specific quantifiable and measurable anticipated improvements for the collection of MIRE fundamental data elements into their Traffic Records Strategic Plan by July 1, 2017.
- 23 CFR Part 924.11(b) requires States to have access to a complete collection of MIRE FDE on all public roads by September 30, 2026. *Public roads* refer to any highway, road,

or street under the jurisdiction of and maintained by a public authority and open to public travel, including non-State-owned public roads and roads on tribal land (23 CFR Part 924.3). *Open to public travel* means that the road section is available during extreme weather or emergency conditions (except during scheduled periods), passable by four-wheel standard passenger cars, and open to the general public for use without restrictive gates, prohibitive signs, or regulation other than restrictions based on size, weight, or class of registration. Toll plazas of public toll roads are not considered restrictive gates [23 CFR 460.2(c)].[(43)]

- 23 CFR Part 924.17 requires States to collect a series of MIRE FDE based on the functional classification and surface type of a road, as follows: 37 MIRE FDE on non-local paved roads, 9 MIRE FDE on local paved roads, and 5 MIRE FDE on unpaved roads. AADT is required for non-local paved roads and local paved roads. This Informational Guide focuses on data collection and AADT estimation for paved rural minor collectors, and both rural and urban local paved roads.

> Transportation agencies can use HSIP funds to collect and analyze safety data, including AADT [23 U.S.C. 148(a)(4)(B)(xiv)].

FHWA *Guidance on State Safety Data Systems*[(44)] clarifies that transportation agencies can use HSIP funds to collect and analyze safety data, including AADT, to identify safety problems and countermeasures, prioritize projects, and evaluate the effectiveness of highway safety improvement projects and programs [23 U.S.C. 148(a)(4)(B)(xiv)]. The term *highway safety improvement project* is defined in 23 U.S.C. 148(a)(4) as "*strategies, activities, and projects on a public road that are consistent with a State strategic highway safety plan and…correct or improve a hazardous road location or feature…or address a highway safety problem.*" Based on this definition, the collection, analysis and improvement of safety data is an eligible project. The term *data improvement activities* means "*a project or activity to further the capacity of a State to make more informed and effective safety infrastructure investment decisions.*" [23 U.S.C. 148(f)(1)(A)]. Safety data collection, analysis, and improvement activities are provided throughout section 148. Examples of activities eligible for HSIP funding are:

1. Collecting, maintaining, and sharing safety data, including MIRE, on all public roads and related systems associated with analytical usage of the data that directly supports HSIP implementation efforts [23 U.S.C. 148(f)(1)(B)].

2. Creating, updating or enhancing a highway basemap of all public roads [23 U.S.C. 148(f)(1)(B)].

3. Improving the State's ability to identify the number of fatalities and serious injuries on all public roadways in the State with a breakdown by functional classification and ownership in the State [23 U.S.C. 148(c)(2)(D)(v)].

4. Improving data timeliness, accuracy, completeness, uniformity, integration, and accessibility [23 U.S.C. 148(c)(2)(A)(i)].

5. Evaluating the effectiveness of safety data system improvement efforts [23 U.S.C. 148(c)(2)(a)(ii)].

6. Evaluating the effectiveness of highway safety improvement projects [23 U.S.C. 148(c)(2)(F)(i)].

7. Improving the ability to link State safety data systems with other data systems within the State [23 U.S.C. 148(c)(2)(A)(iii)].

8. Improving the compatibility and interoperability of safety data with other State transportation-related data systems and the compatibility and interoperability of State safety data systems with data systems of other States and national data systems [23 U.S.C. 148(c)(2)(A)(iv)].

9. Improving the ability to collect data on non-motorized (e.g., pedestrian and bicyclist) crashes [23 U.S.C. 148(c)(2)(A)(vi)].

10. Creating, updating, or enhancing a highway basemap of all public roads in a State [23 U.S.C. 148(f)(1)(B)(i)].

11. Storing and maintaining safety data in an electronic manner [23 U.S.C. 148(f)(1)(B)(iii)].

12. Developing analytical processes for safety data elements [23 U.S.C. 148(f)(1)(B)(iv)].

13. Acquiring and implementing roadway safety analysis tools [23 U.S.C. 148(f)(1)(B)(v)].

1.7 ORGANIZATION

The remaining chapters and appendices in this Informational Guide are:

- **Chapter 2 – Traffic Monitoring Concepts**. This chapter introduces basic traffic monitoring terms and concepts that relate to different types of traffic counts, data, and computation of basic traffic parameters.

- **Chapter 3 – Preparation for AADT Estimation**. This chapter provides information on how to prepare and plan for effective collection and sharing of traffic volume data among target agencies. The chapter examines the first four steps (Figure 2) of FHWA's safety data integration framework: 1) lay the foundation, 2) conduct gap analysis, 3) establish data governance process, and 4) develop data collection and integration plan.

- **Chapter 4 – Random Stratified Sampling**. This chapter describes eight steps of the AADT estimation process shown in Figure 2. The steps include: 1) gather and process non-traffic data, 2) perform data exploratory and correlation analysis, 3) determine performance and sample size needs of current stratification scheme, 4) develop new stratification schemes, 5) compare schemes and select one, 6) select samples, 7) establish and evaluate continuous count program, and 8) conduct counts and develop default AADT estimates. FHWA selected six agencies—Georgia DOT, Minnesota DOT, Montana DOT, New Mexico DOT, North Carolina DOT, and Pennsylvania DOT—for pilot studies that involved analyzing data and developing an AADT estimation work plan for each pilot state. Chapter 4 includes various calculation examples from some of these studies.

- **Chapter 5 – Conclusion**. This chapter describes the most important elements that transportation agencies should take into consideration to improve an existing stratification scheme, develop a new scheme, collect data, and estimate AADT for NFAS roads.

- **Appendix A – Impact of AADT Estimation Errors on Safety Analysis**. This appendix describes a sensitivity analysis that determined the impact of AADT estimation errors on the results of data-driven safety analysis.

- **Appendix B – Automated Estimation of AADT Using Trip Generation Method**. This appendix describes an AADT estimation procedure that incorporates a trip generation method. The method is suitable for residential roads that have one point of entry (i.e., cul-de-sacs). This method has two advantages over many traditional and non-traditional AADT estimation methods. First, it eliminates the need to carry out traffic counts in the field by yielding time and cost savings. Second, it provides more accurate AADT estimates, particularly on urban local roads where the correlations of candidate stratification variables with AADT tend to be weak to negligible.

In the first phase of the project, researchers identified noteworthy practices in data collection and AADT estimation for NFAS roads. Four agencies—Delaware Valley Regional Planning Commission (DVRPC), New York State DOT (NYSDOT), Southeast Michigan Council of Governments (SEMCOG), and Virginia DOT (VDOT)—helped develop detailed case studies of their practices that are available online at https://safety.fhwa.dot.gov/rsdp/safety_casestudies.aspx. The four case studies are:

- **DVRPC: Innovative Traffic Data Sharing Practices**. This case study highlights how DVRPC promotes traffic data sharing with other agencies and makes traffic and GIS data available to the public.[45]

- **NYSDOT: Engagement of Local Agencies in Traffic Volume Collection and Random Sampling Procedures**. This case study highlights two noteworthy practices at NYSDOT on traffic data collection agreements with local agencies and random sampling procedures for selecting traffic count locations.[46]

- **SEMCOG: Innovative Traffic Data Quality Assurance/Quality Control Procedures and Automating AADT Estimation**. This case study highlights two noteworthy practices at SEMCOG regarding short-duration traffic count validation procedures and an automated AADT estimation process.[47]

- **VDOT: Innovative Procedures in Traffic Volume Estimation**. This case study presents how VDOT estimates traffic volumes on secondary local roadways using a trip generation method instead of taking short-duration counts in the field.[48]

Examples and summaries of noteworthy practices from these four agencies are provided in green rectangles throughout this Informational Guide.

CHAPTER 2 — TRAFFIC MONITORING CONCEPTS

2.1 INTRODUCTION

Chapter 2 at a Glance

2.1 Introduction

2.2 Traffic counts

2.3 Traffic data

2.4 Traffic parameter computation

The purpose of traffic monitoring is to describe the use and performance of the roadway system through the collection, processing, and analysis of traffic data. This chapter introduces basic traffic monitoring terms and fundamental concepts that readers need to understand before reading the remaining chapters of this Informational Guide. This chapter does not provide a comprehensive review of traffic monitoring theory but presents the most important terms and concepts necessary to compute or estimate AADT for NFAS roads. These concepts relate to different types of traffic counts, data, and computation of basic traffic parameters. The FHWA TMG provides more information on various components of traffic monitoring programs.[1] Other national references include the American Association of State Highway and Transportation Officials (AASHTO) *Guidelines for Traffic Programs* and Volumes I and II of the FHWA *Traffic Detector Handbook*.[50, 51, 52]

2.2 TRAFFIC COUNTS

A count refers to the tabulation of the quantity of vehicles at a specific point along a road. This point is known as a count station or site. Based on the duration and the traffic equipment used, traffic counts are grouped into two primary categories: continuous and short-duration.

2.2.1 Continuous

Continuous count stations are permanently-installed traffic counters that automatically collect traffic data 24 hours a day and 7 days a week for all days of the year or at least for several months or seasons. Ideally, these stations record traffic data every day of the year; however, for various reasons (e.g., construction, equipment failure, seasonally closed road, inclement weather conditions), gaps in data can occur. Continuous counts refer to volume counts covering all lanes derived from CCSs for 24 hours of each day over all days in a year. Continuous data programs or permanent count programs are part of a broader travel monitoring program and involve maintaining, storing, accessing, and reporting data from CCSs. AADT is only one of the traffic parameters that can be computed using CCS data.

CCSs employ different sensor technologies, broadly categorized into two groups: intrusive and non-intrusive. Intrusive sensors refer to traffic monitoring devices that are installed on top of, under, or in the pavement. Examples of intrusive sensors are inductive-loop detectors, piezo-sensors, strain gauge sensors, fiber optics, magnetometers, and weigh-in-motion (WIM) sensors. Non-intrusive sensors are located above or to the side of the roadway. Examples of non-intrusive technologies are video image processors, microwave radar sensors, laser radar sensors, magnetometer sensors, passive infrared sensors, ultrasonic sensors, and passive acoustic sensors.

CCSs are an important traffic data source but have high installation, operating, and maintenance costs. Accordingly, agencies install them at a few carefully selected locations, limiting their spatial coverage on the network. For locations where CCSs do not exist, more affordable short-duration counts can be used, as described below.

2.2.2 Short-Duration

Short-duration or short-term count stations collect traffic data for a specified period that is less than 365 days per calendar year.[1] The duration of a count typically ranges between a few hours to a couple of weeks. Short-duration count stations can collect data by hour of day or shorter time intervals such as 15 minutes or by individual vehicle storage. The ADT is one of the main outputs that can be computed from short-duration counts. The TMG defines ADT as:

> *The total traffic volume during a given time period (in whole days), greater than one day and less than one year, divided by the number of days in that time period. ADT is also known as raw data and unadjusted or non-factored data.*

One of the goals of taking short-duration counts is to expand and convert their ADT into AADT estimates. This AADT estimation process is widely known as *factoring* and involves calculating the ADT of a short-duration count and multiplying it with one or multiple adjustment factors (e.g., axle correction factor (if a road tube count), time (hour) of day, day of week, month of year (season), and change rate year to year factor). The adjustment factors are typically derived from CCS data. Highway agencies use the counts and the AADT estimates to supply information for individual projects (e.g., corridor studies, pavement design, maintenance, repair, rehabilitation, reconstruction, traffic control studies), develop lane closure policies, safety, meet federal reporting requirements, and provide broad knowledge of roadway use.

Short-duration counting programs refer to the management aspects of non-continuous data collection activities that are part of an overall travel monitoring program. Short-duration count programs are typically divided into coverage count and special needs count subsets. The coverage count subset encompasses the roadway system on a periodic basis to meet both point-specific and area needs, including HPMS reporting requirements. The special needs subset comprises additional counts necessary to meet specific project needs of other users.[1]

The location and frequency of short-duration counts is a function of each agency's policies, funding levels, geographic areas of responsibility, and needs. The ways in which agencies balance the benefits and costs of addressing their objectives against their limited traffic-counting budgets have led to different data collection programs nationwide. Some agencies consider a weeklong count conducted every seven years with data recorded for every hour of each day to be adequate. Others conduct 48-hour counts every three years and record daily counts. The distance between short-duration counts along a roadway is also subject to agency discretion but should follow the HPMS *Field Manual*. The most common types of short-duration traffic counters are PTRs. PTRs are mobile vehicle counters or vehicle classifiers that are temporarily installed in or along the infrastructure and can be easily moved from one location to another.

Common counting equipment used on NFAS roads include low-cost traffic counters connected to hollow rubber tubes that are laid perpendicular across the monitored lanes.[53] When a vehicle passes over a hollow rubber tube, the change in air pressure causes an air switch to close, which sends an electric signal to the counter. The last decade has seen increased use of video recording technologies for traffic volume data collection. Portable video units are secured along the roadside for up to several days and then the recorded traffic video is post-processed using video image processing software to generate hourly or daily vehicle counts and/or classification data.

2.3 TRAFFIC DATA

2.3.1 Variation

Traffic volume patterns can vary temporally and spatially. For example, volumes often change throughout the day. Passenger car and truck traffic typically have different time of day patterns. Urban passenger car volumes tend to peak during the morning and evening commutes, while rural passenger car volumes tend to increase slowly until the evening when the volumes decrease. Truck volume patterns change too depending on several factors such as local activities that generate or attract truck traffic.

Day of week patterns exist for all vehicle types.[1] For example, passenger car volumes are typically constant on weekdays and then decline on weekends. Certain roads used for recreational travel will have constant volumes on weekdays and volumes will increase on weekends. Long-haul truck volumes often remain constant seven days a week for all hours of a day. Short-haul truck volumes remain constant on weekdays and then fall on weekends more than passenger cars. Passenger cars have various uses, whereas short-haul trucks are typically business related and are used infrequently on weekends.

Traffic volumes vary depending on the month of the year. There are numerous factors that contribute to month of year traffic volume variations depending on local socioeconomic activities and land uses. For example, when schools are out of session during summer months and winter break, less school related traffic (buses) is generated. Roads near beaches will have lower volumes in the winter whereas roads near ski resorts may have higher volumes in the winter. Truck traffic experiences monthly variations especially in areas with agriculture or distribution hubs.

Traffic volumes can vary from year to year. When new developments are built, a road with traditionally low and stable traffic volumes can see rapid volume growth. During economic downturns, traffic volumes can decrease from one year to the next. Areas heavily dependent on one economic sector can see dramatic changes in traffic volume from year to year depending on the growth or decline in the sector. For example, when oil prices are high there may be an increase in truck traffic on rural roads with energy development activity until oil prices decrease.

Traffic volumes vary spatially at different geographical scales. For example, traffic volumes vary by State, in different parts of a State, from one roadway to another, and even at different locations along a road. Similar differences occur for motorcycles, cars and trucks. Roads that belong to the same functional class and are nearby to each other could have different traffic volumes due to geographic, socioeconomic, demographic, land use, and other characteristics. Geographical classification can be used as a surrogate measure to describe roads with similar traffic characteristics, including AADT. Geographic stratification is particularly important when different parts of a State experience different travel behavior. For example, roads that experience heavy recreational activity tend to have different traffic patterns and AADTs than roads that do not carry recreational traffic. Even in urban areas where travel is more stable throughout the year, cities with heavy recreational movements have different patterns than cities in the same State without recreational travel.

This Informational Guide focuses on data collection and AADT estimation methods that capture the total vehicle volume in both directions of travel, not separately in each direction.

Some roads experience directional variation where traffic may predominately travel in one direction in the morning and the opposite direction in the afternoon. For example, this pattern can occur in suburban areas where vehicles travel toward the city center in the morning and away from the city center in the afternoon. Although it is important to understand that traffic can vary by direction, this Informational Guide focuses on data collection and AADT estimation methods that capture the total vehicle volume in both directions of travel, not separately in each direction.

2.3.2 Types

Traffic monitoring devices collect one or more types of motorized and non-motorized traffic data. The main types of motorized data include vehicle volumes, vehicle classification, speeds, axle spacing, vehicle and axle weight, vehicle length, signature, gap, headway, and lane occupancy. Non-motorized data mainly refer to bicycle and pedestrian volumes.

Most continuous and short-duration traffic counters that agencies employ on NFAS roads record total vehicle volumes. Agencies use vehicle classification counters less frequently mainly because they tend to be more expensive. Typical situations where vehicle classification data are collected include, but are not limited to, when there is a need to characterize traffic, determine traffic composition, and measure AADT of a particular vehicle class or group of vehicle classes (e.g., trucks).

Existing traffic data collection technologies count vehicles either directly or indirectly. Some technologies count each passing vehicle and others count the number of axles or record array events. Axle correction factors are required to convert axle counts into vehicle volumes. Axle correction factors are computed using vehicle classification data. Section 2.4 of this Informational Guide provides formulas for computing axle correction factors along with other basic traffic parameters.

2.4 TRAFFIC PARAMETER COMPUTATION

This section presents formulas for computing basic traffic parameters using data from CCSs and short-duration counts.

The ADT captures the total vehicle volume at a particular site within a day. ADT can be computed using both CCS and short-duration counts for a given period that is greater or equal to one day, but less than one year. The ADT is calculated as follows:

Equation 2.1:

$$ADT = \frac{1}{n}\sum_{i=1}^{n} VOL_i$$

Where:

VOL_i = total traffic volume on both directions of travel for the i^{th} day.

n = number of days in a year for which traffic volume is collected ($1 \leq n < 365$).

2.4.1 AADT

The AADT is the total vehicle volume at a site on a typical day of the year. In this Informational Guide, the term AADT computation refers to the calculation of AADT using traffic volume data collected by CCSs. On the other hand, the term AADT estimation refers to annualizing short-duration traffic counts by applying one or more adjustment factors or using non-traditional prediction models (e.g., regression) that may account for various types of traffic and non-traffic data (e.g., demographic and socioeconomic data).

The TMG provides different methods to calculate AADT. The most direct method is to calculate the average of all ADT values that are available in a given year. Although this method is simple to apply, it introduces biases when data are missing. To avoid potential sources of bias, the TMG recommends using the following formulation for computing AADT:[1, 54]

Equation 2.2:

$$MADT_m = \frac{\sum_{j=1}^{7} W_{j,m} \sum_{h=1}^{24} \left[\frac{1}{n_{h,j,m}} \sum_{i=1}^{n_{h,j,m}} VOL_{i,h,j,m} \right]}{\sum_{j=1}^{7} W_{j,m}}$$

Equation 2.3:

$$AADT = \frac{\sum_{m=1}^{12} d_m * MADT_m}{\sum_{m=1}^{12} d_m}$$

Where:

$MADT_m$= monthly average daily traffic during the mth month of the year.

$VOL_{i,h,j,m}$ = total volume for the i^{th} occurrence of the h^{th} hour of the day within the j^{th} day of the week during the m^{th} month.

i = occurrence of a particular hour of day within a particular day of the week in a particular month for which traffic volume is available (i = 1, 2, …, $n_{h,j,m}$).

h = hour of the day (h = 1, 2, …, 24).

j = day of the week (j = 1, 2, …, 7).

m = month of the year (m = 1, 2, …, 12).

$n_{h,j,m}$ = number of times the h^{th} hour of the day within the j^{th} day of the week during the m^{th} month has available traffic volume ($n_{h,j,m}$ ranges from 1 to 5 depending on hour of day, day of week, and data availability).

$W_{j,m}$ = the weighting for the number of times the j^{th} day of week occurs during the m^{th} month (either 4 of 5). The sum of the weights in the denominator is the number of calendar days in the month (i.e., 28, 29, 30, or 31).

d_m = the weighting for the number of days (i.e., 28, 29, 30, or 31) for the m^{th} month in a particular year.[54]

This method does not require complete data from all 24 hours of a day and is more accurate than other AADT calculation formulas, especially in cases where data may be missing during some hours or days of a year.

2.4.2 Factors

Short-duration counts usually require several adjustments to expand a raw count into an AADT estimate. Adjustments are necessary to reduce the effects of temporal bias and convert the number of axles, if available, to number of vehicles. The specific set of adjustments needed is a function of when a count was taken within a year, the duration of the count, and the equipment used to collect the count. These adjustments are made by developing and applying appropriate factors.

Factors are unitless ratios mainly computed from CCS data. There are several types of factors such as temporal adjustment factors, axle correction factors, K-factor, D-factor, and peak hour factors. This Informational Guide presents temporal adjustment factors and axle correction factors that are needed to develop AADT estimates from short-duration counts.

2.4.2.1 Temporal Adjustment Factors

Temporal adjustment factors are used to expand short-duration counts into annual estimates (i.e., AADT). The goal of using these factors is to correct temporal bias in short-duration counts by hour of day, day of week, month of year, season, or year (if count not conducted in current year). Adjustment factors can be calculated by dividing the AADT of a CCS by the average traffic volume capturing the duration of the desired adjustment factor. For example, a monthly adjustment factor is the ratio of AADT to monthly average daily traffic. For more information see FHWA's TMG.[1]

Sometimes, two or more adjustment factors are combined. For example, day of week and monthly factors can be combined to create a single factor for each day of week of each month, resulting in 84 adjustment factors per year. In this example, the adjustment factor is the ratio of AADT to monthly average weekday traffic.

Ideally, a short-duration count collected in a certain year should be adjusted with factors developed from continuous count data for that same year. This can create delays in timing of developing adjustment factors because annual continuous count data will not be available until the end of the year. One solution provided in the TMG is to develop temporary adjustment factors by applying last year's factors; computing an average of the three previous year's factors; or computing a 12-month rolling average (for example, the temporary August 2018 factor would be computed using data from July 2017 through August 2018).[1]

2.4.2.2 Axle Correction Factors

Axle correction factors are used to adjust axle counts into vehicle counts. Axle correction factors are developed by dividing the total number of vehicles counted by the total number of axles on those vehicles. Axle factors must be obtained from per vehicle classification or WIM site data. Axle correction factors can vary significantly on different roads. Ideally, the axle correction factor applied to an axle count should come from a vehicle classification count taken nearby on the same road and during the same period. When these types of axle correction factors are not available, the TMG recommends applying a system-wide axle correction factor.

In general, a short-duration axle count is converted to an AADT estimate with the following formula:

Equation 2.4:

$$AADT_i = VOL_i \times F_m \times F_d \times F_h \times F_{a,i} \times F_g$$

Where:

$AADT_i$ = estimated annual average daily traffic at location *i*.

VOL_i = average daily axle volume at location *i*.

F_m = applicable monthly (seasonal) factor.

F_d = applicable day of week factor (if needed).

F_h = applicable hour of day factor (if needed).

$F_{a,i}$ = applicable axle-correction factor for location *i* (if needed).

F_g = applicable yearly change rate factor (if needed).

This formula needs to be modified, as necessary, to account for the traffic count's specific characteristics. For example, if the short-duration count is taken with an inductive loop detector instead of a conventional pneumatic axle sensor, the axle correction factor ($F_{a,i}$) is removed from the formula. Similarly, if the count is taken for seven consecutive days, the day of week factor (F_d) can be removed from the equation. Lastly, change rate factors are only needed if the count was taken in a year other than the year for which AADT is being estimated.

CHAPTER 3 — PREPARATION FOR AADT ESTIMATION

3.1 INTRODUCTION

Chapter 3 at a Glance

This chapter provides information on how to prepare and plan for effective collection and sharing of traffic volume data among target agencies. The chapter recommends following the first four steps of a safety data integration framework published by FHWA.[(5)] The four steps include: 1) lay the foundation, 2) conduct gap analysis, 3) establish data governance process, and 4) develop data collection and integration plan.[(5)] Within these four steps, this chapter presents noteworthy data sharing practices at state and local agencies and provides lessons learned from a 2017 peer exchange on safety data integration and AADT estimation for NFAS roads.

3.1.1 Safety Data Integration Framework

In 2016, FHWA published an *Informational Guide for State, Tribal, and Local Safety Data Integration*.[(5)] The Informational Guide defines data integration as "…*the linking of multiple data sources to meet user's needs.*"[(5)] *Safety data* refers to three core data sources: crash, roadway inventory, and traffic volume data such as AADT. The goal of the 2016 Informational Guide is to help State, Tribal, and local agencies meet federal requirements pertaining to safety data integration and use of integrated safety data:[(55)]

> *Consistent with the purpose and scope of the HSIP, a State shall have in place a safety data system to perform safety problem identification and countermeasure analysis [23 U.S.C. 148 (c)(2)(A)]. The statute also specifies that a State shall advance the capabilities of the State for data collection, analysis, and integration in a manner that includes all public roads, including non-State-owned public roads and roads on tribal land in the State [23 U.S.C. 148 (c)(2)(D) and (D)(ii)].*

The 2016 Informational Guide introduced a safety data integration framework (Figure 4) that includes nine steps. The first four steps are part of the Preparation phase of the integration process. These preparation steps are also necessary to establish AADT data collection and sharing practices. Step 5 involves identifying training needs and connects the preparation steps with the implementation Steps 6 through 9.

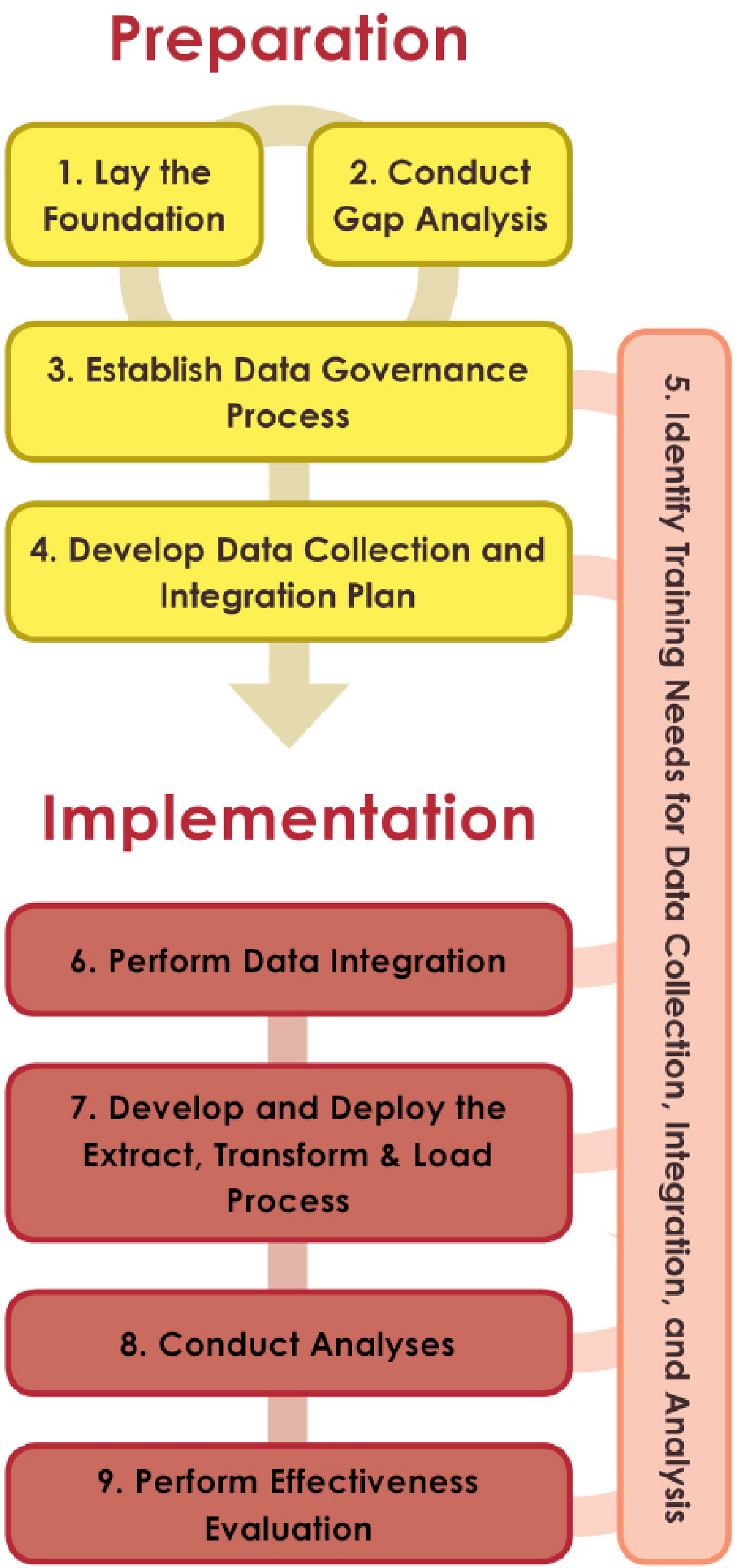


Figure 4. Flowchart. Nine-Step Safety Data Integration Framework.[5]

The following sections describe the preparation steps (Steps 1 through 4) of the safety data integration framework by focusing on those elements that relate to AADT data collection and sharing. However, larger safety data integration efforts need to consider many MIRE-FDEs, not just AADT.

3.2 STEP 1: LAY THE FOUNDATION

Laying the foundation for effective cooperation and coordination among target agencies is the first preparation step for collecting and sharing AADT data. Considering the extensive and diverse use of traffic volumes in several fields, various stakeholders from all target agencies should participate in this effort:

- Executive managers and leaders.
- Traffic monitoring staff including data managers, data analysts, and data technicians.
- Safety program managers, safety engineers, and crash data analysts.
- GIS managers, enterprise data managers and roadway inventory data stewards.
- Information technology staff.
- Planners and design engineers/managers.
- Maintenance engineers/managers.
- Infrastructure managers.

The leaders of each target agency need to determine the staff that should participate in this collaborative effort. Frequently, state agencies take the lead in a safety data integration effort, due to the greater spatial extent of their jurisdiction over a road network. However, other structures, where local agencies provide leadership, also exist.[5] This Informational Guide does not suggest that a specific agency should take the lead. It is emphasized, nonetheless, that collaboration, partnerships, and frequent coordination among target agencies is critical for the success of this effort.

A critical activity during the first step of data integration is the development of effective multi-agency coordination. For the success of a data integration project, it is important that:

- The executive management is fully invested in the project and project leaders have gained approval for a strategic data integration plan and secured required resources.[56]
- Project leaders need to be mindful of proprietary interests of stakeholders, long-standing practices for processing, using and accessing the data, and existing independent systems that various agencies may have developed over time.[56]

- Stakeholders need to develop a sense of ownership of the final product to achieve buy-in, trust, and cooperation. This can be achieved by informing and involving all project participants and by collecting and addressing each participant's concerns.(56)
- Participants need to articulate clear goals, establish formal data sharing agreements and memoranda of understanding (MOUs), and foster productive communication by enforcing rules for respectful dialogue during group meetings.(57)

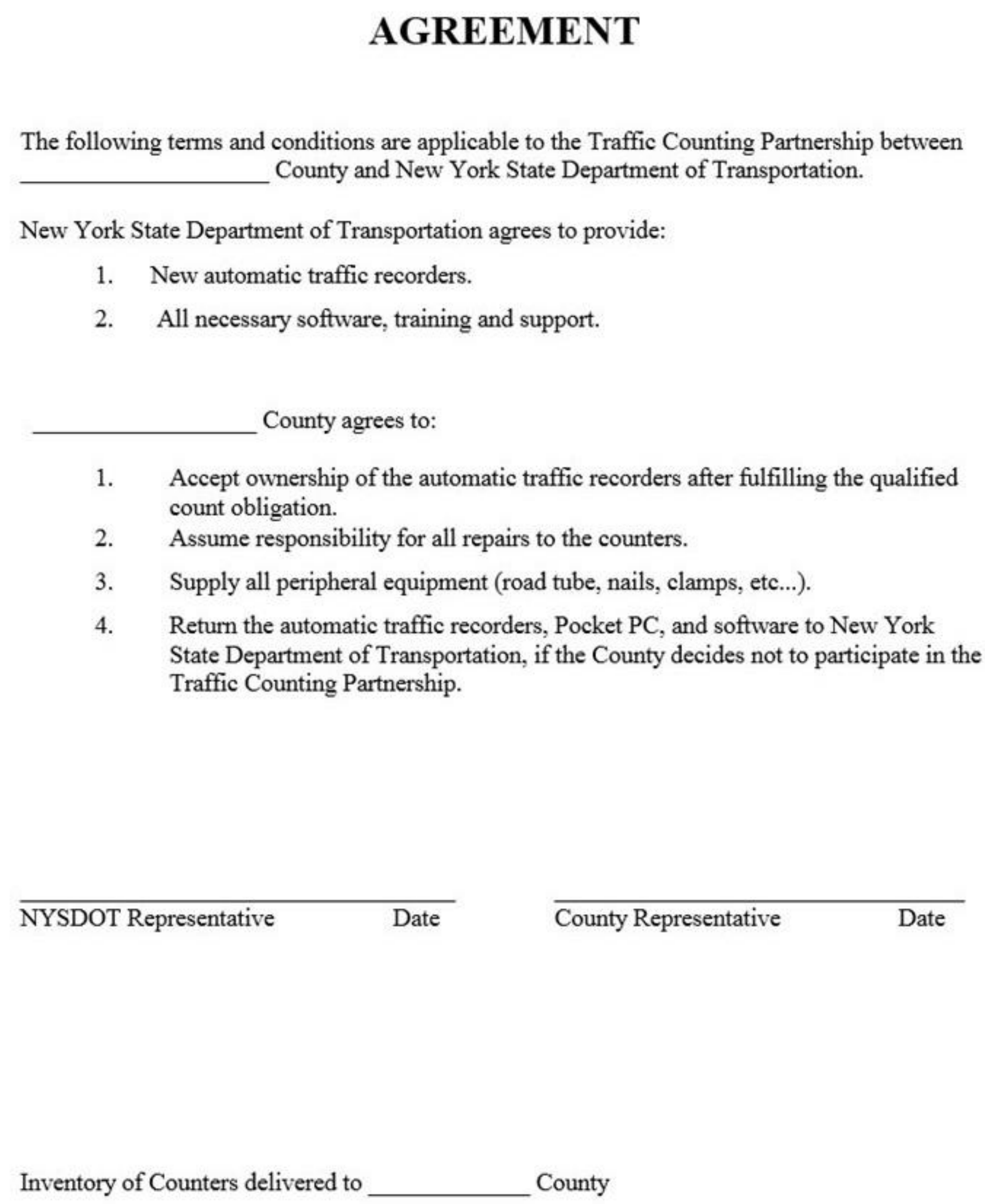
The *FHWA Informational Guide for State, Tribal, and Local Safety Data Integration* describes four case studies with the Arizona DOT, the Indiana DOT, the Navajo DOT, and the Rhode Island DOT. Based on the case studies, the report provides a list of lessons learned about partnerships, summarized as follows:

- There might be agencies that are not directly related to transportation issues but might add value to a data integration project.
- A data integration project might require more time and resources from participating agencies than initially expected.
- A data sharing MOU can be helpful to define the purpose of the project, expectations, shared responsibilities, and set a project mission and goals.

New York State Department of Transportation – Partnership Agreements with Local Agencies for Data Collection(46)

The New York State Department of Transportation (NYSDOT) estimates AADT annually on 115,000 miles of public roads using data from thousands of short-duration counts.(46) NYSDOT conducts only 2 percent of these counts. Contractors and local agencies conduct 84 percent and 14 percent of the counts, respectively. NYSDOT executes partnership agreements with local agencies to conduct counts. NYSDOT uses a memorandum of agreement (MOA), Figure 5, to facilitate these partnerships.

As part of this agreement, NYSDOT purchases and provides traffic counters and supporting equipment, software, and training to local agencies, which in turn have to conduct a minimum of two counts per counter per year for five years. Local agencies take the majority of counts on NFAS roads that NYSDOT would not have otherwise counted. If a county does not fulfill its obligation to the state, it must return the equipment to NYSDOT.



AGREEMENT

The following terms and conditions are applicable to the Traffic Counting Partnership between ____________________ County and New York State Department of Transportation.

New York State Department of Transportation agrees to provide:

1. New automatic traffic recorders.
2. All necessary software, training and support.

__________________ County agrees to:

1. Accept ownership of the automatic traffic recorders after fulfilling the qualified count obligation.
2. Assume responsibility for all repairs to the counters.
3. Supply all peripheral equipment (road tube, nails, clamps, etc...).
4. Return the automatic traffic recorders, Pocket PC, and software to New York State Department of Transportation, if the County decides not to participate in the Traffic Counting Partnership.

NYSDOT Representative	Date	County Representative	Date

Inventory of Counters delivered to _____________ County

Source: Michael Fay, Director, Highway Data Services Bureau, NYSDOT

Figure 5. Scanned Document. NYSDOT Traffic Counting MOA.[46]

Lessons learned from NYSDOT's partnerships with local agencies are:[46]

- A mutually beneficial partnership will reduce costs for the DOT and provide hardware, software, training, and data analysis to the local agency.
- The minimum number of counts can be set so that the DOT will at least break even when providing local agencies with traffic counters and related equipment, training, and support compared to the cost of outsourcing data collection activities.
- Working with the manufacturer of the traffic data recorders is crucial to ensure data compatibility.
- Adequate training and standards are necessary to ensure valid data collection.
- Developing good working relationships with other agencies and understanding their needs, priorities, and objectives can improve the probability of success.

In summary, *Step 1 Lay the Foundation* should incorporate the following activities:

- Secure the commitment of executive management.
- Forge partnerships with data integration stakeholders.
- Establish MOUs and/or data sharing agreements.
- Establish communication processes to inform and involve all stakeholders.

3.3 STEP 2: CONDUCT GAP ANALYSIS

A gap analysis compares the current state to a desired state of a program, determines existing assets and program strengths, and identifies needs, potential deficiencies, and necessary improvements to reach the desired conditions. In the case of AADT, the gap analysis involves not only identifying counted and uncounted segments, but also reviewing and determining other key elements of a program including, but not limited to, existing resources, costs, equipment, data, technical capabilities, and business practices and procedures.

The main benefits of conducting a gap analysis include time and cost savings related to data collection, management, and accessibility, and the identification of opportunities to improve data quality and completeness. Target agencies can realize these benefits by maximizing the use of existing resources, minimizing unnecessary data collection efforts, eliminating inefficient processes, and implementing cost-effective practices and procedures to meet their needs and MIRE FDE requirements.

According to the TMG, transportation agencies should conduct a comprehensive strategic evaluation of their entire traffic monitoring program at least once every five years.[1] This comprehensive evaluation should include all aspects of a program covering all roadway functional classes, including NFAS roads. A targeted gap analysis that focuses on NFAS roads can be a part of the comprehensive evaluation of an agency's entire program, but agencies can also conduct it independently, depending on their schedule and priorities.

It is important to establish a diverse team to perform the gap analysis. The team should include subject matter experts from different functional areas, departments, or sections of an agency. The team members should collectively have the experience and knowledge required to identify, gather, review, and in some cases analyze various traffic, roadway, financial, and administrative elements, as well as relevant business practices and procedures. The following subsections describe the most important activities, elements, processes, and procedures that a gap analysis should consider.

3.3.1 Traffic Volume Data

Analysts should gather all historical and recent traffic volume data from all partner agencies and compile them, if possible, into a single database. For completeness, analysts should include data from CCSs, if available on NFAS roads, and mark them accordingly to distinguish them from short-duration counts.

> Gathering as many traffic counts as possible from both internal and external sources can reduce the number of counts required for sampling purposes (see section 4.4.3), resulting in data collection cost savings.

The main data attributes of interest include, but are not limited to:

- Unique identification (ID) number of count or CCS.
- HPMS functional class.
- Traffic volume counting method (e.g., CCS, PTR, statistical method, etc.).
- Count technology (e.g., total volume, vehicle classification).
- Entity that took the count and provided the data (e.g., contractor, in-house staff, partner agency).
- Traffic equipment vendor and software version.
- Start and end dates and times of a count.
- Road name.

- Linear referencing system (LRS) route ID.
- LRS location point.
- Latitude and longitude (or other linear reference point if geographic coordinates are not available).
- AADT (or ADT if counts are not factored).
- AADT year.
- Direction and/or lane of travel reported.
- AADT estimation method, if multiple methods are in place (e.g., factoring, trip generation method, regression model, neural network).
- Amount of missing data, if any at all.
- Restrictions such as:
    - Construction or other activity affected traffic flow, but not traffic pattern.
    - Traffic counting device problem (e.g., malfunction or overflow).
    - Weather affected traffic flow, but not traffic pattern.
    - Construction or other activity affected traffic flow and traffic pattern.
    - Weather affected traffic flow and traffic pattern.

3.3.2 Network Segmentation

Agencies need to review their LRS roadway network, and update it, as needed, by adding potentially new and missing NFAS roads. The development of a sampling plan requires a complete and well-defined universe of roads that has been properly sectionalized. Ideally, agencies should segment the network using existing AADT data. Though this may be possible on higher functional classification roads that have high coverage with count data, many states have limited traffic volume data on NFAS roads.

To overcome this challenge, agencies should create intersection-based segments. That is, each segment should start and end at consecutive access points such as intersections and ramps, so that the AADT does not vary along each segment. The intersection-based segmentation can more accurately capture the actual counted and uncounted portions of the network, compared to other types of roadway segmentations that agencies may use for inventory and other purposes. For example, many agencies create homogenous sections, so that all roadway inventory elements (e.g., number of lanes, lane width, shoulder width, etc.) are constant along each section, even if AADT does not vary from one section to the next. This may result in multiple consecutive segments that can have the same AADT. From an AADT estimation perspective, consecutive segments that do not have intermediate access points (i.e., the AADT does not vary from one segment to the next) can be merged into a single segment. This will result in longer segments that reduce the number of samples (i.e., short-duration counts) required to develop default AADT estimates, as explained in Chapter 4.

It is important to document the exact location of each segment to assure that cyclical updates, field reviews, traffic counts, etc., are performed on the appropriate roadway sections.[2] Agencies should follow FHWA's *HPMS Field Manual*; *All Road Network of Linear Referenced Data (ARNOLD) Reference Manual*; and *Applications of Enterprise GIS for Transportation (AEGIST) Guidebook* to make necessary modifications to their roadway network.[2, 58, 59]

3.3.3 Counted and Uncounted Segments

One of the main gaps that this analysis aims to identify and quantify is the total roadway mileage and the corresponding percent of uncounted segments on NFAS roads. To fill this gap, analysts need to geolocate available traffic counts and identify the counted and uncounted segments on the network. Each counted segment can contain one or more AADT values that may stem from different years, AADT estimation methods, or agencies. If multiple AADT values are available for the same location or segment, a process needs to be in place to determine the official AADT value for each year. This process needs to incorporate criteria for selecting the authoritative count type, AADT estimation method, and data source. For more information see FHWA's *All Road Network of Linear Referenced Data (ARNOLD) Reference Manual*, and *Applications of Enterprise GIS for Transportation (AEGIST) Guidebook*.[58, 59]

After assigning AADT values to the network, analysts should summarize at a minimum the number, the total roadway mileage, and the corresponding percent of counted segments and uncounted segments by functional classification and rural/urban designation (i.e., 6R, 7R, and 7U), as well as for all NFAS roads together. These aggregate statistics can help analysts better understand what percent of the NFAS network does not have AADT data and where agencies need to devote future data collection and AADT estimation efforts and resources. Note that the number of counted and uncounted segments is used to calculate the number of short-duration counts required for sampling purposes, as described in Chapter 4.

3.3.4 Other Elements for Review

In addition to determining counted and uncounted segments, the gap analysis should consider, at a minimum, the following elements:

- **Data collection costs:** Estimate average costs required to conduct counts in-house and costs for outsourcing data collection activities.

  - In-house: Estimate direct and indirect costs for collecting different types of continuous and short-duration traffic data in-house. Examples of direct costs include, but are not limited to, the capital, labor, and materials required to purchase, install, operate, and maintain traffic equipment, yearly calibration of equipment and costs to gather and process data. Materials may include the traffic equipment, peripherals (e.g., cables), tools, and hardware. Examples of indirect costs include employee benefits, computer operations, administration, vehicle depreciation, and others. Target agencies should develop separate cost estimates, at a minimum, for each type of traffic equipment (e.g., CCS, portable traffic recorder) and produced data type (e.g., total volume, vehicle classification, speed, weight). In cases where data collection costs for the same type of equipment and output vary geographically, target agencies should consider developing separate cost estimates by region.
  - Outsourcing: Estimate average costs required by contractors to conduct counts. Similar to the in-house cost estimates, target agencies should develop separate cost estimates by data type and region, if needed.
- **Budget.** Estimate budget, if available, for traffic volume data collection on NFAS roads for the next data collection cycle or similar periods (e.g., for the next year, three years, five years, and 10 years).
- **Traffic equipment**. Determine number of available CCSs and portable traffic data recorders by type of equipment (e.g., total volume, classification, WIM), data output (e.g., volume, speed, weight, number of axles), and status (e.g., active, inactive, abandoned). In the case of CCSs, determine the geographic location (e.g., route ID and distance from origin, coordinates, etc.) of each station, along with the name and the FHWA functional classification of the road where the station is located.
- **Personnel**. Determine number of traffic monitoring program staff, review their roles and responsibilities, and identify those who are tasked with the collection, processing, management, and archiving of short-duration traffic data. Agencies need to develop a clear understanding and quantify the manpower and resources required to conduct and process a certain number of counts (e.g., 5,000) within a year.

3.3.5 Practices and Procedures

The gap analysis should involve reviewing, and ideally documenting, practices and procedures related to AADT estimation. Below is a list of relevant questions that will help agencies not only conduct this review, but also communicate and share their practices with their partners. It is important to answer these questions before developing a data collection and integration plan:

- **Roadway stratification**
  - Have you stratified the NFAS roadway network by creating groups of roads with similar AADT and developing default AADT values for each group?
  - If yes, did you stratify the network manually or by applying a statistical method?
  - What data attributes did you use to stratify the network and why?
  - Have you validated the accuracy of the default AADT estimates or the variability of each roadway group?
- **Sampling**
  - Do you apply sampling procedure(s) to select locations or roadway segments of future counts?
  - If yes, what sampling procedure(s) do you use?
  - How do you apply the sampling procedure(s) (e.g., spreadsheet, statistical program, scripts, other)?
- **Data collection**
  - Do you conduct short-duration counts at predetermined locations, known as historical sites?
  - What types and how many counts do you take in-house per year?
  - What types and how many counts do you outsource per year?
  - What types and how many counts do other agencies take per year?
  - What types and how many counts do you obtain from other agencies per year?
- **Factoring**
  - Do you apply temporal adjustment factors to annualize short-duration counts?
  - If yes, what types of temporal adjustment factors do you use?
  - Do you calculate adjustment factors using data from CCSs located on NFAS roads or higher functional classes?
  - Do you apply axle correction factors to the counts?
  - If yes, how do you calculate the axle correction factors?
- **Non-traditional AADT estimation**
  - Do you estimate AADT using non-traditional methods such as statistical (e.g., regression) and machine learning (e.g., neural network) methods?
  - If yes, what is the cost of developing the models?

    - What is the cost of applying the models?

- **Data management**
    - In what format(s) do you receive or gather traffic volume data?
    - Where do you store the data and who manages the database(s)?
    - Have you established data quality assurance (QA) and quality control (QC) criteria?
    - How do you apply QA/QC procedures (e.g., spreadsheet, software program, other)?
    - Have you established criteria for deleting, retaining, and archiving data?
    - How do you share the data internally and in what format?
    - How do you share the data with external entities and in what format?

Lessons learned about gap analysis conducted in previous safety data integration case studies include:[5]

- Local agency participation is fundamental to the success of the gap analysis and can be encouraged by providing benefits from the partnership. These benefits might include better data, more efficient reporting, improved asset management tools, and other analytic support.
- The gap analysis is only as good as the feedback and data provided by participants and may require an iterative approach to update data sets and refine stakeholder needs over time.
- The gap analysis is linked to the data governance step and should be repeated as needed. A data governance group may be useful to coordinate activities among partners and define data needs and gaps.
- Data gap analyses are essential to every data integration project and should include stakeholders from all affected agencies and business units. Small changes to data integration plans at the beginning of a project can have huge positive impacts and outcomes. Data gap analyses are the foundation for subsequent steps in the data integration process.

In summary, *Step 2 Conduct Gap Analysis* should incorporate the following activities:

- Gather traffic volume data from all partner agencies and compile them, if possible, into a single database.

- Update the LRS roadway network by including all NFAS roads and determine the total roadway mileage and the corresponding percent of counted and uncounted segments.
- Review and quantify, if possible, other important elements of traffic monitoring programs such as data collection costs, budget, existing permanent and portable traffic equipment, personnel, and other available resources.
- Review and document relevant business practices and procedures such as roadway stratification, sampling, data collection, factoring, AADT estimation, and data management.

3.4 STEP 3: ESTABLISH DATA GOVERNANCE PROCESS

Data governance addresses data systems and management issues by defining data standards, data definitions, data authority and ownership, data access rights and usage, and data lifecycles. Data governance helps agencies assure that their plans to address data gaps will result in desired improvements. The *FHWA Data Governance Plan* defines six strategic data governance goals and related objectives: leadership, quality, prioritization, cooperation, flexibility, and utilization.[60]

3.4.1 Leadership

Agencies need to identify champions and establish a data governance committee to monitor data integration. The committee is responsible for:

- Understanding data needs of all partner agencies.
- Identifying how partner agencies use and manage existing data.
- Developing metadata for existing data sources.
- Establishing data standards, QA/QC requirements, and data workflows.
- Documenting data governance procedures and developing training material. [5]

The data governance committee should consist of managers, data collectors, and users to ensure that efficient processes are developed in support of all user needs.

3.4.2 Quality

Agencies need to establish data standards, QA/QC procedures, and measures of data quality to ensure data are sufficient for the intended uses. It is important to define how partner agencies should collect, process, archive, secure, maintain, and disseminate data internally and externally. Agencies can quantify data quality in relation to timeliness, accuracy, completeness, uniformity, interoperability, and accessibility. These measures allow data users to make decisions about how the data might support a specific decision-making process.

In the case of traffic volume data, agencies can adopt TMG's traffic monitoring formats and instructions (TMG, Chapter 7) that States follow to report traffic data to FHWA.[1] TMG provides data definitions, naming conventions, data structures, field descriptions, reporting requirements, and examples not only for traffic volume data, but also for station, speed, vehicle classification, weight, and non-motorized data. The ASCII text format is acceptable for all motorized data.

***New York State Department of Transportation – Data Requirements for Collecting Short-Duration Counts*[46]**

NYSDOT developed a guide, titled *New York State Traffic Monitoring Standards for Short Count Data Collection*, to help NYSDOT staff, local agencies, and contractors meet data collection requirements.[61] The standards help NYSDOT ensure that the data collected by local agencies integrate seamlessly into NYSDOT's database. The guide includes minimum standards for short-duration counts, safety, traffic count sites, and other data types. NYSDOT requires traffic counts to comply with FHWA's TMG.[1] Participating agencies transfer data to NYSDOT usually weekly through email or file transfer protocol following NYSDOT procedures for file naming and data transfer. NYSDOT requires specific information to identify count locations and ensure data validity. They also conduct quality control checks of all traffic count data using manual procedures or automatic checks built into a traffic count software.

In addition to data standards, the TMG discusses the importance of implementing automated QA/QC procedures for traffic data. It provides a series of QC checks that the Travel Monitoring Analysis System and the HPMS submittal software perform on AADT values that states submit to FHWA. It also presents six case studies that describe innovative QA/QC procedures.[1]

Southeast Michigan Council of Governments – Innovative Traffic Data QA/QC Procedures[47]

SEMCOG receives every year around 3,000 short-duration counts from local agencies and conducts validity checks to ensure quality data are used for analysis. Since SEMCOG does not collect traffic data itself, local agencies upload their traffic counts to a central database. Some of these data serve local agencies' specific needs, and do not meet SEMCOG's requirements for AADT estimation. Therefore, SEMCOG identifies and excludes invalid data from AADT analysis, but the data remain in the database so that the local agency that collected the data can view and access them.

SEMCOG works with a software vendor to ensure that the database can support all traffic data collection systems that local agencies use. This eliminates the need to convert data and expedites the upload process by allowing local agencies to upload data themselves. When local agencies upload data, the software runs 15 validity checks that are built into the system. The system flags any errors that appear, and local agencies can remove the flagged data or submit all the data. Of the 15 validity checks built into the database system, the software provider developed some, and SEMCOG specifically requested others. These procedures check for missing count intervals, duplicate counts, tolerance compared to previous counts, directional split, and vehicle classification percentages. In addition to the 15 built-in checks, SEMCOG developed 46 validity checks to clean and filter data downloaded from third-party software to SEMCOG's internal database. These procedures provide an additional layer of data cleaning and filtering to complement the data cleaning processes embedded in the third-party software database.

Lessons learned from SEMCOG's validity checks include the following:

- Vendor selection is critical. With the number of agencies and amount of customization required to fully implement the procedures, an off-the-shelf product would not have worked. SEMCOG vetted the vendor to ensure it would be able to customize its software to meet the specific needs of all agencies.
- Having in-house technical expertise helps ensure that the program accomplishes the intended purpose and is sustainable. This requires coordination and buy-in from IT personnel.

- Gathering and using data collected by local agencies can increase the number of traffic counts and eliminate duplicate data collection efforts. However, local agencies may collect data for purposes other than AADT estimation, thus creating the need for validity checks.
- Developing validity checks that exceed the procedures built into third-party software is necessary to better customize procedures and handle erroneous data.
- Creating validity checks that flag and exclude erroneous data can greatly increase the accuracy and reliability of data used in different analyses.

3.4.3 Prioritization

Agencies need to prioritize efforts to address data gaps and needs. In the case of AADT, the gap analysis will likely identify more uncounted segments than what many agencies can practically count using their existing budgets and resources. As a result, agencies may select to count only a representative sample of segments on their network. Chapter 4 provides more information on how to calculate the sample size required within a stratum.

At the beginning of a year, agencies should develop a clear understanding of all the counts that need to be conducted. The partner agencies need to work together to decide which data gaps are critical in the short-term and which can wait for some time. For example, agencies should identify and prioritize potential uncounted segments for which traffic data are needed not only to develop AADT estimates, but also for other purposes and projects (e.g., special projects, safety improvement projects, pavement maintenance projects). This prioritization can minimize the need for taking additional or duplicate counts. The data governance committee can help agencies communicate and prioritize their gaps and needs. By carefully reviewing traffic count segments, location, and data requirements, it is often possible to significantly reduce the total number of counts required to meet various needs of several users.

3.4.4 Cooperation

Agencies need to collaborate, establish data sharing practices, and execute MOUs. Partners should coordinate to reduce duplication in the number and location of permanent and short-duration counts. A single count can supply information (e.g., vehicle volumes, weight, speed) that many agencies can potentially use for different purposes including intersection studies, signal warrants, pavement design, turning movements, safety analysis, and environmental studies. Communicating, coordinating, and sharing traffic volume data can yield several benefits for all stakeholders. Access to additional permanent and short-duration counts will provide data for filling data gaps, quality assurance, saving money, and facilitating data reporting and analysis if all data are integrated and stored in a central database.

However, sharing data among agencies may create several challenges and concerns that the data governance committee should identify and address by accounting for all partners' needs and developing appropriate implementation strategies. Examples of relevant challenges and recommended strategies to address them are:

- Difficulties in integrating traffic volume data that can have different data format, type, structure, resolution, duration, and outputs. The data governance committee should identify and address these issues by establishing common data standards, data sharing practices, and MOUs. The need for formal data sharing agreements is as important as it is in laying the foundation (Step 1). Having a scalable enterprise-wide data warehousing solution in place can benefit all stakeholders.
- Data security and safety concerns because of increased exposure of data to new users. Further, data owners and custodians may be bound by certain agreements that limit data sharing, use, or access to the data. The data governance committee should address these issues separately for each data set and agency by establishing formal data governance policies.
- Different data management and maintenance practices among agencies raise questions about who should update the data, when, and how often. Agencies set up their data refresh cycles based on their needs, statutory requirements, and Federal regulations. Partners must agree on responsibilities for managing traffic volume data and maintaining the basemap or LRS that provide a common foundation for the transportation data that partner agencies share. These responsibilities include notifying the data custodians for new traffic volumes, network changes, updating the basemap or LRS, and releasing updated versions of the basemap or LRS. Maintenance and updates of the LRS and traffic volume data should occur at intervals feasible and acceptable to partner agencies. LRS updates should define the date of the change to a roadway feature, so that analysts can determine when a roadway modification occurred, what the AADT was on the modified segment, and take the effect of the change into account. A simple mechanism to engage local partners and promote system adoption is to fund the system maintenance using state funds. The *FHWA Guide for State, Tribal, and Local Safety Data Integration* provides more information on how to address these issues. [(5)]
- Query performance issues because of integrating multiple data layers and systems that are physically in different locations. Data queries might execute significantly slower if data layers and tables reside in distributed systems, compared to a unified physical master data system. Although it might be easier to deal with data maintenance and custodian issues through distributed systems, it is critical to consider minimum user

requirements to ensure that analytical tools can use the data effectively. One solution is to use web services and web data feeds. [5]

Southeast Michigan Council of Governments – Traffic Data Sharing Practices[47]

Before 2001, SEMCOG received traffic data from local agencies in over 10 different formats and spent too much time converting and uploading the data into their system. To address these issues, SEMCOG now maintains a centralized traffic count database that local agencies use, so all data are compatible and easily transferable to the system. SEMCOG provides the database software and login information to each local agency so users can deploy the software locally. SEMCOG works with the software vendor to ensure that the software can support all traffic data collection systems used by local agencies. This allows each agency to collect traffic data with its own equipment and processes, just as it did before using the software. With the common software, each agency downloads data from its counters and uploads the data to the centralized database system. The software has built-in validity checks that require each agency to certify that the data are valid; however, agencies can bypass these checks. This typically only happens when an agency collects data for a specific project, such as peak-hour counts or one-directional counts. These data are not appropriate for AADT estimation but must be retained in the database for use by the agency that collected the data.

Local agencies have their own data collection plans and equipment. SEMCOG and local agencies have a user's group that meets to discuss data collection schedules and locations. SEMCOG occasionally requests local agencies count specific locations. They will hire consultants to collect data when local agencies are not able to take counts. Most of the counts that local agencies collect are short-duration counts, but may also take counts that cover shorter periods or fewer lanes or directions to meet their needs.

3.4.5 Flexibility

Agencies need to communicate creative and innovative solutions that meet all stakeholders' needs. The data governance committee should help agencies share their experiences and ideas with all stakeholders and generate solutions by considering input from all partners.

Delaware Valley Regional Planning Commission – Innovative Traffic Data Sharing Tool[45]

The DVRPC has developed an interactive web platform, the Traffic Count Viewer, that provides public access to traffic and non-traffic data that DVRPC and other external entities collect. DVRPC gathers different types of short-duration counts from various agencies, cleans and processes the data, and stores them in a regional database. Traffic Count Viewer communicates with the database, allowing users to view, filter, and download traffic counts. Users can directly connect to DVRPC's ArcGIS server map services and extract GIS layers, metadata, and traffic data in a tabular format. Further, DVRPC provides disaggregated data that reside in its database. DVRPC, transportation engineers, planners, developers, market analysts, and the general public have realized several benefits from this tool:

- Increased efficiency of the data collection program by creating and maintaining a central data depository. Users do not have to extract and process data from multiple remote data sources.
- Elimination of duplicate data collection efforts, resulting in time and cost savings for data partners and users.
- Quick and easy access to data regardless of users' objectives, background, and knowledge level in database administration and data management.
- Improved relationships with external entities by offering no-cost access to a comprehensive data source.
- Improved data transparency by allowing users to access DVRPC's ArcGIS server and download different types of data.

Lessons learned from DVRPC's practices include:

- Consider ways to collect data once with elements that meet the evolving needs of different users.
- Try to gather traffic data from various sources and create a central data repository while making sure the data meet the needs of as many users and agency functions as possible.
- Consider using open-source code and data libraries to develop tools that can have multiple end-users within and outside the organization.
- Try to have people with a background in GIS and database administration, which can benefit tool development and implementation.

- Inform managers and executives on cost savings and other benefits achieved through more-efficient processes.
- Foster people's willingness to change existing systems and business practices, learn how to use new technologies, and adapt to new, fast-evolving environments.
- Seek to have the right people in the room, which helps with decision-making.
- Involve all data users from various business areas and consider the needs and preferences of different agency functions. This helps secure broad buy-in and support.
- Relate the costs for data collection and management to the hidden cost of not having data or a data warehouse.

3.4.6 Utilization

Agencies need to improve the access and use of data. The data governance committee should help agencies communicate and overcome potential technical barriers and data access restrictions that may exist because of sensitive information and federal and state laws. Partner agencies need to develop user guidelines on how to access and properly use the data for analytical purposes.

In summary, *Step 3 Establish Data Governance Process* should incorporate the following activities:

- Identify data governance leadership, establish a data governance committee to monitor and guide data integration, and define the responsibilities of the committee.
- Establish a data quality assurance program including data standards, data accuracy, and measures of data quality.
- Establish priorities to address data gaps and needs identified in Step 2.
- Establish policies that set criteria and limits for using, sharing, and accessing each data type.
- Identify opportunities for cross-organizational collaboration, data sharing, and data integration, and establish related MOUs.
- Communicate innovative solutions among stakeholders.
- Promote appropriate data usage among stakeholders.

3.5 STEP 4: DEVELOP DATA COLLECTION AND INTEGRATION PLAN

A data collection and integration plan specifies the actions needed to reach the desired state defined in the gap analysis (Step 2). The plan describes the activities and the responsible parties in each of the previous steps. A coordinating body of stakeholders should participate in the plan development. The Traffic Records Coordinating Committee (TRCC) of each state or the data governance group could take a leadership role in the plan development. The joint FHWA and NHTSA report *State Traffic Records Coordinating Committee Noteworthy Practices* describes common practices of effective TRCC groups.[57]

In the case of AADT, the plan should describe at a minimum the AADT estimation methods that partner agencies will use along with relevant data collection needs and requirements for each method. Chapter 4 provides information that can help agencies choose appropriate stratification methods and determine data and other relevant requirements. For example, if partner agencies choose to apply traditional traffic-count based methods, their plan should describe how they will conduct sampling, who will take counts in the field, where, when, how often, and for how long.

General lessons learned from previous pilot studies that developed data collection and integration plans are:

- Starting the process to develop the plan can be difficult. A kickoff meeting with project stakeholders has been a useful strategy. Project stakeholders for the data integration plan could be the same or similar to the data governance committee or the state's TRCC. It is important that participating agency representatives are prepared to discuss objectives, work plans, and their role in the data integration project at the kickoff meeting. MOUs might help formalize the group and formally task it to deliver a plan that partner agencies can endorse and adopt.

- Establishing data integration project roles and commitments is critical. Unless cooperative relationships already exist, each participating agency should commit to a level of data sharing appropriate for the agency's available data and capabilities in terms of technology and staffing. Agencies should identify whether they plan to participate as data integrators, data providers, or data maintainers. Data version control is an important element that agencies should also address. Having a data version control process or system in place will yield benefits for several internal and external data users in the short-term, but particularly in the long run.

- Document how the resulting data resources meet the needs identified in the gap analysis. This can be achieved by documenting the requirements of business and analysis applications for various stakeholders, and then defining how the resulting data resources meet these requirements. If the data integration plan requires the development of a new database, the database developer should ensure that applications in use by stakeholders will be able to use the data in the format produced by the new database, or that procedures are in place to convert the data into a usable format.

- The data collection and integration plan should include a description of use cases for the integrated data to ensure that all stakeholder needs are met.
- It might be advantageous to structure the plan in a way that allows for quick successes, prioritizing activities that are comparatively easy to implement.
- Highlight dependencies and necessary preceding activities so that it becomes evident how the plan depends on activities within and outside the scope of the data integration project. This will make it easier to understand necessary schedule changes if related activities are not proceeding as planned.

In summary, *Step 4 Develop Data Collection and Integration Plan* should incorporate the following activities:

- Start data integration plan activities in conjunction with gap analysis and data governance efforts.
- Identify data integrator, provider, and maintainer roles for the data integration project.
- Identify a list of necessary tasks to complete the data integration project, including a list of actions within each task and a definition of how tasks depend on each other.

CHAPTER 4 — RANDOM STRATIFIED SAMPLING

4.1 INTRODUCTION

Chapter 4 at a Glance

This chapter describes an eight-step process that agencies can use to develop AADT estimates for NFAS roads. The process aims to improve potentially existing stratification schemes and develop new random stratified sampling schemes using readily available data such as U.S. Census Bureau data. The eight steps are shown in Figure 6. Before describing these steps, it is important to review relevant statistical terms and concepts that are used in this chapter.

4.1.1 Basic Definitions and Terms

Sampling refers to the process through which a *sample* of objects is extracted from the entire *population* of objects. In this Informational Guide, each NFAS road segment or section is an individual *object*, and the *population* refers to all NFAS road segments of a state transportation network (Section 3.3.2 *Network Segmentation* describes how agencies should partition the LRS network). The term *sample* refers to a subset of segments that have been extracted from a population and need to be counted. The selected segments are often called *sample segments* or simply *samples*.

The purpose of sampling is to develop as accurate AADT estimates as possible, without counting every segment on the extensive NFAS road network. There are two broad categories of sampling: *random* and *non-random sampling*. In *random* or *probability sampling* every roadway segment of the network has a known positive probability of being included in the sample. Conversely, in *non-random* or *non-probability sampling* the analyst selects the sample based on subjective criteria. The main advantage of random sampling is that the selected sample tends to be more representative of the entire population. Step 6 (section 4.7) provides more information about selecting samples, including research findings according to which random sampling results in more accurate AADT estimates than non-random sampling. [10, 13, 62]

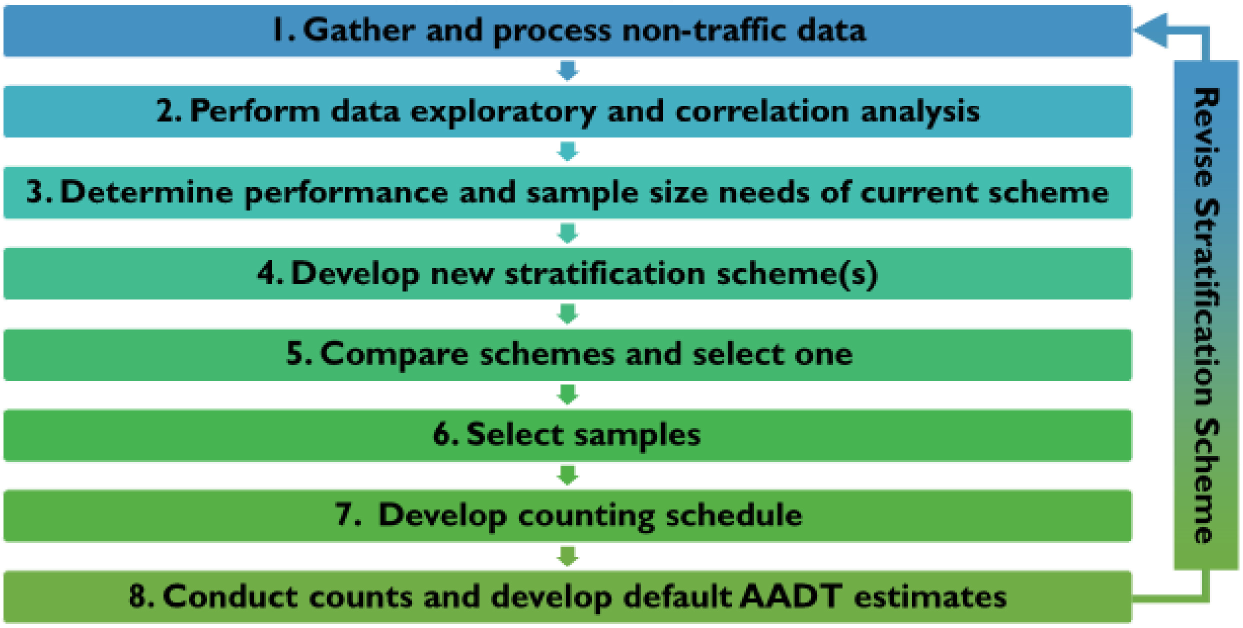


Figure 6. Flowchart. Basic Steps of Developing and Revising a Random Stratified Sampling Scheme.

4.1.2 Sampling Methods

There are various methods to design a random sampling scheme. The methods mainly differ in whether and how the population is divided into smaller groups, and the rules and procedures by which samples are selected. Some of the most common and well-documented random sampling methods are:

- Simple sampling – It involves selecting a sample of objects from the entire population without partitioning the population into strata. It is the simplest form of sampling and frequently used as a baseline to determine potential gains obtained (in the accuracy of a target estimate) when more advanced sampling methods are used.

- Stratified sampling – It involves dividing the population into groups, called *strata*, and then drawing a sample from each *stratum*. Due to limited availability of AADT data on NFAS roads, the stratification of the network is typically based on one or multiple characteristics such as functional classification, rural/urban designation, population density, etc. If the AADT variability is lower within individual strata than across strata, then stratification will permit an appreciable reduction in the total number of the samples required to develop default AADT estimates for a given confidence and precision level.

- Systematic sampling – It involves creating an ordered list of all objects in the population, then randomly selecting an object from the first *k* objects, and thereafter, selecting every *kth* object on the list.

- Cluster sampling – It involves dividing the population into naturally formed groups, called *clusters*, and then drawing a sample of clusters from the population. Note the difference between stratified sampling and cluster sampling. In stratified sampling, the sample includes objects from each stratum, whereas, in cluster sampling the sample includes objects only from the chosen clusters.

- Multistage sampling – It involves selecting a sample by using a combination of different sampling methods.

Among the various types of sampling methods that exist in the literature, this Informational Guide recommends using random stratified sampling to estimate AADT for NFAS roads. The purpose of stratifying the NFAS road network is to create strata that are internally homogenous, to the extent possible, in terms of AADT.

Each method has specific objectives, uses, strengths, and weaknesses. For more information on these methods see Cochran (1977), Lehtonen and Phakinen (1996), and Thompson (2012).[63, 64, 65] Among the various types of sampling methods that exist in the literature, this Informational Guide recommends using random stratified sampling to develop default AADT estimates for NFAS roads. The purpose of stratifying the NFAS road network is to create strata (i.e., groups of roads) that are internally homogenous in terms of AADT. The main challenge is that many states have limited traffic volume data on NFAS roads and therefore, cannot use AADT as a stratification variable. To overcome this challenge, agencies should stratify the network using roadway, administrative, and other non-traffic variables such as demographic and socioeconomic characteristics that are readily available and may be good surrogates for AADT. Note that stratified sampling can provide gains over other sampling techniques when the stratification variables are correlated with AADT and hence can explain some of the AADT variability.[8, 9, 63, 64, 65] Therefore, before developing a stratification scheme, it is important to determine which non-traffic variables may be good candidates for stratification purposes.

It is important to highlight that for safety analysis applications the goal is to develop default AADT estimates that are as close (in magnitude) as possible to actual traffic volumes at individual sites. In other applications (not examined in this Informational Guide) where stratified sampling is employed, the intent is to predict a precise mean value for a group of objects as a whole. This distinction is important because, as explained in the TMG (Chapter 3), the key to meeting the first purpose is to have more groups and very homogenous groups of roads, whereas in the second purpose the key is to have fewer groups but more samples within each group.[1]

The stratified sampling methodology described herein accounts for the following:

- Resource constraints within target agencies.
- Limited availability of permanent and short-duration count data on NFAS roads.
- Potential existence of a stratification scheme and default AADT estimates.
- Statistical needs of target agencies.
- Variability of AADT data on NFAS roads.

Before developing a random stratified sampling scheme, agencies should follow the four preparation steps described in Chapter 3. Analysts should place emphasis on Step 2 Gap Analysis and ensure that they conduct, at a minimum, the following activities:

- Gather traffic volume data from various internal and external sources, as described in section 3.3.1.
- Update and segment the NFAS road network, as described in section 3.3.2.
- Geolocate traffic counts and determine counted and uncounted segments, as described in section 3.3.3.

These activities are important because they can potentially reduce the number of sample counts and yield cost savings (for more information read section 4.4). The remaining eight sections in this chapter describe the eight steps of the AADT estimation process illustrated in Figure 6.

4.2 STEP 1 – GATHER AND PROCESS NON-TRAFFIC DATA

The first step of the process is to gather and process various external non-traffic variables, some of which may be good surrogates for AADT. A frequently asked question is: "*Which external variables should agencies gather and use to stratify their NFAS road network?*" Based on previous findings[26, 28, 30, 31] and research conducted during the development of this Guide, Table 3 provides a short list of readily available U.S. Census Bureau variables that, in general, tend to have higher correlations with AADT compared to other Census variables. To facilitate the data extraction process, Table 3 provides for each Census variable its data source, table name, field name, and web link(s) to download the data.

This Informational Guide recommends calculating the geographical density of each variable listed in Table 3. This calculation involves dividing a variable, measured within a given geographical unit (e.g., total population within a Census block group), by the land area (in square miles) of that unit. In general, as shown in section 4.3, the density of a Census variable (e.g., population density within a Census block group) typically has a higher correlation with AADT than the raw unadjusted Census variable (e.g., total population within a Census block group) that does not account for the size of the geographical unit of interest (e.g., area of Census block group). Agencies can also develop composite variables by combining two or more variables into a single variable. A typical example of a composite variable is population and employment density [Pop_Empl_Den=(Pop+Empl)/ALAND], which captures the number of residents and employees per square mile of land.(11) Another example is the density of jobs in residence and workplace areas [RAC_WAC_Den=(RAC+WAC)/ALAND].

Table 3. Readily Available U.S. Census Bureau Variables.

Variable Description (Abbreviation[a])	Data Source(s)	Table Name	Field Name
Total population (Pop)	ACS[b]	X01_Age_and_Sex	B01001e1
Total housing units (HU)	ACS	X25_Housing_Characteristics	B25001e1
Occupied housing units (OHU)	ACS	X25_Housing_Characteristics	B25002e2
Aggregate number of rooms (Agg_Rooms)	ACS	X25_Housing_Characteristics	B25019e1
Aggregate number of vehicles (Agg_Veh)	ACS	X25_Housing_Characteristics	B25046e1
Workers (>16 years) who did not work at home (Workers)	ACS	X08_Commuting	B08011e1
Aggregate income in the past 12 months (Agg_Inc)	ACS	X19_Income	B19313e1
Aggregate earnings in the past 12 months (Agg_Earn)	ACS	X19_Income	B19061e1
Employment (labor force 16 years and over) (Empl)	ACS	X23_Employment_Status	B23025e2
Area of land (in square meters) (Area)	ACS/TIGER[c]	It varies by shapefile	ALAND
Total number of jobs by residence area (RAC)	Census LEHD[d]	RAC_S000_JT00	C000
Total number of jobs by workplace area (WAC)	Census LEHD	WAC_S000_JT00	C000
Total population (C_Pop)	Decennial Census[e]	Summary_File_01	Pop10
Total housing units (C_HU)	Decennial Census	Summary_File_01	Housing10

[a] The abbreviations were developed by the authors (not by the source agencies) and used for simplicity throughout this Informational Guide.
[b] American Community Survey (ACS) data estimates are provided by the U.S. Census Bureau at different geographical levels and formats at:

- https://www2.census.gov/geo/tiger/TIGER_DP/
- https://data.census.gov/
- https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-data.html
- https://www2.census.gov/programs-surveys/acs/summary_file/
- https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml

[c] The area of the land (ALAND field) is one of several data attributes included in various geodatabases. Each geodatabase contains five-year ACS estimates developed for a specific year, state, and geographical unit. For example, the geodatabase "ACS_2017_5YR_BG_13.gdb.zip" contains 2017 ACS estimates at the Census block group level for Georgia (13). The geodatabases are available at:

- https://www2.census.gov/geo/tiger/TIGER_DP/

[d] Longitudinal Employer-Household Dynamics (LEHD) data are provided by the U.S. Census Bureau at the block level at: https://lehd.ces.census.gov/data/
[e] Decennial census data are provided by the U.S. Census Bureau at different geographical levels and formats at:

- https://data.census.gov/
- https://www2.census.gov/
- https://www.census.gov/cgi-bin/geo/shapefiles/index.php
- ftp://ftp2.census.gov/
- ftp://ftp2.census.gov/geo/tiger/
- https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml

The data sources included in Table 3 are briefly described below:

- ACS: The American Community Survey collects data continuously and develops demographic, housing, socioeconomic, employment and other types of annual and five-year estimates. One-year estimates are available for selected geographic areas with at least 65,000 people. One-year estimates are disaggregated at the Census tract level. On the other hand, ACS developed five-year estimates at the block group and tract levels using a much larger sample size extracted from more geographical areas.[(67)]

- Census LEHD: The U.S. Census LEHD Origin-Destination Employment Statistics (LODES) datasets include employment data at the Census block level. In particular, they release two datasets, called residence area characteristics (RAC) and workplace area characteristics (WAC). RAC contains the number of jobs/workers by home Census block, whereas WAC includes the number of jobs/workers by work Census block.[(68)] Analysts should aggregate both variables at the Census block group level or tract level to match the geographical resolution of the ACS estimates.

- Decennial Census: Summary File 1 (SF1) contains data gathered during the population census that is conducted every ten years. The data are available at the block level and include housing, demographic, social, and economic characteristics.[(69)] Analysts should aggregate the data at the Census block group or tract level to match the geographical resolution of the ACS and LEHD estimates, if used in the analysis.

This Informational Guide recommends downloading U.S. Census data at the block group level or tract level.[1] The reason being is that Census variables disaggregated at the block level or aggregated at large geographical units (e.g., by county) tend to have lower correlations with AADT resulting in less homogenous strata.

This Informational Guide recommends calculating the geographical density of specific Census variables aggregated at the Census block group or tract level.

Note that the list of variables in Table 3 is not meant to be exhaustive. Agencies can use it as a starting point and potentially expand it by gathering additional variables from other data sources that may be unique to each state or region. For example, in the absence of a national land use database, analysts should search if land use data exist for their area of jurisdiction and analyze them in Step 2 along with other external variables. In general, land use data (e.g., residential, industrial, agricultural, commercial, educational land use, etc.) can partially capture some of the AADT variability and may be potentially useful for roadway stratification purposes.[21, 26, 28, 29, 34]

After downloading and processing external datasets, analysts should ideally integrate the various non-traffic variables into the LRS network following FHWA's *All Road Network of Linear Referenced Data (ARNOLD) Reference Manual*, and *Applications of Enterprise GIS for Transportation (AEGIST) Guidebook*.[58, 59] Agencies should use the updated network to perform the exploratory analysis described in Step 2, as long as traffic volume data exist for NFAS roads. If no volume data are available, agencies can skip Steps 2 and 3 and proceed directly to Step 4. In this case, after agencies collect traffic volume data on NFAS roads, they should revise the original stratification scheme by revisiting all eight steps of the entire process.

[1] Many Census variables are available at different geographical levels of aggregation such as Census block, block group, tract, zip code, county subdivision, county, etc. For example, the Census block is the smallest geographical unit. Multiple Census blocks form a block group, and multiple block groups form a Census tract.

In summary, *Step 1 Gather and Process Non-Traffic Data* should incorporate the following activities:

- Download Census data.
- Calculate geographical density of Census variables at the block group or tract level.
- Gather state-specific land use data, if available.
- Integrate data into the LRS network.

4.3 STEP 2 – PERFORM DATA EXPLORATORY AND CORRELATION ANALYSIS

The purpose of this step is to conduct a data exploratory and correlation analysis to better understand the data, identify potential outliers, explore the relationships among variables, and ultimately determine potentially good surrogates for AADT for use in Step 4. The analysis should involve calculating basic descriptive statistics and developing frequency histograms, boxplots, scatterplots, and correlation matrices. It is reasonable to perform the analysis for distinct roadway groups defined by one or more variables such as roadway functional classification and rural/urban designation.

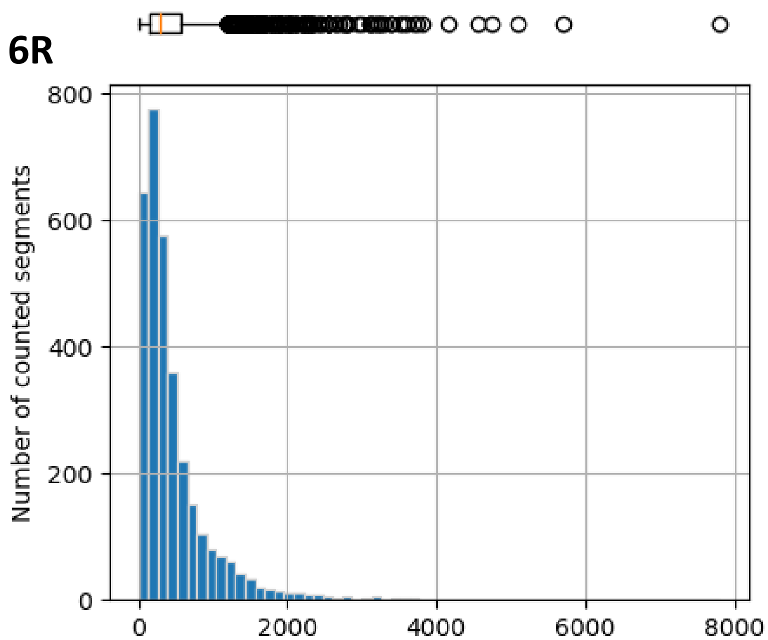
Some general trends that are frequently observed within the three roadway functional classifications of interest (i.e., 6R, 7R, and 7U) include the following:

- Suspiciously high AADT values may be present in the data suggesting further investigation. Analysts need to identify and remove potential outliers. Possible causes of outliers include, but are not limited to, incorrect (functional) classification of roadway segments, unusual traffic volumes due to special events, human errors, equipment malfunction, etc. Figure 7 shows an example of an AADT frequency histogram, boxplot, and descriptive statistics. The figure shows several high AADT values that may be potential outliers. As a general rule of thumb, agencies should review counts that are above the following traffic volume values:
    - 6R: >5,500 vehicles per day (vpd)
    - 7R: >3,500 vpd
    - 7U: >12,000 vpd

  Note that these are general criteria for reviewing suspiciously high traffic volumes. These threshold values may vary from one state to another. For example, the median

AADT within 6R in Minnesota is 303 vpd, whereas that in North Carolina is more than triple (1,100 vpd). Therefore, the threshold values will be higher in the case of North Carolina. Likewise, other descriptive statistics may vary by state. These differences show how much traffic can vary geographically, highlighting the need to perform this data exploratory and correlation analysis separately for each state.

- The standard deviation is often higher than the mean AADT. In other words, the coefficient of variation (=standard deviation/mean) is typically greater than one (>1.0).
- Among the three functional classifications, urban local roads (7R) tend to have higher traffic volumes, followed by rural minor collectors (6R), and rural local roads (7R).



Sample size		3250
Mean		469.84
Median		302.50
Mode		40
Std. Deviation		537.65
Coeff. of Var.		1.14
Variance		289065.67
Skewness		3.65
Minimum		5
Maximum		7800
Percentiles	25	155.00
	50	302.50
	75	560.00

Figure 7. Graph. Example of AADT Frequency Histogram, Boxplot, and Descriptive Statistics Indicating Existence of Outliers.

An important activity in Step 2 is to calculate the degree of correlation between AADT and each of the non-traffic variables prepared in Step 1. The Pearson product-moment correlation coefficient, *r*, is a measure of the relationship between two continuous variables. It describes the extent to which two sets of data are related. Most spreadsheets and statistical software can compute the Pearson *r*.[2] Figure 8 shows examples of correlation coefficients between AADT and various Census variables for two states. The black bold numbers (e.g., **0.37**) range between 0.04 and 0.57 and indicate statistically significant correlations at the 0.01 level (two-tailed). The black (not bold) numbers (e.g., 0.04) range from 0.03 to 0.05 and suggest statistically significant correlations at the 0.05 level (two-tailed). Values less than or equal to 0.02 are not statistically significant. The non-significant correlations are shown in dark red and parentheses (e.g., (0.01)).

[2] The Microsoft Office Excel functions =correl() and = pearson() return correlation coefficients between two datasets. If the Pearson *r* is applied to variables that are nonlinearly related, it will underestimate the relationship between the variables; in these cases, other correlation coefficients may be more appropriate.[71]

Variable Abbreviation	State A			State B		
	Functional Class & Rural/Urban Code			Functional Class & Rural/Urban Code		
	6R	7R	7U	6R	7R	7U
U.S. Census Bureau Variables						
Agg_Earn	0.21	0.10	0.10	0.28	0.11	0.10
Agg_Inc	0.22	0.11	0.09	0.27	0.11	0.08
Agg_Rooms	0.17	0.10	0.10	0.20	0.09	(0.02)
Workers	0.24	0.11	0.11	0.23	0.11	0.08
Agg_Veh	0.27	0.17	0.10	0.19	0.06	(0.00)
Empl	0.25	0.12	0.11	0.23	0.11	0.08
HU	0.16	0.11	0.08	0.17	0.07	0.04
OHU	0.19	0.12	0.09	0.22	0.09	0.05
Pop	0.20	0.10	0.11	0.22	0.09	0.04
C_Pop	0.19	0.09	0.09	0.19	0.08	(0.02)
C_HU	0.13	0.10	0.07	0.14	0.06	0.03
WAC	0.33	0.28	0.20	0.21	0.18	0.18
RAC	0.20	0.09	0.10	0.25	0.09	0.06
WAC_RAC	0.35	0.26	0.21	0.29	0.19	0.18
Pop_Empl	0.22	0.11	0.11	0.23	0.10	0.06
Density (den) of U.S Census Bureau Variables						
Agg_Earn_Den	0.39	0.21	0.05	0.38	0.27	0.22
Agg_Inc_Den	0.43	0.23	0.04	0.40	0.26	0.22
Agg_Room_Den	0.39	0.20	0.05	0.38	0.29	0.27
Worker_Den	0.54	0.31	0.06	0.41	0.27	0.28
Agg_Veh_Den	0.37	0.20	0.06	0.41	0.29	0.29
Empl_Den	0.57	0.32	0.06	0.40	0.27	0.28
HU_Den	0.39	0.22	0.04	0.36	0.26	0.26
OHU_Den	0.40	0.22	0.04	0.38	0.26	0.27
Pop_Den	0.44	0.23	0.06	0.39	0.27	0.27
C_Pop_Den	0.38	0.20	0.05	0.38	0.26	0.27
C_HU_Den	0.34	0.20	(0.02)	0.35	0.26	0.26
WAC_Den	0.53	0.45	0.11	0.18	0.21	0.15
RAC_Den	0.41	0.22	0.05	0.40	0.26	0.27
WAC_RAC_Den	0.53	0.42	0.11	0.29	0.25	0.18
Pop_Empl_Den	0.48	0.26	0.06	0.40	0.27	0.28

Figure 8. Graph. Examples of Correlation Coefficients Calculated for Two Agencies.

General observations and findings from Figure 8 and other similar correlation analyses conducted in the pilot studies of this project are summarized below:

- Overall, the density variables (see abbreviations in Table 3) that often exhibit the highest correlations with AADT are:
    - Employment density (= Empl / ALAND)

- Worker density (= Workers / ALAND)
- Population density (= Pop / ALAND)
- Occupied housing unit density (= OHU / ALAND)
- Density of jobs by workplace area (= WAC_S000_JT00_C000 / ALAND)
- Density of jobs by residence area (= RAC_S000_JT00_C000 / ALAND)

However, the correlations may vary from one state to another. A variable that may be strongly correlated with AADT within a specific roadway functional classification of a given state may have a weaker relationship with AADT in another state. Therefore, the recommendation in this Informational Guide is to separately perform a correlation analysis for each state if count data are available on NFAS roads. If count data are not available, agencies should initially stratify their network (in Step 4) using one or more of the variables listed above in combination with other readily available data such as roadway functional classification and rural/urban designation. After collecting traffic volume data in subsequent years, agencies should revise the initial stratification scheme.

- The geographical density of Census variables tends to have higher correlations with AADT than the original Census variables that users can download online.
- Higher correlations are expected for densities calculated at the Census block group or tract levels, as opposed to smaller or larger geographical units.
- The correlations tend to decrease in the following order: rural minor collectors (6R), rural local roads (7R), and urban local roads (7U).
- Correlations calculated by functional classification and rural/urban code (6R, 7R, and 7U) are typically higher compared to those calculated for all NFAS roads together at the state level.

The variables *Total Population* (field B01001e1) and *Total Housing Units* (field B25001e1) that are estimated every year by ACS tend to have higher correlations with AADT than the corresponding decennial census variables (*Total Population* and *Total Housing Units* from the 2010 census) when the analysis is performed for the nine-year period (e.g., 2001-2019) following the last decennial census. Therefore, agencies should consider using the decennial census variables *Total Population* and *Total Housing Units* if they are planning to conduct a correlation analysis for a particular census year (i.e., 2000, 2010, 2020, 2030, etc.). For all other years, agencies should use the corresponding ACS estimates.

In summary, *Step 2 Perform Data Exploratory and Correlation Analysis* should incorporate the following activities:

- Calculate basic descriptive statistics.
- Develop frequency histograms and boxplots.
- Perform correlation analysis by roadway functional classification and rural/urban designation.

4.4 STEP 3 – DETERMINE PERFORMANCE AND SAMPLE SIZE NEEDS OF CURRENT SCHEME

The purpose of this step is to validate the performance and determine the sample size needs of an existing stratification scheme, if any. Agencies that have not developed a stratification scheme and default AADT estimates cannot perform the calculations in Step 3; however, these calculations are necessary for each new scheme developed in Step 4. In Step 3, agencies should determine the following:

a) The accuracy of default AADT estimates.

b) The AADT variability within each stratum, as well as the overall variability of a scheme.

c) The number of samples needed within a stratum, as well as for the whole scheme.

d) The precision and confidence intervals of default AADT estimates.

Among these performance metrics, the accuracy of the default AADT estimates is of the utmost importance for safety analysis. The remaining sections describe how to calculate these metrics, whereas Step 5 explains how to use them to compare current and new schemes, and ultimately select one.

4.4.1 Accuracy of Default AADT Estimates

Agencies should determine the accuracy of potentially existing default AADT estimates, if any. The recommendation is to first calculate the absolute percent error (APE) for each counted segment as follows:

Equation 4.1:

$$APE_k = \frac{|AADT_{Default,\ i} - AADT_k\ |}{AADT_k} \times 100$$

Where:

APE_k = absolute percent error at counted segment *k*.

$AADT_{Default,\ i}$ = default AADT of stratum *i*, which contains counted segment *k*.

$AADT_k$ = AADT calculated from a CCS or other traffic monitoring device or derived from a short-duration count at segment *k*.

After calculating APEs, analysts should determine the median APE for each stratum, as well as for the entire scheme using simple spreadsheets. Agencies should use the same equations to determine the accuracy of new AADT estimates to be developed in Step 4.

Among several performance metrics, the AADT accuracy, calculated as the median APE within each stratum, is the most important for safety analysis applications.

Example 1: Calculation of median APE of existing stratification scheme.

Agency A stratified their NFAS roads by functional classification and rural/urban designation (6R, 7R, 7U) several years ago. The scheme includes three default AADT estimates – one estimate per stratum as shown in Table 4.

Table 4. Current Scheme and Default AADT Estimates of Agency A.

Stratum Code	Default AADT
6R	124
7R	58
7U	736

To calculate these estimates, agency A used permanent and short-duration count data that were available when they developed the scheme. Over the last few years, agency A has conducted 1,024 counts on NFAS roads: 146 counts within 6R, 439 counts within 7R, and 439 counts within 7U. Table 5 shows some of the counted segments within each stratum and the corresponding APEs. The columns are:

- Column A = number of counted segment (*k* = 1, 2, …, 1,024)

- Column B = $AADT_k$
- Column C = code of stratum which contains counted segment *k*
- Column D = $AADT_{Default,\ i}$
- Column E = APE_k, e.g., E2 = (ABS(D2-B2)/B2)*100 = 83.8%
- Column F = Median APE by stratum, e.g., for 6R: F2 = median(E2:E147) = 80.5%
- Column G = Median APE of scheme, e.g., G2 = median(E2:E1025) = 83.5%

Table 5. Calculation of Median Absolute Percent Error.

#	A	B	C	D	E	F	G
1	Count Number (*k*)	$AADT_k$	Stratum Code	$AADT_{Default,i}$	APE_k	Median APE per Stratum	Median APE of Scheme
2	1	765	6R	124	83.8%	80.5%	83.5%
3	2	450	6R	124	72.4%	80.5%	83.5%
…	…	…	…	…	…	80.5%	83.5%
147	146	950	6R	124	86.9%	80.5%	83.5%
148	147	1050	7R	58	94.5%	93.8%	83.5%
149	148	340	7R	58	82.9%	93.8%	83.5%
…	…	…	…	…	…	93.8%	83.5%
586	585	320	7R	58	81.9%	93.8%	83.5%
587	586	1860	7U	736	60.4%	74.2%	83.5%
588	587	2120	7U	736	65.3%	74.2%	83.5%
…	…	…	…	…	…	74.2%	83.5%
1025	1,024	2,470	7U	736	70.2%	74.2%	83.5%

The goal of agency A is to improve the accuracy of these estimates (83.5%) either by improving the current scheme or developing a new one. Step 4 provides information on how to address this goal.

4.4.2 Within-Stratum and Scheme Variability

As previously explained, the purpose of stratifying the network is to develop as homogenous groups of roads as possible with respect to AADT. To determine the within-stratum homogeneity, agencies should calculate the coefficient of variation (*C*) for each stratum. The coefficient of variation is the ratio of the standard deviation of AADT within a stratum to the average AADT of the stratum. To calculate *C* agencies should use AADT values calculated from CCSs (if available), other traffic monitoring devices, or short-duration counts within each stratum. Analysts can use simple spreadsheets and statistical programs to perform these calculations. After calculating the coefficient of variation of each stratum, the next step is to calculate a weighted average coefficient of variation (*WACV*) for the entire scheme as follows:

Equation 4.2

$$WACV = \frac{\sum_{i=1}^{s}(n_i \times C_i)}{\sum_{i=1}^{s}(n_i)}$$

Where:

WACV = weighted average coefficient of variation of a stratification scheme.

s = total number of strata within the scheme.

n_i = number of counted segments within stratum *i*.

i = 1, 2, …, s.

C_i = coefficient of variation within stratum *i*.

Example 2: Calculating WACV of existing stratification scheme.

Using data from the previous example, Table 6 contains the following columns:

- Column A = stratum code
- Column B = default AADT estimate developed several years ago using historical counts
- Column C = number of counts conducted over the last few years within each stratum
- Column D = mean AADT calculated using recent count data
- Column E = median AADT calculated using recent count data
- Column F = standard deviation of AADT calculated using recent count data
- Column G = coefficient of variation per stratum, e.g., for stratum 6R: G2 = F2/D2
- Column H = *WACV* of entire scheme

Table 6. Calculation of Coefficient of Variation and WACV.

#	A	B	C	D	E	F	G	H
1	Stratum Code	Default AADT	Number of Counts (n)	Mean AADT	Median AADT	Standard Deviation	Coeff. of Variation (C)	WACV
2	6R	124	146	692	590	781.5	1.13	1.23
3	7R	58	439	646	530	847.0	1.31	1.23
4	7U	736	439	1,688	1,320	2013.3	1.19	1.23

The *WACV* is calculated as follows:

$$WACV = \frac{(n_1 C_1 \ + \ n_2 C_2 + \ n_3 C_3)}{(n_1 \ + \ n_2 + \ n_3)} = \frac{(146 \times 1.13 \ + \ 439 \times 1.31 + \ 439 \times 1.19)}{(146 \ + \ 439 + \ 439)} = 1.23$$

The coefficient of variation of a stratum affects the required number of samples, as shown in the next section.

4.4.3 Sample Size

The *HPMS Field Manual* (Chapter 6) provides the following sample size estimation formula:[(2)]

Equation 4.3:

$$n_i = \frac{\frac{Z_i^2 C_i^2}{d_i^2}}{1 + \left(\frac{1}{N_i}\right)[\left(\frac{Z_i^2 C_i^2}{d_i^2}\right) - 1]}$$

Where:

n_i = required sample size within stratum *i*

Z_i = value of the standard normal statistic (Table 7) for a specific confidence level (two-sided)

C_i = coefficient of variation (described in the previous section) within stratum *i*

d_i = desired precision level (or allowable error) as a proportion of the AADT

N_i = total number of all counted and uncounted segments within stratum *i*

Table 7. Value of Z for Different Confidence Levels.

Confidence Level	Value of Z	Z Squared
90 percent	1.645	2.706
80 percent	1.282	1.644
70 percent	1.040	1.082

FHWA guidelines *Travel Estimation Procedures for the Local Functional System*(9) and research studies that focused on low functional classification roads(8, 11, 12) simplified equation 4.3 by retaining only its numerator:

Equation 4.4:

$$n_i = \frac{Z_i^2 C_i^2}{d_i^2}$$

The rationale behind this simplification is that when *N* is large, the denominator of equation 4.3 approaches 1.0 and becomes insignificant.(8, 9, 11, 12) As *N* increases, the required sample size reaches a maximum value, which is equal to the one obtained from equation 4.4. In general, equation 4.4 results in larger sample sizes than equation 4.3, but when *N* is large, the two equations produce the same results, and therefore equation 4.4 is easier to apply.

Figure 9 shows how the number of samples varies with respect to the three parameters (*C*, *Z*, and *d*) included in equation 4.4. The required sample size increases for higher confidence levels and tighter precision levels. Considering that analysts select a confidence and precision level based on their needs, the required number of samples within a stratum entirely depends on the coefficient of variation of the stratum. The more homogenous a stratum, the lower the within-stratum variability (i.e., lower coefficient of variation), and therefore, the lower the number of required samples, yielding cost savings. This highlights the importance of stratifying the network with the aim to reduce the within-stratum variability rather than to exercise administrative convenience (e.g., to easily manage future counts) which is likely to yield internally heterogeneous strata that will require more counts.

Coefficient of Variation (C)	Confidence Level - Precision Level			
	90-5	90-10	80-10	70-15
2.0	4,330	1,082	657	192
1.9	3,908	977	593	174
1.8	3,507	877	533	156
1.7	3,128	782	475	139
1.6	2,771	693	421	123
1.5	2,435	609	370	108
1.4	2,122	530	322	94
1.3	1,829	457	278	81
1.2	1,559	390	237	69
1.1	1,310	327	199	58
1.0	1,082	271	164	48
0.9	877	219	133	39
0.8	693	173	105	31
0.7	530	133	81	24
0.6	390	97	59	17
0.5	271	68	41	12
0.4	173	43	26	8
0.3	97	24	15	4
0.2	43	11	7	2
0.1	11	3	2	0

Figure 9. Graph. Number of Samples Required for Different Coefficients of Variation, Confidence Levels, and Precision Levels.

Conducting more counts within a stratum will improve the precision of the AADT estimate, but will likely not improve its accuracy (median APE).

As described at the beginning of this chapter, the accuracy of default AADT estimates is important for safety analysis applications. The key to improving the AADT accuracy is to have more strata and very homogenous strata, rather than fewer strata and more samples within each stratum.[1] Conducting more counts within a stratum will improve the precision of the AADT estimate, but will likely not improve its accuracy (median APE). Note that in this Informational Guide, the precision refers to the maximum expected difference between the true mean AADT of the entire population within a stratum and an AADT estimate developed from a sample extracted from that stratum. Therefore, by increasing the number of samples, the default AADT estimate becomes closer to the true AADT of the population of a stratum, but not necessarily closer to the true AADT of each individual segment included in the stratum. Steps 4 and 5 provide more information on this topic.

The key to improving the AADT accuracy is to have more strata and very homogenous strata, rather than fewer strata and more samples within each stratum.

As a starting point, agencies should use lower confidence and precision levels (e.g., 70-15) to calculate the required sample size within each stratum. After taking more counts, analysts should calculate a new coefficient of variation for each stratum and reapply equations 4.3 or 4.4 to determine the need for collecting more counts within each stratum.

<u>Example 3</u>: Calculation of sample size of existing stratification scheme.

Using the three coefficients of variation calculated in the previous example, one can calculate the sample size required for each stratum for different confidence and precision levels. In this example, both equations 4.3 and 4.4 were used to illustrate their differences. Table 8 includes the following columns:

- Column A = stratum code
- Column B = total number of counted and uncounted segments within a stratum
- Column C = number of counts conducted in recent years within each stratum
- Column D = coefficient of variation per stratum
- Columns E-J = sample sizes calculated using equations 4.3 and 4.4 (shown in parentheses) for three pairs of confidence and precision: 90-5, 80-10, and 70-15.

Table 8. Required Sample Sizes for Different Confidence-Precision Levels.

#	A	B	C	D	E	F	G	H	I	J
1	Stratum Code	Total Number of Segments (N)	Number of Counts (n)	Coeff. of Var. (C)	90-5 (4.3)	90-5 (4.4)	80-10 (4.3)	80-10 (4.4)	70-15 (4.3)	70-15 (4.4)
2	6R	2,054	146	1.13	826	1,382	190	210	60	61
3	7R	37,648	439	1.31	1,770	1,858	280	282	82	82
4	7U	13,035	439	1.19	1,372	1,533	229	233	68	68

For example, the sample size calculation for 6R at 70-15 confidence-precision level using equation 4.3 is:

$$n_{6R} = \frac{\frac{Z_{6R}^2 C_{6R}^2}{d_{6R}^2}}{1 + \left(\frac{1}{N_{6R}}\right) [\left(\frac{Z_{6R}^2 C_{6R}^2}{d_{6R}^2}\right) - 1]} = \frac{\frac{1.040^2\ 1.13^2}{0.15^2}}{1 + \left(\frac{1}{2{,}054}\right) [\left(\frac{1.040^2\ 1.13^2}{0.15^2}\right) - 1]} = 60\ samples$$

Agency A meets this sample size requirement because it has already conducted 146 counts (>60) within 6R. However, if agency A would like to develop a default AADT estimate at 80-10 confidence-precision level, it would have to count at least 44 (=190-146) new segments. This shows the importance of gathering as much traffic volume data as possible from internal and external entities during the preparation steps of the process (see Chapter 3).

4.4.4 Precision and Confidence Interval

For a given *n*, the precision (expressed as a proportion or percentage) of a default AADT estimate for stratum *i* is calculated as follows:[1]

Equation 4.5:

$$d_i = t_{1-\frac{\alpha}{2},n-1} \frac{C_i}{\sqrt{n_i}}$$

Where:

d_i = precision interval as a proportion or percentage of the default AADT of stratum *i*

$t_{1-\frac{\alpha}{2},n-1}$ = value of student's t distribution that corresponds to (1-α/2) confidence level and n-1 degrees of freedom

n_i = number of counts conducted within stratum *i*

C_i = coefficient of variation within stratum *i*

Note that a t-score is appropriate when the sample size is small (typically less than 30), whereas a z-score when the sample size is large (at least 30). The absolute precision interval is calculated by substituting the coefficient of variation with the standard deviation of AADT:

Equation 4.6:

$$d_i = t_{1-\frac{\alpha}{2},n-1} \frac{S_i}{\sqrt{n_i}}$$

Where:

d_i = absolute precision interval of the default AADT of stratum *i*

S_i = standard deviation of AADT within stratum *i*

The standard equation for estimating the confidence intervals for a simple random sample is:

Equation 4.7:

$$B_i = \overline{AADT_i} \pm t_{1-\frac{\alpha}{2},n-1} \frac{S_i}{\sqrt{n_i}}$$

Where:

B_i = upper and lower boundaries of the confidence interval of a default AADT estimate for stratum *i*

$\overline{AADT_i}$ = average AADT of stratum *i*

Example 4: Calculation of precision and confidence interval of default AADT estimates.

Using data from the previous example and equations 4-5 and 4-6, one can calculate the precision of the current default AADT estimates. Table 9 includes the following columns:

- Column A = stratum code
- Column B = number of counts conducted in recent years within each stratum
- Column C = average AADT within each stratum
- Column D = standard deviation of AADT within each stratum (see Table 6)
- Column E = coefficient of variation of AADT per stratum (see Table 6)

- Columns F-H = precision interval (proportion) calculated using equations 4.5 (shown in parentheses) for confidence level 90 (Column F), 80 (Column G), and 70 (Column H)
- Columns I-K = absolute precision interval calculated using equations 4.6 (shown in parentheses) for confidence level 90 (Column I), 80 (Column J), and 70 (Column K)

Table 9. Precision of Default AADT Estimates for Different Confidence Levels.

#	A	B	C	D	E	F	G	H	I	J	K
1	Stratum Code	Number of Counts (n)	Mean AADT	St. Dev. (S)	Coeff. Of Var. (C)	90 (4.5)	80 (4.5)	70 (4.5)	90 (4.6)	80 (4.6)	70 (4.6)
2	6R	146	692	781.5	1.13	0.15	0.12	0.10	106	83	67
3	7R	439	646	847.0	1.31	0.10	0.08	0.07	66	52	42
4	7U	439	1,688	2013.3	1.19	0.09	0.07	0.06	158	123	100

For example, in the case of 6R, the precision of the default AADT is estimated with 70% confidence from equation 4-6 as follows:

$$d_{6R} = t_{1-\frac{\alpha}{2},n-1}\frac{S_{6R}}{\sqrt{n_{6R}}} = t_{0.15,145}\frac{S_{6R}}{\sqrt{n_{6R}}} = 1.04\frac{781.5}{\sqrt{146}} = 67$$

Based on equation 4-7, the confidence interval of the default AADT estimate for 6R is:

$$B_{6R} = AADT_{6R} \pm t_{1-\frac{\alpha}{2},n-1}\frac{S_{6R}}{\sqrt{n_{6R}}} = 692 \pm 67$$

This means that State A can be 70 percent confident that the true AADT of all counted and uncounted segments within 6R is between 625 vpd (=692-67) and 759 vpd (=692+67).

In summary, *Step 3 Determine Performance and Sample Size Needs of Current Scheme* should incorporate the following activities:

- Calculate accuracy of default AADT estimates, if any.
- Determine AADT variability within each stratum, as well as the overall variability of a scheme.

- Compute the sample size required within each stratum, as well as for the whole scheme.
- Calculate precision and confidence intervals of default AADT estimates.

4.5 STEP 4 – DEVELOP NEW STRATIFICATION SCHEME

The purpose of Step 4 is to improve potentially existing schemes or develop new schemes that produce as accurate AADT estimates as possible by considering budgetary constraints. The selection of a scheme will be done in Step 5. Before improving or developing schemes, readers need to be aware of the following important considerations:

- <u>Number of strata and sample size</u>: In general, the accuracy of default AADT estimates tends to improve (under certain conditions as described in Step 5) as the number of strata within a scheme increases. However, by increasing the number of strata, the total number of samples required within a scheme increases as well. This makes the selection of a scheme and the number of strata within a scheme more challenging. Step 5 provides more information on how to compare schemes and select one.
- <u>Homogeneous strata</u>: As explained in Step 3, the number of samples required within a stratum (to develop a default AADT estimate at a given confidence and precision level) decreases as the homogeneity of the stratum increases. In other words, a stratum whose roadway segments have similar AADT will require fewer samples than another stratum that has the same number of segments but higher AADT variability (see section 4.4.3).

The next section describes how to stratify the network in the absence of traffic volume data on NFAS roads, while section 4.5.2 describes how to develop or improve a stratification scheme when traffic volume data already exist.

4.5.1 Stratification Without Traffic Volume Data

If traffic volume data are not available for NFAS roads, agencies cannot perform the data exploratory and correlation analysis described in Step 2. In this case, the recommendation is to initially develop a basic stratification scheme using variables that are likely to capture some of the AADT variability. The suggested variables include:

- Roadway functional classification and rural/urban designation (i.e., 6R, 7R, 7U). This can be a logical starting point to divide the entire heterogeneous population into three more homogenous groups, which should be further subdivided using some of the variables/methods listed below.

- Geographic and land use-based stratification. Based on general knowledge of the network, and land use data, if available, users should divide the entire population or the three functional classifications geographically. The stratification can be based on known industrial, agricultural, commercial, residential, recreational, or other geographic and traffic characteristics of the network.

- U.S. Census Bureau data. Analysts should divide the network or the groups created from the aforementioned methods using one or more of the following composite variables (see field names in Table 3) that, generally speaking, tend to have stronger relationship with AADT compared to raw Census variables that are available online:

    - Employment density (= Empl / ALAND)
    - Worker density (= Workers / ALAND)
    - Population density (= Pop / ALAND)
    - Occupied housing unit density (= OHU / ALAND)
    - Density of jobs by workplace area (= WAC_S000_JT00_C000 / ALAND)
    - Density of jobs by residence area (= RAC_S000_JT00_C000 / ALAND)

  The simplest way to divide (or discretize) each of these continuous variables into bins is to calculate and use percentile values[3]. For example, one can use the 33rd and 66th percentiles to divide a variable into three bins: low, medium, and high. Creating four bins would require using the 25th, 50th, and 75th quartile values as bin thresholds. A more effective way to discretize continuous variables is to use decision trees (see section 4.5.2.3); however, decision trees require the use of statistical software.

After developing an initial stratification scheme, agencies should randomly select samples as described in Step 6, establish and evaluate a continuous count program (Step 7), and start taking counts (Step 8). Then, they need to revise the original scheme by following all eight steps of the process.

[3] The Microsoft Office Excel functions =percentile() and =quartile() return percentile and quartile values of a continuous variable, respectively.

4.5.2 Stratification With Traffic Volume Data

During the preparation phase (Chapter 3), agencies should make efforts to gather potentially existing traffic volume data from internal and external sources, so that they can enhance the stratification process and reduce data collection costs. Because many agencies have counted a small portion of their NFAS road network, this section provides information on how to develop or improve a stratification scheme using limited or larger amounts of traffic volume data. Assuming that the quality of the data is acceptable, the higher the portion of counted segments on the network, the higher the anticipated efficiency of a scheme.

The remaining sections describe how to:

- Improve an existing scheme by updating its default AADT estimates.
- Develop a new scheme by applying the traditional (manual) stratification.
- Develop a new scheme by applying decision trees that are predictive modeling methods used in statistics and machine learning.

> Decision trees usually create the most homogenous strata but require the use of statistical programs.

Among these three options, the decision trees usually provide the most homogeneous strata because they create groups by minimizing the within-stratum variability. However, they require the use of statistical programs.

4.5.2.1 Update Current Scheme

A simple way to improve an existing scheme without modifying its strata, is to update its default AADT estimates. Agencies should first calculate the median AADT within each stratum using recent count data. The median AADT values should be used as the new default AADT estimates of the scheme. Then, analysts should determine the accuracy of the updated default AADT estimates as described in section 4.4.1 and illustrated in the example below.

> A simple way to improve an existing scheme without modifying the stratification criteria, is to update the default AADT estimates using recent counts.

<u>Example 5</u>: Updating and determining accuracy of default AADT estimates.

As explained in Example 1, agency A stratified their NFAS roads by functional classification and rural/urban designation (6R, 7R, 7U), and developed three default AADT estimates several years ago. Table 10 shows the original default AADT values estimated when the scheme was developed, the number of recent counts, and the median AADT of recent counts.

Table 10. Old and New Default AADT Estimates of Agency A.

Stratum Code	Original Default AADT	Number of Counts (n)	Median AADT (Updated Default AADT)
6R	124	146	590
7R	58	439	530
7U	736	439	1,320

In Example 1, the APEs and the median APE of the scheme were calculated by considering the original default AADT values as the estimated AADT. In this example, the median AADT values are used as the default AADT estimates. Table 11 shows some of the counted segments within each stratum and the corresponding errors. The columns are:

- Column A = number of counted segment (k = 1, 2, …, 1,024)
- Column B = AADT derived from count k
- Column C = code of stratum which contains counted segment k
- Column D = median AADT of each stratum (see Table 10)
- Column E = APE_k, e.g., E2 = (ABS(D2-B2)/B2)*100 = 22.9%
- Column F = Median APE by stratum, e.g., for 6R: F2 = median(E2:E147) = 66.2%
- Column G = Median APE of scheme, e.g., G2 = median(E2:E1025) = 68.3%

Table 11. Accuracy Metrics of Updated Default AADT Estimates.

#	A	B	C	D	E	F	G
1	Count Number (*k*)	$AADT_k$	Stratum Code	$AADT_{Default,i}$	APE_k	Median APE per Stratum	Median APE of Scheme
2	1	765	6R	590	22.9%	66.2%	68.3%
3	2	450	6R	590	31.1%	66.2%	68.3%
…	…	…	…	…	…	66.2%	68.3%
147	146	950	6R	590	37.9%	66.2%	68.3%
148	147	1050	7R	530	49.5%	70.5%	68.3%
149	148	340	7R	530	55.9%	70.5%	68.3%
…	…	…	…	…	…	70.5%	68.3%
586	585	320	7R	530	65.6%	70.5%	68.3%
587	586	1860	7U	1,320	29.0%	66.1%	68.3%
588	587	2120	7U	1,320	37.7%	66.1%	68.3%
…	…	…	…	…	…	66.1%	68.3%
1025	1,024	2,470	7U	1,320	46.6%	66.1%	68.3%

By updating the default AADT estimates of the current scheme using recent counts, the median APE decreased from 83.5% to 68.3%. Note that the three strata (6R, 7R, 7U) of the original scheme did not change (i.e., the same strata were used in Examples 1 and 5). Therefore, the within-stratum variability, the overall scheme variability, and the required samples will be the same as those calculated in Step 3 (Examples 2, 3, and 4).

Updating the default AADT estimates does not require a lot of time and resources and may significantly improve the AADT accuracy, particularly if a scheme was developed or last updated a long time ago. The median APE of the updated scheme should be the baseline for comparing an existing scheme against new schemes. The next logical questions are "*Can one further improve the accuracy of updated AADT estimates? If yes, how?*" The next sections address these questions.

4.5.2.2 Traditional Stratification

The traditional approach involves manually dividing the network into groups of roads using one or more variables. The key to developing an efficient scheme is to use stratification variables that are good surrogates for AADT. As described in section 4.5.1, a potential starting point is to perform the first level of stratification based on one or a combination of the following characteristics:

- Functional classification and rural/urban designation. The pilot studies in this project revealed that stratifying the entire population of NFAS roads by 6R, 7R, and 7U can capture some of the AADT variability and also provide for administrative convenience and simplicity for implementation.

- Geographic and land use-based stratification. Specific areas within a state often carry similar traffic volumes. General knowledge of the network and potentially land use data, if available, should be used to determine whether the traffic volumes in these areas are indeed homogeneous and similar to those initially expected. Industrial, agricultural, commercial, residential, recreational, or other geographic characteristics of the network may reduce the AADT variability within the entire population or the three functional classifications.

- U.S. Census Bureau Data. Analysts should divide the entire population or the previously defined groups using one or more Census variables that (based on the results from Step 2) have the strongest relationship with AADT. Generally speaking, the higher the correlation between AADT and a non-traffic variable, the higher the likelihood that the variable can better explain the AADT variability and result in more homogenous strata. A simple way to split a continuous variable into bins is to use the 25th, 50th, and 75th quartiles or other percentile values (e.g., 33rd and 66th percentiles) as break-points. A more effective way to construct more homogenous bins within a variable and overall a more efficient scheme is to use decision trees (see section 4.5.2.3).

The key to developing an effective stratified scheme is to use good surrogates for AADT. The higher the correlations between AADT and the stratification variables, the higher the likelihood that the produced strata will be internally homogeneous.

<u>Example 6</u>: Developing a new traditional stratification scheme for agency A.

Agency A wanted to improve the accuracy of the updated scheme presented in the previous example. The state divided each of the functional classifications 6R and 7R into three strata: low, medium, and high density of housing units (Table 12). Likewise, functional classification 7U was divided into three strata: low, medium, and high employment density. The Census variables were split based on the 33rd and 66th percentile values of each variable. These variables had higher correlations with AADT within these functional classifications compared to other Census variables. Table 12 includes the following columns:

- Column A = number of stratum
- Column B = functional classification and rural/urban designation
- Column C = housing unit density bin (i.e., low, medium, high)
- Column D = employment density bin (i.e., low, medium, high)
- Column E = number of recent counts within each stratum

- Column F = median AADT, used as the default AADT of each stratum
- Column G = coefficient of variation of AADT per stratum (see calculation in section 4.4.2)
- Column H = median APE per stratum (see calculation in section 4.4.1)
- Column I = required sample size (equation 4.4) for 70-15 confidence and precision level

Table 12. Characteristics and Performance of New Traditional Stratification Scheme.

#	A	B	C	D	E	F	G	H	I
1	No.	F. Class. Rural/ Urban Code	Housing Unit Density	Empl. Density	Number of Counts	Median AADT	Coeff. of Var.	Median APE	Sample Size
2	1	6R	Low	-*	76	234	1.16	56.9%	65
3	2	6R	Medium	-	53	637	0.94	59.4%	42
4	3	6R	High	-	17	1,485	0.55	31.7%	15
5	4	7R	Low	-	173	172	1.32	65.2%	84
6	5	7R	Medium	-	139	409	1.31	64.0%	82
7	6	7R	High	-	120	600	0.97	70.1%	45
8	7	7U	-	Low	230	943	1.18	61.1%	67
9	8	7U	-	Medium	52	1,101	1.15	68.7%	64
10	9	7U	-	High	157	1,237	0.99	68.2%	47
11	-	-	-	-	-	-	**1.14**	**63.8%**	**511**

* The dashes mean no data (empty cells).

Compared to the previous scheme shown in Example 5, the new scheme above produced more accurate AADT estimates (the median APE improved to 63.8%) and more homogeneous strata (the *WACV* decreased to 1.14). However, because the number of strata increased from three to nine, the total number of samples required for 70-15 confidence-precision level increased from 211 (see Example 3) to 511. Decision trees can further improve the accuracy of AADT estimates and the within-stratum variability (see section 4.5.2.3).

Note that traditional schemes that rely entirely on administrative variables such as counties have practical advantages over other traditional (non-administrative) schemes that may require more data, time, and effort to develop. The main advantages are:

- Administrative variables are readily available within all agencies, so there is no need to gather and process Census and other types of non-traffic data.

- It is easy to stratify the network (e.g., by county) and implement administrative strata.
- The strata are clearly defined geographically simplifying the administration of future counts.

The main disadvantage of administrative schemes is that they often contain highly heterogeneous strata that require a significant number of sample counts, making the schemes inefficient and expensive. Consider that county boundaries were originally developed for administrative purposes – not to capture AADT variability. A county may contain a high number of different types of roads that may have significantly different traffic volumes. The following example compares a county-based scheme against a non-county-based scheme that was developed using three stratification variables.

Traditional stratification schemes developed manually using administrative variables such as counties often result in a high number of heterogeneous strata that require significantly more samples than other schemes developed using better surrogates.

Example 7: Comparison of county-based and non-county-based schemes.

Agency X developed two simple stratification schemes. Each scheme is based on a single variable. The first scheme (Table 13) is a county-based scheme that includes 87 strata – one stratum for each county. The second scheme (Table 14) includes only four strata that correspond to low, low-medium, medium-high, and high density of jobs in residence and workplace areas (RAC_WAC_Den). Step 1 (section 4.2) explains how to calculate this variable using Census LEHD data. The four bins were constructed based on the 25th, 50th, and 75th percentile values of the variable.

Table 13. Characteristics and Performance of County-Based Scheme.

#	A	B	C	D	E	F
1	County No.	Number of Counts	Median AADT	Coeff. of Var.	Median APE	Sample Size
2	1	168	655	1.44	72.4%	101
3	2	160	355	1.16	75.2%	66
…	…	…	…	…	…	…
87	86	103	275	1.10	66.7%	59
88	87	64	218	0.91	62.4%	41
89	-*	-	-	**1.18**	**63.8%**	**6,783**

* Dashes mean no data (empty cells).

Table 14. Characteristics and Performance of Non-County-Based Scheme.

#	A	B	C	D	E	F	G
1	No.	WAC_RAC_Den	Number of Counts	Median AADT	Coeff. of Var.	Median APE	Sample Size
2	1	Low	2,863	95	1.16	63.5%	66
3	2	Low-Medium	2,881	220	1.08	58.5%	57
4	3	Medium-High	2,878	630	1.19	60.6%	69
5	4	High	2,873	1,450	1.06	59.7%	55
6	-*	-	-	-	**1.12**	**60.6%**	**247**

* Dashes mean no data (empty cells).

The last line in both tables (**bold numbers**) shows the WACV (Column E), the median APE (Column F), and the total required sample size at 70-15 confidence-precision level (Column G) of each scheme. A quick comparison between the two schemes reveals the following:

- Though the second scheme includes only four strata, the overall variability of the scheme (WACV=1.12) is lower than that of the county-based scheme (WACV=1.18). This shows that counties are highly heterogeneous in terms of AADT. It also suggests that disaggregating the four strata into more groups using good surrogates for AADT will likely further decrease the WACV.

- Though the second scheme includes only four default AADT estimates (Column D), one for each stratum, the median APE (60.6%) of the scheme is lower than that (63.8%) of the first scheme. Disaggregating the four strata into more groups using good surrogates for AADT will likely further improve the AADT accuracy.

- The number of samples (Column G) required for the first scheme (247) is substantially lower than that (6,783) required for the county-based scheme.

In short, the non-county-based scheme provides more accurate AADT estimates and can yield significant cost savings compared to the county-based scheme. These benefits outweigh the extra time spent to develop the second scheme, which can be further improved by disaggregating the four strata into more (homogeneous) groups using other variables that may be good surrogates for AADT.

4.5.2.3 Decision Trees

Decision trees belong to the larger umbrella of classification and regression trees (CART) that Breiman et al. first introduced in 1984.[72] The goal of decision trees is to predict the value of a target (dependent) variable (e.g., AADT) based on several input (independent) variables (e.g., Census variables, functional classification, rural/urban designation, counties, etc.). Classification trees are appropriate when the target variable is nominal or discrete, whereas in regression (or decision) trees the target variable is continuous such as AADT. Among several purposes, users can develop decision trees to:

- Create homogeneous strata with respect to AADT and calculate default AADT estimates – one estimate for each stratum.
- Discretize continuous variables.
- Identify most influential variables.

Note that there are other more advanced machine learning methods. A typical example is random forests that are simply a collection of multiple decision trees that have been generated using random subsets of data.(73) These methods are more complex and many consider them as 'black boxes' that cannot be easily interpreted. Because of implementation and practical considerations associated with these methods, this Informational Guide focuses on decision trees that are easier to understand, present, develop, and implement and can provide significant gains over the traditional stratification approach.

Figure 10 illustrates an example of a simple decision tree that includes two variables: FC_RU (functional classification combined with rural/urban designation), and HU_Den (housing unit density). A decision tree is a top-to-bottom (or left-to-right) flow chart that includes nodes interconnected with branches. The topmost node in a tree is the root node. Each of the remaining nodes that are split into two nodes is an internal node. The nodes that are not split are the terminal nodes or the final strata of the decision tree. For example, the decision tree shown in Figure 10 includes seven nodes created at two levels of growth: the root node (Node 1 is at Level 0), two internal nodes (Nodes 2 and 3 are at Level 1), and four strata (Nodes 4 through 7 are at Level 2). Annotations are shown in *red italicized letters*.

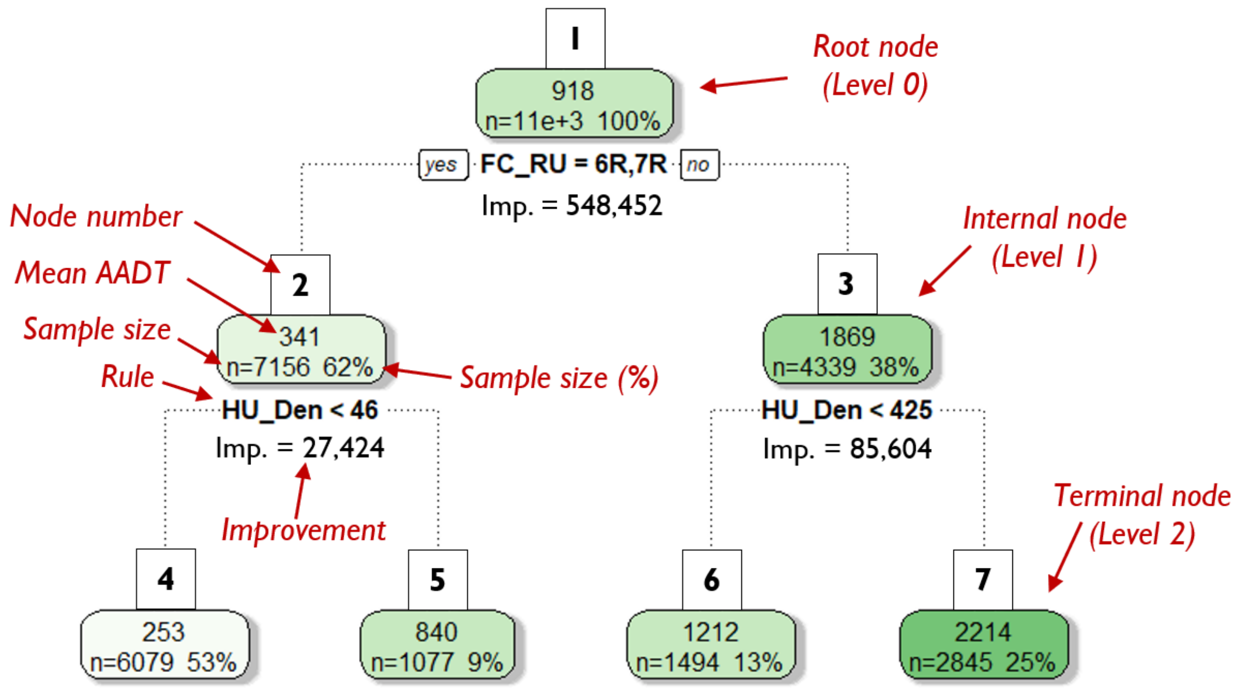


Figure 10. Flowchart. Example of a Decision Tree Developed in R.

To develop a tree, users need to select a target variable (AADT) and one or more independent variables. Decision trees are constructed and numbered from top-down, starting with the root node. The CART-development algorithm determines the value (or classes) of the independent variable that results in the largest possible reduction in heterogeneity of the target variable. After splitting the root node into two child nodes, the algorithm continues to split each new node until a predetermined stopping criterion is met. The tree predicts a target value for each final node. In other words, it estimates a default AADT value for each stratum.

Though many splitting rules can be established, most of them are based on the notion of 'impurity', which is a measure of the degree of heterogeneity within a node. When all cases within a node have the same value for the dependent variable, the node is considered to be homogenous or 'pure' and requires no further splitting. A commonly used impurity measure for continuous variables is the least-squared deviation, which is computed as the within-node variance.

To interpret a tree, one needs to know the following basic principles:

- The root node and each internal node has a single rule, which can be one of the following:
    - A categorical independent variable can have one or more class labels. For example, in Figure 10 the rule of Node 1 is FC_RU = 6R or 7R.

- A continuous independent variable can be less, equal, or greater than a specific value. For example, in Figure 10 the rule of Node 2 is HU_Den < 46.

- The left branch of a node always means that the rule is met (i.e., the answer is 'Yes'), whereas the right branch means that the rule is not met (i.e., the answer is 'No').

With these principles in mind, one can determine the stratification criteria of each terminal node. For example, consider the tree shown in Figure 10. To determine the stratification criteria of Stratum 6, the user has to start from Node 1 and follow the path that leads to Stratum 6:

- Follow the right branch of Node 1, which means that the first rule is not met. In other words, the first stratification criterion for Stratum 6 is FC_RU=7U.

- Follow the left branch of Node 3, which means that the rule of Node 3 is met. In other words, the second stratification criterion for Stratum 6 is HU_Den<425.

All 1,494 counted segments within Node 6 meet these two criteria. Table 15 shows the characteristics of the decision tree in a table format. Based on the stratification criteria of the terminal nodes (Column B in Table 15), analysts can assign a default AADT (Column E) to each uncounted segment on the network. For example, assume that an uncounted segment has the following attributes: FC_RU=7R and HU_Den=100. According to the tree depicted in Figure 10, the rule at Node 1 is met, and therefore the user must follow the left branch. Then, the rule at Node 2 is not met, therefore, the right branch leads to Stratum 5 (AADT=840 vpd).

Table 15. Example of a Decision Tree in a Table Format.

A	B	C	D	E	F
Node	Stratification Criteria or Rules	Parent Node	Sample Size (%)	Mean AADT	Improvement
1	-*	-	11,495 (100%)	918	548,452
2	FC_RU=(6R or 7R)	1	7,156 (62%)	341	27,424
3	FC_RU=7U	1	4,339 (38%)	1,869	85,604
4	FC_RU=(6R or 7R) and HU_Den<46	2	6,079 (53%)	253	-
5	FC_RU=(6R or 7R) and HU_Den≥46	2	1,077 (9%)	840	-
6	FC_RU=7U and HU_Den<425	3	1,494 (13%)	1,212	-
7	FC_RU=7U and HU_Den≥425	3	2,845 (25%)	2,214	-

* Dashes mean no data (empty cells).

Most statistical programs produce decision trees in a diagram and table formats. Some of them provide the improvement (Column F) in an impurity measure when a node is split, and the overall importance of each independent variable (Table 16). The importance of a variable accounts for all the (impurity measure) improvements achieved at the nodes that were split based on that independent variable.

Table 16. Example of Independent Variable Importance.

Independent Variable	Importance	Normalized Importance
HU_Den	657,398	100%
FC_RU	548,452	83%

Decision trees allow users to control several parameters such as:[73, 74]

- Maximum tree depth – It controls the maximum number of levels of growth beneath the root node. By increasing the maximum depth, the tree tends to produce more strata. Ideally, analysts should produce trees for different depths (e.g., depths three to seven) and then compare the trees and select a scheme as described in Step 5.

- Minimum number of objects to split a node – It controls the minimum numbers of objects required for splitting a parent node into two child nodes. Increasing the minimum value tends to produce trees with fewer nodes.

- Minimum number of objects within a child node – It controls the minimum numbers of objects required within a child node. Increasing the minimum value tends to produce trees with fewer nodes.

- Minimum change in improvement – It is the minimum decrease in the impurity measure to split a node. If the minimum value is not reached, the node will not be split. Increasing the minimum value tends to produce trees with fewer nodes and vice versa.

- Maximum risk difference to prune a tree – It controls whether and how a tree is pruned to avoid overfitting. After a tree is constructed, users can select to prune it to the smallest subtree that has an acceptable risk value. Increasing the maximum risk difference tends to produce simpler trees and vice versa.

- Maximum number of sample folds used in cross-validation – It controls the number of subsets used for cross-validation purposes. If the user selects to perform cross-validation, the dataset is divided into a predetermined number of sample folds and multiple trees are constructed. The first tree is trained using all objects except those in the first sample fold. The second tree is generated based on all objects except those in the second sample fold, and so on. Each tree is validated using the sample fold that was excluded when the tree was created. A misclassification risk is estimated for every validated tree. The end product is one final tree, in which the final risk estimate is the average of all risks from all validated trees.

The main advantages of decision trees over the traditional stratification approach are:

- They generally produce more homogeneous strata and therefore tend to require fewer samples yielding cost savings.
- They are intuitive and easy to explain to technical teams and stakeholders.
- They do not require normalization and scaling of data.
- They are not significantly impacted by outliers and missing values, compared to other statistical methods.

The main advantages of decision trees over the traditional stratification approach and other methods are:(74)

- They generally produce more homogeneous strata compared to the traditional stratification approach, and therefore tend to require fewer samples yielding cost savings. In the traditional approach, analysts typically select and use a small number of independent variables to develop a scheme, and also manually discretize each variable. In contrast, decision trees can automatically scan a much larger number of variables and determine the optimal threshold within each variable that provides the best separation of a dataset.
- They are intuitive and easy to explain to technical teams and stakeholders.
- They do not require normalization and scaling of data.
- They are not significantly impacted by outliers and missing values, compared to other statistical methods.
- They are as easy to implement as traditional stratification schemes because both methods produce a set of stratification criteria and a default AADT estimate for each stratum. In other words, there is no need to implement complex equations or 'black boxes' that some machine learning methods produce.
- They determine the most influential variables and quantify their importance.
- They can use the same independent variables more than once in different parts of the tree. This capability can uncover complex interdependencies among variables.
- They are nonparametric and therefore, do not rely on data having a particular type of distribution.

- They allow users to relax stopping rules, overgrow a decision tree, and then prune it back to decrease its size. This approach minimizes the probability that important structure in the data set will be overlooked by stopping too soon.
- They can incorporate various validation methods, including cross-validation, to assess the goodness of fit of a tree more accurately.

The main disadvantages of decision trees are:

- They require statistical programs to develop.
- They often require more time to train a model than other statistical and machine learning methods.
- They can produce different trees by changing some of the parameters listed above, even if the same (dependent and independent) variables are used.
- They can be difficult to present to stakeholders if they are large and contain many nodes.

In summary, *Step 4 Develop New Stratification Scheme* should incorporate some of the following activities:

- Update default AADT estimates of potentially existing scheme.
- Develop one or multiple schemes by applying the traditional stratification approach.
- Develop one or multiple decision trees using statistical programs.

4.6 STEP 5 – COMPARE SCHEMES AND SELECT ONE

The purpose of this step is to compare the schemes improved and developed in the previous step and select one. To conduct this comparison, agencies should determine at a minimum the number of strata, the median APE (section 4.4.1), and the required sample size (section 4.4.3) of each scheme. The WACV (section 4.4.2) may also help analysts to better understand the homogeneity of the schemes. Plotting these metrics will allow analysts to visually examine and compare the performance and sample size requirements of the schemes.

For example, a pilot study conducted in this FHWA project with agency X compared 36 stratification schemes that include the agency's current scheme, an updated version of the current scheme, 28 new manual (M) schemes (i.e., traditional schemes), and six decision trees (DT). Table 17 shows the schemes sorted in an ascending order by the number of strata per scheme. State X developed their current scheme (35M) several years ago based on three variables: city population, counties, and route system, which captures roadway ownership. Scheme 36M involved updating the current scheme by developing a new set of default AADT estimates using recent count data.

Table 17. Examples of Traditional Schemes and Decision Trees.

No.	Variables[a] (Number of Strata[b])	No.	Variables (Number of Strata)
1M[c]	FC_RU (3)	19M	FC_RU, WAC (12)
2M	Pop (4)	20M	FC_RU, Pop_Den (12)
3M	HU (4)	21M	FC_RU, HU_Den (12)
4M	Empl (4)	22M	FC_RU, Empl_Den (12)
5M	RAC (4)	23M	FC_RU, RAC_Den (12)
6M	WAC (4)	24M	FC_RU, WAC_Den (12)
7M	Pop_Den (4)	25M	FC_RU, WAC_RAC_Den (12)
8M	HU_Den (4)	**26DT**	**All – Stopped at Level 4 (16)**
9M	Empl_Den (4)	27M	FC_RU, Pop_Den, Empl_Den (27)
10M	RAC_Den (4)	28M	FC_RU, Pop_Den, RAC_Den (27)
11M	WAC_Den (4)	29M	FC_RU, Pop_Den, HU_Den (29)
12M	RAC_WAC_Den (4)	**30DT**	**All – Stopped at Level 5 (29)**
13DT[d]	**All – Stopped at Level 2 (4)**	31M	FC_RU, Pop_Den, WAC_Den (34)
14DT	**All – Stopped at Level 3 (8)**	**32DT**	**All – Stopped at Level 6 (48)**
15M	FC_RU, Pop (12)	**33DT**	**All – Stopped at Level 7 (69)**
16M	FC_RU, HU (12)	34M	County (87)
17M	FC_RU, Empl (12)	35M	Current Scheme (94)
18M	FC_RU, RAC (12)	36M	Updated Scheme (94)

[a] The abbreviations of the variables are provided in Step 1.
[b] Total number of strata within each scheme.
[c] M = Manual traditional scheme.
[d] DT = Decision tree. The decision trees are highlighted in **bold letters**. All independent variables were used as inputs to train each decision tree.

Figure 11 displays the metrics of these schemes. The horizontal axis shows the number of strata within each scheme. The schemes are shown above each chart, and like Table 17, they are sorted by the number of their strata to facilitate the comparison. The six decision trees are highlighted in bold and their corresponding data points are enlarged to easily distinguish them from those of the manual schemes. The three vertical axes from left to right show the median APE, the sample size required at 70-15 confidence-precision level, and the WACV of each scheme, respectively.

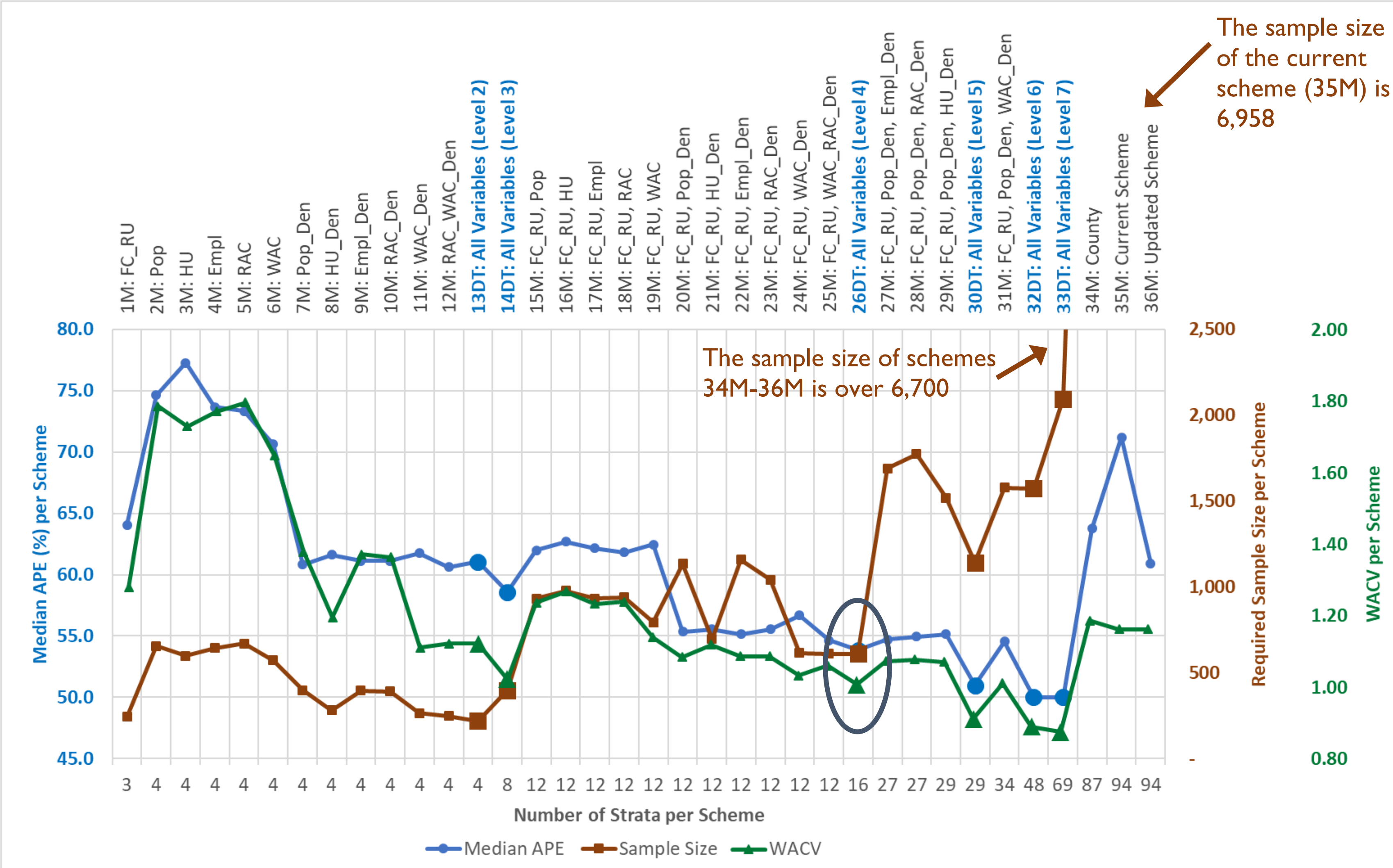


Figure 11. Graph. Median APE, Required Sample Size, and WACV of Various Stratification Schemes.

Among all 36 schemes, decision tree 26DT (highlighted in an oval) has the advantage of producing the fourth most accurate set of default AADT estimates by requiring fewer counts compared to other schemes that result in similar levels of AADT accuracy. It also contains fewer strata than the three best performing schemes (30DT, 32DT, and 33DT), and therefore, it is easier to implement. By comparison, decision tree 30DT improves the accuracy of the estimates by approximately five percent but requires 87 percent more counts than scheme 26DT. It also includes 13 more strata that may require additional time from an implementation perspective. The second most accurate scheme is 32DT, which compared to scheme 26DT, improves the AADT accuracy by seven percent, but requires a much larger sample size (158 percent increase) and contains 32 more strata. Compared to 32DT, the most accurate scheme (33DT) does not provide any improvement in AADT accuracy, yet it requires 33 percent more counts. This shows that further dividing the 48 strata of scheme 32DT is meaningless, because the available surrogates cannot capture additional AADT variability within smaller bins.

One of the main findings from this stratification analysis is that scheme 32DT improves the AADT accuracy of the current scheme (35M) by 30 percent, but most importantly it significantly reduces the required number of samples (by a factor of 0.23) from 6,958 to 1,574. That is more accurate AADT estimates and substantial cost savings. Further, traditional county-based schemes (34M-36M) tend to produce many internally heterogeneous strata that require a large number of samples. Stratifying the network by functional classification and rural/urban designation (model 1M) is more effective than using strata developed from single raw unadjusted Census variable (2M-6M). Likewise, density variables (7M-12M) are better surrogates than raw Census variables (2M-6M).

Overall, agencies should select one of the best performing schemes in terms of AADT accuracy (i.e., median APE) by considering available budgets. If, for example, agency X can afford to conduct the number of counts required by the second best performing scheme, 32DT, then, this scheme should be preferred over scheme 26DT. Agencies should also report and communicate the AADT estimation accuracy of the final scheme selected, so that internal and external end users are aware of the anticipated levels of error.

In general, the accuracy of default AADT estimates is a function of several interrelated factors, of which the most important are:

- Number of strata.
- Degree of correlation between stratification variable(s) and AADT.
- Stratification method.

Generally speaking, as the number of strata increases, the accuracy tends to improve, but the number of required samples increases. After a certain point, the accuracy improves at a much lower rate, but the required sample size continues to increase at a high rate (e.g., from 30DT to 32DT, and from 32DT to 33DT). The main reason is that even the best surrogates typically have moderate correlations (e.g., 0.3-0.6 as shown in Figure 8) with AADT. That is the largest percent of the AADT variability that these variables can explain is often captured during the early stages of the stratification process, when the entire population is divided into the first few strata. Beyond a certain 'critical' point, further subdividing existing strata does not significantly improve the within-stratum variability. This happens because the surrogates cannot effectively capture how AADT varies within smaller volume ranges. The magnitude of this 'critical' point depends on the degree of correlation between the stratification variables and AADT. In a hypothetical scenario where the correlations between AADT and the stratification variables are very strong (e.g., 0.8-0.9), the critical point will shift to the right. This means that more strata can be created by reducing the within-stratum variability without experiencing a significant increase in the required sample size.

Beyond a certain point, further dividing the strata of a scheme results in a marginal improvement in AADT accuracy (median APE), but a significant increase in the required sample size.

Further, some stratification methods are more effective and efficient than others. As described in the previous step, decision trees and other machine learning methods such as random forests have several advantages over the traditional stratification approach. The main advantage is that they tend to produce more homogeneous strata, and therefore, more accurate AADT estimates more efficiently. The improvement in homogeneity becomes more evident when there is a large number of inputs that the decision tree algorithm can analyze exhaustively, repeatedly, and efficiently in every step of the tree growth process. Computationally, this would be a difficult and time-consuming task to perform using spreadsheets. Training a decision tree using several independent variables increases the likelihood of capturing some of the AADT variability within smaller strata, where a single variable may not effectively explain. The main disadvantage of spending more time to gather and process data for more variables is outweighed by the expected increase in within-stratum homogeneity and AADT accuracy.

In summary, *Step 5 Compare Schemes and Select One* should incorporate some of the following activities:

- Determine the number of strata, the median APE, and the required sample size of each scheme developed in Step 4.
- Develop plots of these metrics and compare the performance and sample size requirements of the schemes.

- Determine critical point beyond which the AADT accuracy improves marginally, but the required sample size increases substantially.

4.7 STEP 6 – SELECT SAMPLES

The purpose of this step is to select sample locations. In line with FHWA guidelines, the recommendation is to randomly select new samples, as opposed to repeatedly count the same predetermined 'historical' sites that agencies often select based on subjective criteria.[1, 2, 9] The main advantages of randomly selecting and counting different segments in each cycle, compared to repeatedly counting the same 'historical' locations are:

- Higher accuracy of AADT estimates. Several studies have found that randomly selected counts tend to result in more accurate AADT estimates.[8, 13, 62] For example, Frawley (2007) compared count volumes from historical stations in Texas against count volumes from randomly selected sites.[13] The study found that the median volumes from randomly selected sites were significantly lower than those of historical counts in the same areas. These volumes were lower because typically the historical sites are located on local streets at or near intersections with collectors or arterial streets, where volumes tend to be higher. Historical count sites are not usually found deep in neighborhoods, away from major streets. The randomly selected sites are distributed evenly throughout the network and therefore, provide a better representation of NFAS roads.

- More effective stratification and higher precision of AADT estimates. Counting new segments in each cycle practically increases the percent of the counted portion of the NFAS network and the sample size of the stratification analysis (i.e., the dependent variable contains more records). This, in turn, improves the stratification process, the reliability of the results, and the precision of the estimates, as shown in section 4.4.4. Precision and sample size are inversely proportional to the second power. This means that halving precision requires four times the sample size.[8] In contrast, counting the same historical sites in each cycle does not increase the sample size of the analysis and therefore, the aforementioned benefits cannot be realized.

- Ability to validate the accuracy of the AADT estimates from previous years. Counting new segments allows analysts to validate the accuracy of potentially existing AADT estimates.

The recommendation in this Informational Guide is to randomly select samples, as opposed to count the same historical sites in each data collection cycle.

The main drawback of randomly selecting samples is that it increases the administrative effort. More specifically, it involves developing and repeating a random sample selection procedure, developing annual counting schedules, identifying sites, and updating relevant systems and databases with count and location information. Although the human aspects of traffic counting may be complicated by this approach, the equipment aspects do not present much of a problem due to low traffic volumes on most NFAS roads.[(8)]

After computing the number of samples needed in each stratum (see section 4.4.3), analysts can randomly select samples using a random number generator available in simple calculation spreadsheets. This approach assigns an equal probability of selection to each segment within a stratum. First, analysts need to create a list of uncounted segments within a stratum and then generate a random number[4] for each segment. After sorting the segments in an ascending or descending order by these random numbers, analysts can select a certain number of samples required for each stratum. The selected segments now become the stratum sample. This random sampling process continues until each stratum has the required number of samples.

Any random sample selected in the described manner is representative. However, the possibility of selecting a bad sample does exist. To ensure good representation, the segments in the sample should be evenly distributed geographically. To assess the level of representation, it may be necessary to plot the selected samples on a map and visually examine if they are evenly distributed geographically. If some samples are clustered together rather than geographically distributed, it may be necessary to reselect some of the segments to ensure a more dispersed sample.[(8)]

[4] The Microsoft Office Excel functions “=rand()” and “=randbetween()” generate random numbers.

New York State Department of Transportation – Random Sampling Data Collection Procedure[46]

NYSDOT conducted a one-time project to collect additional NFAS traffic data. Over the last few years, NYSDOT conducted about 8,000 short-duration counts under a special project to collect a random sampling of local roads to support AADT data collection. NYSDOT supplemented its existing count data with a target of counting at least 10 percent of the mileage in each of the 1,500 municipalities in the state to ensure wide distribution of data. NYSDOT used its existing local highway inventory to select count locations. All locations were collectively sampled, including mainlines, alleys, cul-de-sacs, and dead ends.

To randomly select samples for counting, NYSDOT extracted NFAS road segments from its statewide inventory of public roads. The total mileage of NFAS road segments in each municipality was compared to the mileage of segments with traffic counts. A random number was generated for each segment in municipalities with counts on less than 10 percent of the total mileage. NYSDOT sorted each municipality individually by the random number and selected segments to be counted until reaching 10 percent of the mileage. About 8,000 segments were selected for counts, in addition to the already counted segments, to reach the 10 percent coverage of NFAS roads. Contractors then conducted short-duration traffic counts and provided the data to NYSDOT.

After randomly selecting samples, agencies should determine specific projects (e.g., special projects, safety improvement projects, pavement maintenance projects, research projects, etc.) that will require data in the next year or two. This involves coordinating with other internal and external entities that need the traffic volume data or plan to collect data themselves. This coordination should occur on a continuous basis to ensure counts for special projects are collected when needed. Agencies should determine how counts can be combined to make the best use of available resources, and then develop a schedule to use the available data collection crews and equipment efficiently. The intent of these activities is to reduce count duplication and increase the efficiency of the data collection staff. The TMG provides more information on this topic.[1]

Sampling is not needed if an agency has already counted their NFAS segments. In this case, the agency can continue to collect traffic volume data on six to ten-year cycles depending on their needs and available resources. The TMG provides more information on how to structure a short-duration count data collection program.[1] For example, one simple approach is to randomly separate all roadway segments into groups and count one of these groups each year. However, this approach does not always make the most efficient use of data collection staff and equipment. Grouping counts geographically leads to more efficient collection of data, but results in the need to account for geographic bias when computing AADT and growth rates.[1]

This Informational Guide recommends a minimum count duration of 48 hours for NFAS roads. Research findings have shown that longer duration counts produce modest, but statistically significant improvements in count accuracy.[75, 76] For example, Krile et. al. (2015) found that AADT estimates derived from 48-hour counts, compared to 24-hour counts, result in approximately a five percent increase in the probability that the estimates are within +/- 10 percent of the actual AADT.[75]

This Informational Guide recommends a minimum count duration of 48 hours for NFAS roads.

In summary, *Step 6 Select Samples* should incorporate some of the following activities:

- Select samples randomly using random procedures.
- Review selected samples on a map and make adjustments, if needed.
- Determine special and other projects that require traffic volume data.
- Coordinate with partner agencies to avoid duplication of counts.

4.8 STEP 7 – ESTABLISH AND EVALUATE CONTINUOUS COUNT PROGRAM

The purpose of this step is to establish and evaluate a continuous count program, in accordance with guidelines provided in FHWA's TMG.[1] The primary (but not the only) objective of a program is to develop temporal adjustment factors to expand short-duration counts to AADT. This objective is the basis for establishing the number and location of CCSs. Each agency should determine a balance point between having more CCSs (increasing the accuracy and reliability of analyses that depend on CCS data) and reducing the expenditures required to operate and maintain the CCSs.

This Informational Guide recommends establishing and evaluating a continuous count program in accordance with guidelines provided in FHWA's TMG.

Chapter 3 of the TMG describes a seven-step process (Figure 12) that agencies should follow to 1) develop a new continuous traffic volume program, 2) check to ensure compatibility with TMG guidance, and 3) evaluate a program.

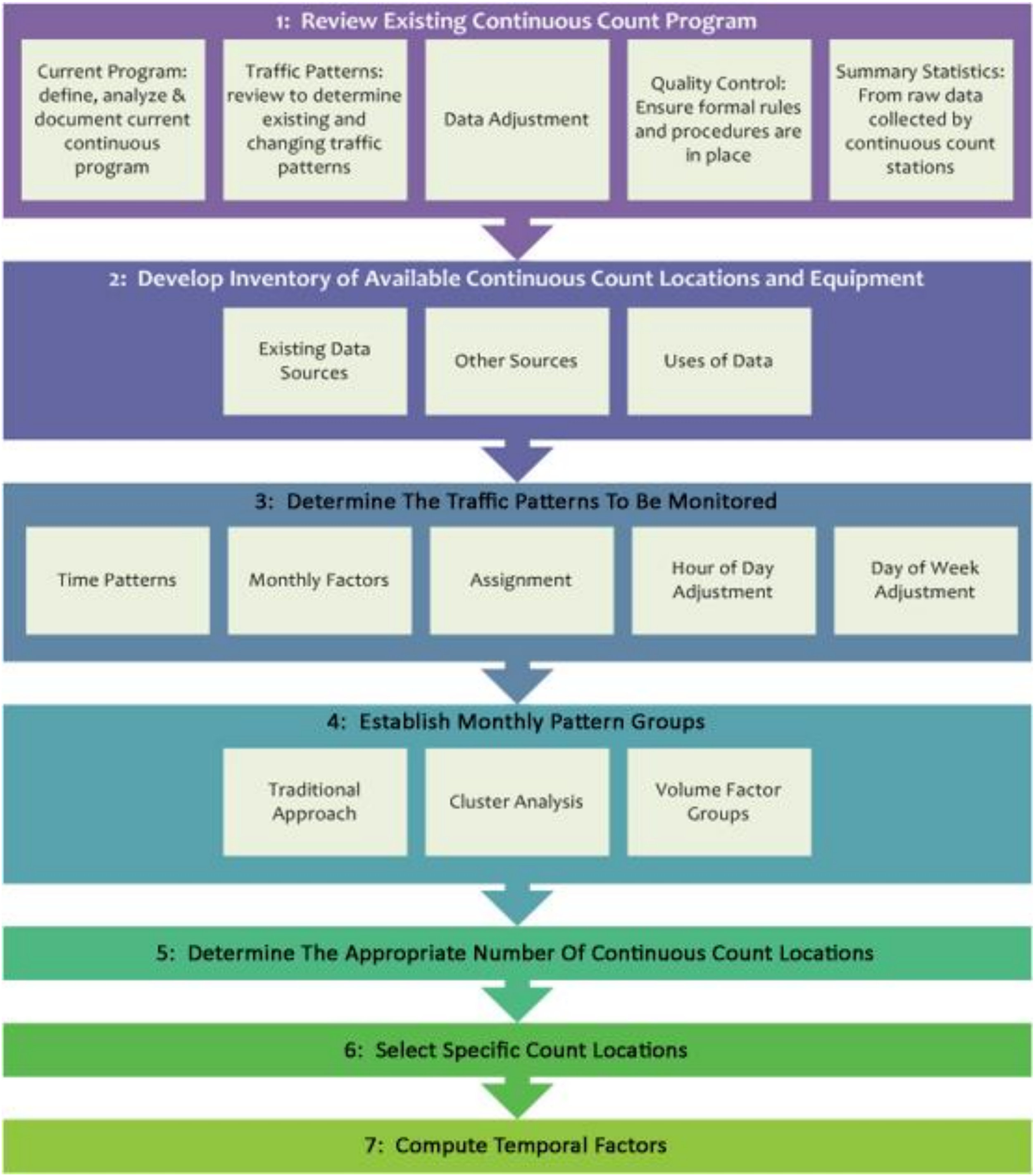


Figure 12. Flowchart. Establishment and Evaluation of Continuous Count (Traffic Volume) Program.[1]

The seven steps of this process are summarized below:

- Review existing continuous count program. This step involves defining, analyzing, and documenting the current program; determining hourly, daily, and monthly traffic patterns; understanding how data are adjusted; determining quality control procedures and rules, and checking whether they are performed as intended; and creating summary statistics from the raw CCS data. These activities are also included in the preparation steps described in Chapter 3 of this Informational Guide.
- Develop inventory of continuous count locations and equipment. This step involves performing an inventory of existing and planned CCSs, as well as other data collection devices that can supply continuous volume data; and determining how the continuous count data are currently being used, who the customers are, and which data products are being produced.
- Determine traffic patterns to be monitored. This step involves reviewing variations in time patterns; computing monthly factors at each site; reviewing how short-duration counts are assigned to factor groups; determining hour of day adjustment factors; and reviewing how volumes are distributed by day of week.
- Establish monthly pattern groups. This step involves creating monthly pattern groups using one or more of the following methods: a) the traditional approach is based on general knowledge of the system combined with visual interpretation of monthly patterns; b) cluster analysis is a statistical classification method that allows for independent determination of similarity between groups and identification of travel patterns that may not be intuitively obvious to the analyst; and c) volume factor groups.
- Determine appropriate number of CCSs. This step involves determining the total number of locations needed in each factor group to achieve the desired precision level for the composite group factors. The recommended reliability levels for NFAS roads are 10 to 15 percent precision with 95 percent confidence for each individual group, excluding recreational groups where no precision requirement is specified. When these reliability levels are applied, the number of CCSs needed is usually five to eight per factor group, although cases exist where more locations are needed. The actual number of locations needed is a function of the variability of traffic patterns within that group and the precision desired; therefore, the required sample size may change from group to group.

- Select count locations. This step involves determining which CCSs should be included in each factor group to meet the required levels of factor reliability. If there is a shortage of current CCSs within a group, the agency should select new locations to place continuous counters within this group. If a surplus of CCSs within a group exists, then redundant locations are candidates for discontinuation unless needed for other purposes.
- Compute temporal factors. This step involves calculating temporal adjustment factors that agencies should use to annualize short-duration counts.

Chapter 3 of the TMG provides more information about each step of the process.(1)

In summary, *Step 7 Establish and Evaluate Continuous Count Program* should incorporate the following:

- Review existing continuous count program.
- Develop inventory of continuous count locations and equipment.
- Determine traffic patterns to be monitored.
- Establish monthly pattern groups.
- Determine appropriate number of CCSs.
- Select count locations.
- Compute temporal factors.

4.9 STEP 8 – CONDUCT COUNTS AND DEVELOP DEFAULT AADT ESTIMATES

The purpose of this step is to collect traffic volume data and develop AADT estimates – one estimate for each stratum. This Informational Guide recommends using, if possible, traffic equipment that counts vehicles instead of axles. Though this recommendation restricts the use of older, less capable equipment and potentially raises the level of complexity, it eliminates the need to collect classification data and compute axle correction factors, and most importantly avoids additional sources of bias introduced by applying axle correction factors. Magnetic detectors placed in the center of a lane, loop detectors, and other types of non-intrusive equipment described in the TMG are appropriate for counting vehicles.

This Informational Guide recommends using traffic equipment that counts vehicles instead of axles.

After taking short-duration counts, agencies should calculate the ADT of each count and expand it into an AADT estimate by multiplying the ADT by appropriate temporal adjustment factors, as described in the TMG.[(1)] If analysts stratify the network manually, they should simply calculate the median[5] AADT within each stratum and use it (the median AADT) as the default AADT estimate of the stratum. Note that analysts should use the median, not the mean[6]. Frawley (2007) describes that medians and means are equal in the case of symmetrical (i.e., normal) distributions. However, the mean can be largely affected by potential outliers that frequently exist in traffic volume data of NFAS roads.[(13)]

This Informational Guide recommends calculating the median AADT (as opposed to the mean AADT) within each stratum.

As agencies collect traffic volume data, the initial strata may change. For the first few years after initial development of a scheme, the process should be revisited ideally every year or every two years. After that, the stratification process should be revised every three years, if possible. Change rate factors are necessary to adjust counts taken in previous years. Due to limited CCS data on NFAS roads, yearly change rate factors can be estimated using Census population data; however, research is needed to examine more advanced yearly change rate estimation methods for NFAS roads.

In summary, *Step 8 Conduct Counts and Develop Default AADT Estimates* should incorporate some of the following activities:

- Collect traffic volume data using vehicle counting equipment, if possible.
- Calculate ADT for each count.
- Expand the ADT of each count by multiplying it with appropriate temporal adjustment factors to develop an AADT estimate.
- Determine median AADT for each stratum.
- Assign median AADT to each uncounted segment within a stratum.

[5] The Microsoft Office Excel function “=median()” returns the median of an array of values.

[6] The Microsoft Office Excel function “=average()” returns the mean of an array of values.

CHAPTER 5 — CONCLUSION

This Informational Guide presents information on how to collect data and estimate AADT for NFAS roads. The expectation is to use the AADT estimates in data-driven safety analysis, as defined by the HSIP Final Rule. The Guide presents a framework (Figure 13) that consists of two major parts: *Preparation* and *AADT Estimation*.

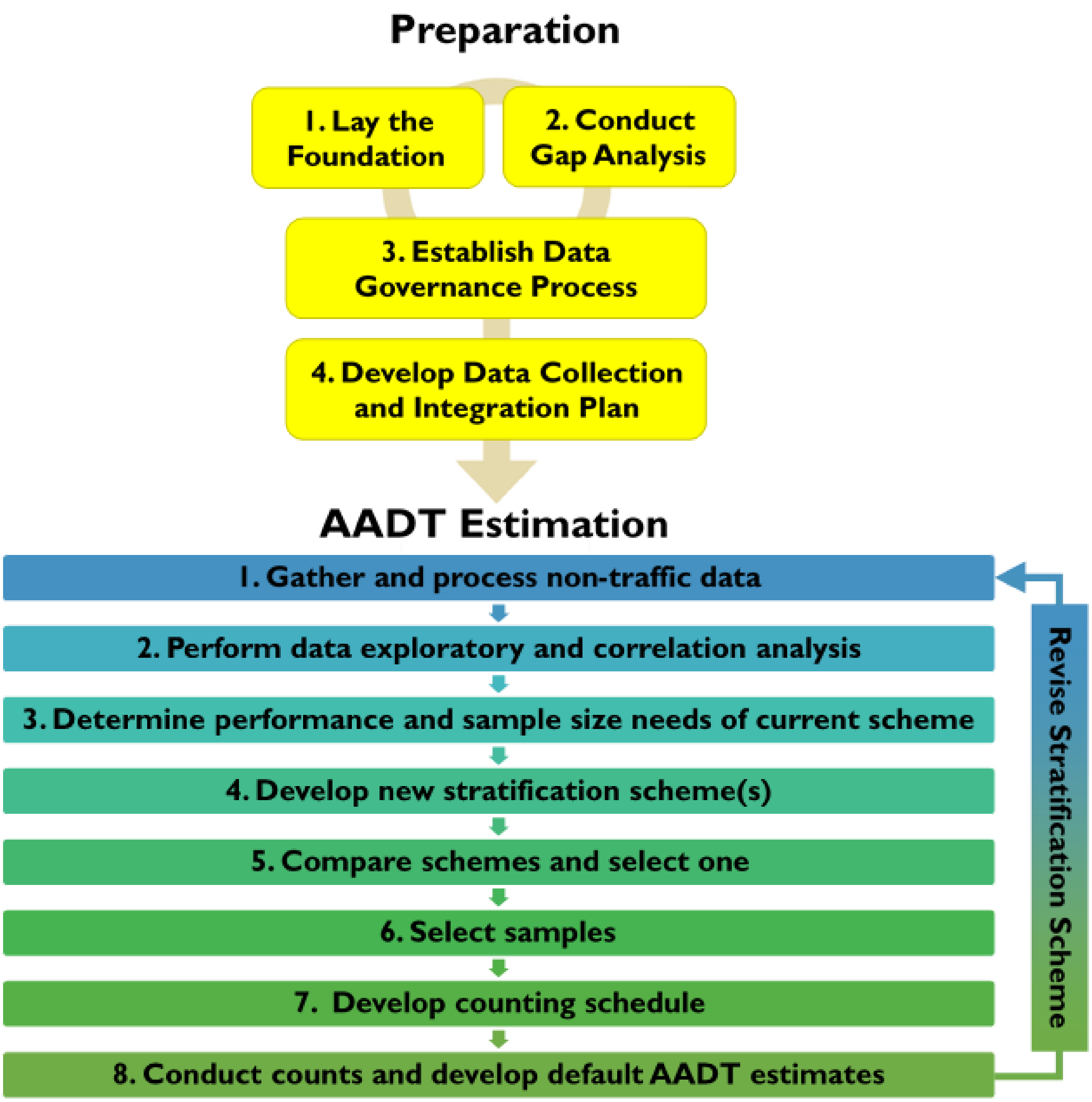


Figure 13. Flowchart. Process to Collect Data and Estimate AADT for NFAS Roads.

The first part includes four basic steps that are necessary to prepare for effective data collection and sharing of traffic volume data among agencies. These steps are part of a larger safety data integration process that FHWA published in 2016. The second part, called *AADT Estimation*, includes eight steps that describe how to improve an existing stratification scheme, develop new schemes, collect traffic volume data, and estimate AADT for NFAS roads.

The intent of this framework is to assist both experienced traffic monitoring staff and those who are new to traffic data collection and AADT estimation. The framework includes methods suitable for agencies that a) do not collect data nor estimate AADT for NFAS roads, and b) desire to improve their practices and the accuracy of their AADT estimates. For this reason, the framework incorporates both traditional stratification approaches, as well as non-traditional classification methods such as decision trees.

Some of the key elements in developing a stratification scheme and default AADT estimates for NFAS roads are:

- Among the various types of sampling methods that exist in the literature, this Informational Guide recommends using random stratified sampling.
- The purpose of stratifying the NFAS road network is to create strata that are internally homogenous and externally heterogeneous, to the extent possible, in terms of AADT.
- The key to developing an effective stratified scheme is to use good surrogates for AADT. The higher the correlations between AADT and the stratification variables, the higher the likelihood that the produced strata will be internally homogeneous.
- Geographical densities of specific Census variables aggregated at the Census block group or tract level tend to be more effective in developing a stratification scheme than raw unadjusted Census variables that are available online.
- Among several performance metrics, the AADT accuracy, calculated as the median APE within each stratum, is the most important metric for safety analysis applications.
- The key to improving the AADT accuracy is to have more strata and very homogenous strata, rather than fewer strata and more samples within each stratum.
- A simple way to improve an existing scheme without modifying the stratification criteria, is to update the default AADT estimates using recent counts.
- Traditional stratification schemes developed manually using administrative variables such as counties often result in a high number of heterogeneous strata that require significantly more samples than other schemes developed using better surrogates.

- Decision trees have several advantages over traditional (manual) stratification approaches. For example, they generally produce more homogeneous strata and therefore tend to require fewer samples yielding cost savings; they are intuitive and easy to explain to technical teams and stakeholders; they do not require normalization and scaling of data; and they are not significantly impacted by outliers and missing values, compared to other statistical methods.

- The main disadvantages of decision tress are: they require the use of statistical programs; they often require more time to train a model than other statistical and machine learning methods; they can produce different trees by changing parameter values, even if the same dependent and independent variables are used; and they can be difficult to present to stakeholders if they are large and contain many nodes.

- Beyond a certain point, further dividing the strata of a scheme results in a marginal improvement in AADT accuracy (median APE), but a significant increase in the required sample size.

- Conducting more counts within a stratum will improve the precision of the AADT estimate but will likely not improve its accuracy (median APE).

- Randomly selecting samples results in more accurate AADT estimates, as opposed to counting the same historical sites in each data collection cycle.

- This Informational Guide recommends the following:

    - A minimum count duration of 48 hours for NFAS roads.

    - Establishing and evaluating a continuous count program in accordance with guidelines provided in FHWA's TMG.

    - Using traffic equipment that counts vehicles instead of axles.

    - Calculating the median AADT (as opposed to the mean AADT) within each stratum.

Transportation agencies can use HSIP funds to collect, estimate, maintain, and share safety data, including AADT, on all public paved roads and related systems associated with analytical usage of data that directly supports HSIP implementation efforts. AADT is one of several MIRE-FDE that agencies must integrate to reduce crashes, fatalities, and serious injuries. By making better data available to decision makers, agencies will make more efficient spending decisions which in turn results in more lives saved per dollar spent on safety. This view of safety decision-making extends to efforts in several functions within an agency, not just those specifically aimed at improving safety.

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APPENDIX A – IMPACT OF AADT ESTIMATION ERRORS ON SAFETY ANALYSIS

SUMMARY

This Appendix presents a sensitivity analysis[1] that aimed to determine the impact of traffic volumes on the results of data-driven safety analysis. In this analysis the research team used 2013-2017 traffic count, roadway network, and crash data from North Carolina. The study developed six SPFs for the lower functional classifications (6R, 7R, and 7U) and then applied the empirical Bayes (EB) method that is recommended in AASHTO's *Highway Safety Manual* (HSM).[2] The sensitivity analysis included six steps: 1) applying the EB method, 2) determining the rank of each segment based on the results obtained from Step 1, 3) determining the percentile of the rank of each segment, 4) increasing the AADT of each segment by 10, 50, 100, 250 and 500 percent by keeping the rest of the segments and variables unchanged, 5) repeating Steps 1-4 separately for each segment and AADT percent increase, and 6) calculating the percentile rank change of each segment by comparing the initial rank of each segment (no AADT change) against the rank obtained when AADT was increased by a certain percent. In line with previous research findings[3], the results show that AADT estimation errors do not significantly affect the expected crash frequencies derived from the EB method and the associated percentile rank changes. The AADT affects the number of crashes predicted by SPFs. However, the EB method accounts for both predicted number of crashes and historical crashes, but the latter have a higher weight in the calculation of expected number of crashes.

A.1 BACKGROUND

States must develop an HSIP that "*emphasizes a data-driven, strategic approach to improving highway safety on all public roads that focuses on performance*".[4] Due to the emphasis on data-driven strategies, many studies have focused on understanding the relationship between crashes and external variables. The data-driven methods included in the first edition of the HSM are widely used to predict crashes on a specific roadway facility.[2] Part C of this manual provides a list of predictive models that can be used to estimate crash counts on a roadway using alternative variables such as segment length, traffic volume, and geometric characteristics. These models, widely known as SPFs, predict crash frequencies with the aim to prioritize candidate safety improvement projects and different design alternatives. The HSM provides a series of SPFs for three major facility types: (1) rural two-lane two-way roadways; (2) rural multilane highway; and (3) urban and suburban highways. For each location type, these SPFs can be used to estimate the number of crashes during a given period under certain base conditions. The general recommendation is to calibrate existing SPFs or develop new SPFs using local data, and then apply advanced predictive methods such as the empirical Bayes (EB) method that account for both observed and predicted number of crashes.

A.2 OVERVIEW OF EB METHOD

The EB method calculates the expected number of crashes for a defined period before and after a safety treatment was implemented at a particular site. The EB method can handle two major data issues: sparse datasets and regression to the mean (RTM) bias. RTM bias occurs when a site experiences an abnormally high or low number of crashes in one year, followed by a return to a more typical crash frequency the following year. Because crashes do not occur in a systematic way, it is unlikely that short analysis periods (e.g., one year) can fully capture the true frequency of crashes, resulting in crash prediction errors. To overcome RTM bias, the EB method uses both the observed number of crashes at a particular site and the predicted number of crashes at similar sites.

An SPF is an equation that predicts the average number of crashes per year at a specific site as a function of exposure (i.e., AADT and segment length) and, in some cases, roadway or intersection characteristics. SPFs can be developed for specific facility and crash types using local data, or by calibrating existing SPFs (e.g., HSM SPFs). The predicted number of crashes (*N*) at a particular site can be estimated by multiplying three components: base SPF ($C_{Predicted}$), CMFs, and a calibration factor, as shown in the following equation.

Equation A.1:

$$N = C_{Predicted} \times \mathrm{C} \times \prod CMF$$

For example, exposure is represented by the segment length and AADT associated with the roadway segment as shown by the following baseline SPF:

Equation A.2:

$$C_{Predicted} = \exp[\beta_0 + \beta_1 \times \ln(L) + \beta_2 \times \ln(AADT)]$$

Where:

$C_{Predicted}$ = predicted crash frequency under base conditions

β_0, β_1 = parameter coefficients

L = segment length

CMFs account for deviations from base conditions in relation to roadway and geometric characteristics, and traffic control devices. In some cases, (e.g., crash data variation between different jurisdictions or different time periods within the same jurisdiction), applying a calibration factor may be a more efficient approach than developing a new SPF that requires more time and data. Calibration factors can be estimated by:

Equation A.3:

$$C = \frac{\sum_{i=1}^{n} N_{obs,i}}{\sum_{i=1}^{n} N_{pre,i}}$$

Where:

$N_{Obs,i}$ = observed annual average crash frequency

$N_{Pre,i}$ = predicted annual average crash frequency

n = sample size, equal to the number of sites in the calibration process

The EB method is based on a weighted average principle. It has been widely used in many safety studies and is recommended by the HSM. It uses a weight factor, w to combine observed ($C_{Observed}$) and predicted crash frequencies ($C_{Predicted}$) to estimate the expected crash frequency, $C_{Expected}$:

Equation A.4:

$$C_{Expected} = w \times C_{Predicted} + (1 - w) \times C_{Observed}$$

Where:

$C_{Expected}$ = expected crash frequency

$C_{Predicted}$ = predicted crash frequency obtained from SPF

$C_{Observed}$ = observed crash frequency

w = weight factor that depends on the over-dispersion parameter (k) of the SPF

A.3 METHODOLOGY

Hauer (2015) states: "*a parametric SPF is a mathematical function of traits (variables) and parameters. The activity of fitting a parametric SPF to data alternates between choosing the variables from which the model equation is to be made, determining the form of the function (i.e., how the variables and parameters should combine into an equation), estimating the value of the parameters, and examining the goodness of the fit.*"(5) The schematic of this concept is presented in Figure 14.

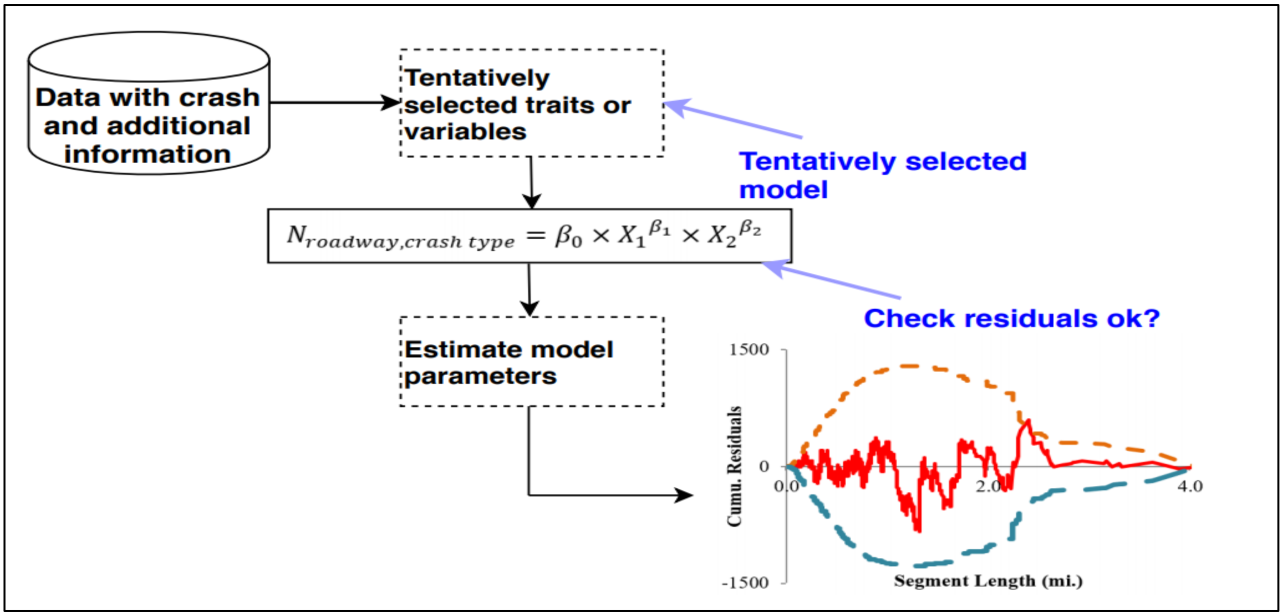

Figure 14. Flowchart. Parametric SPF Development Process.[1]

The SPF development for NFAS roads in North Carolina included the following steps:

- Step 1: Data preparation. Acquired crash, roadway inventory, and traffic volume data, and assigned crashes to the corresponding segments of the roadway network.
- Step 2: Exploratory data analysis. Compiled data for candidate independent variables, performed correlation analysis to identify the best predictors, and conducted exploratory data analysis to identify patterns and clusters.
- Step 3: SPF development. Developed negative binomial models for the desired roadway networks separately for all five injury types [fatal injury (K); incapacitating injury (A); non-incapacitating injury (B); possible injury (C); and no injury or property damage only (O)], as well as for KABC crashes only. The researchers validated models using residual plots. If the residual plots were not in the range of the best fit model, decision trees or other data partitioning algorithms were developed to identify potential clusters inside the data. Instead of using the whole data, researchers developed SPFs for the clustered data, cross-examined the residuals, and repeated the previous steps until a good-fit model was developed.

A.3.1 Data Preparation and Exploratory Data Analysis

To better understand the relationship between various roadway characteristics and safety performance on NFAS roads in North Carolina, it was first necessary to assemble a comprehensive database of traffic crash, roadway inventory, and traffic volume data for the study network. The data were obtained from different sources for the five-year period 2013 through 2017. The precision of SPFs largely depends on the quality of the data. SPF development requires a comprehensive crash database that contains various information and data such as route id, route name, milepost, control section, geographic coordinates, collision type, and severity type among others.

Table 18 shows annual crash frequencies on NFAS roads in North Carolina. The data show that 444,863 crashes happened during the study period (30 percent of these crashes involve some type of injury). From 2013 to 2017, NFAS roads experienced a 12 percent increase in crashes. The crash database does not differentiate between segment and intersection-related crashes, though past studies have showed the significance of making this distinction.(6) This study considered all crashes without separating segment and intersection-related crashes. The SPFs developed in this study can be improved by excluding intersection-related crashes if more data become available (e.g., distance of crash location from closest intersection).

Table 18. Crash Counts by Injury Type and Year.

Year	K	A	B	C	O	Unknown	Total
2013	483	706	6,716	16,685	56,577	2,446	83,613
2014	468	719	6,840	16,998	56,410	2,492	83,927
2015	506	796	7,040	18,955	60,282	2,783	90,362
2016	519	1,009	7,216	19,138	62,585	2,792	93,259
2017	496	1,515	7,545	17,494	63,722	2,930	93,702
Grand Total	**2,472**	**4,745**	**35,357**	**89,270**	**299,576**	**13,443**	**444,863**

For each functional classification (6R, 7R, 7U), two SPFs were developed: one for total crashes (KABCO) and another one for KABC crashes. The original dataset contained several candidate predictors. Shoulder type, shoulder width, median type, and median width were considered for the analysis. After performing a correlation analysis, only two variables were found to be the best predictors: segment length (miles) and AADT (vpd).

A.3.2 SPF Development

SPFs were developed using AADT data from permanent sites and short-term counts. The model structure, the overdispersion parameter, and the loglikelihood of each SPF are listed in Table 19.

Table 19. SPF Characteristics.

Func. Class.	Crash Severity	Safety Performance Function	Over-dispersion Parameter	Log-likelihood
7R	KABCO	$N_{7R,Tot} = 2.479 * Length^{0.962} * AADT^{0.035}$	0.353	20090.20
7R	KABC	$N_{7R,KABC} = 0.632 * Length^{1.005} * AADT^{0.034}$	0.348	-5624.30
7U	KABCO	$N_{7U,Tot} = 1.691 * Length^{0.842} * AADT^{0.071}$	0.952	-808.10
7U	KABC	$N_{7U,KABC} = 0.488 * Length^{1.062} * AADT^{0.071}$	0.772	-1,286.60
6R	KABCO	$N_{6R,Tot} = 2.432 * Length^{0.988} * AADT^{0.090}$	0.406	10,188.20
6R	KABC	$N_{6R,KABC} = 0.641 * Length^{1.023} * AADT^{0.084}$	0.326	-826.70

Regression models examine the average effects of the associated variables and ignore subgroup effects in the model development. As a result, models are often geared towards the population mean, without considering site-specific patterns. This study developed decision tree algorithms to determine the clustering effect. The results support the model development for each functional classification separately. Figure 15 illustrates the observed versus expected KABCO crashes for the three functional classifications.

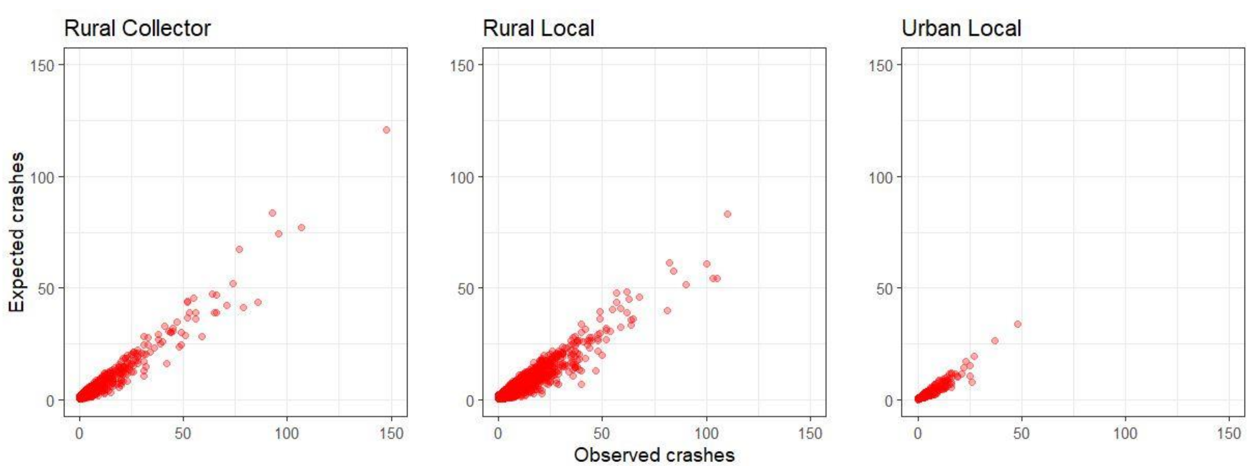

Figure 15. Scatterplots. Observed vs. Expected Crashes.

The model fitting is judged by its residuals, which are the differences between the number of recorded crashes and the predicted crash counts. A model is thought to fit well if the residuals are close to zero. The Cumulative Residual (CURE) plot is a good visualization to show how well or poorly an SPF can predict crashes for various values of an independent variable, which is plotted on the x-axis of the plot. A horizontal stretch of the CURE plot infers to a region of the variable where the estimates are unbiased. On the contrary, in regions where the CURE plot consistently drifts up or down the estimates are biased. The CURE plot for an unbiased SPF is needed to be in the boundary of two standard deviations. The CURE plots (KABCO crashes) for both segment length and AADT are shown in Figure 16 and Figure 17.

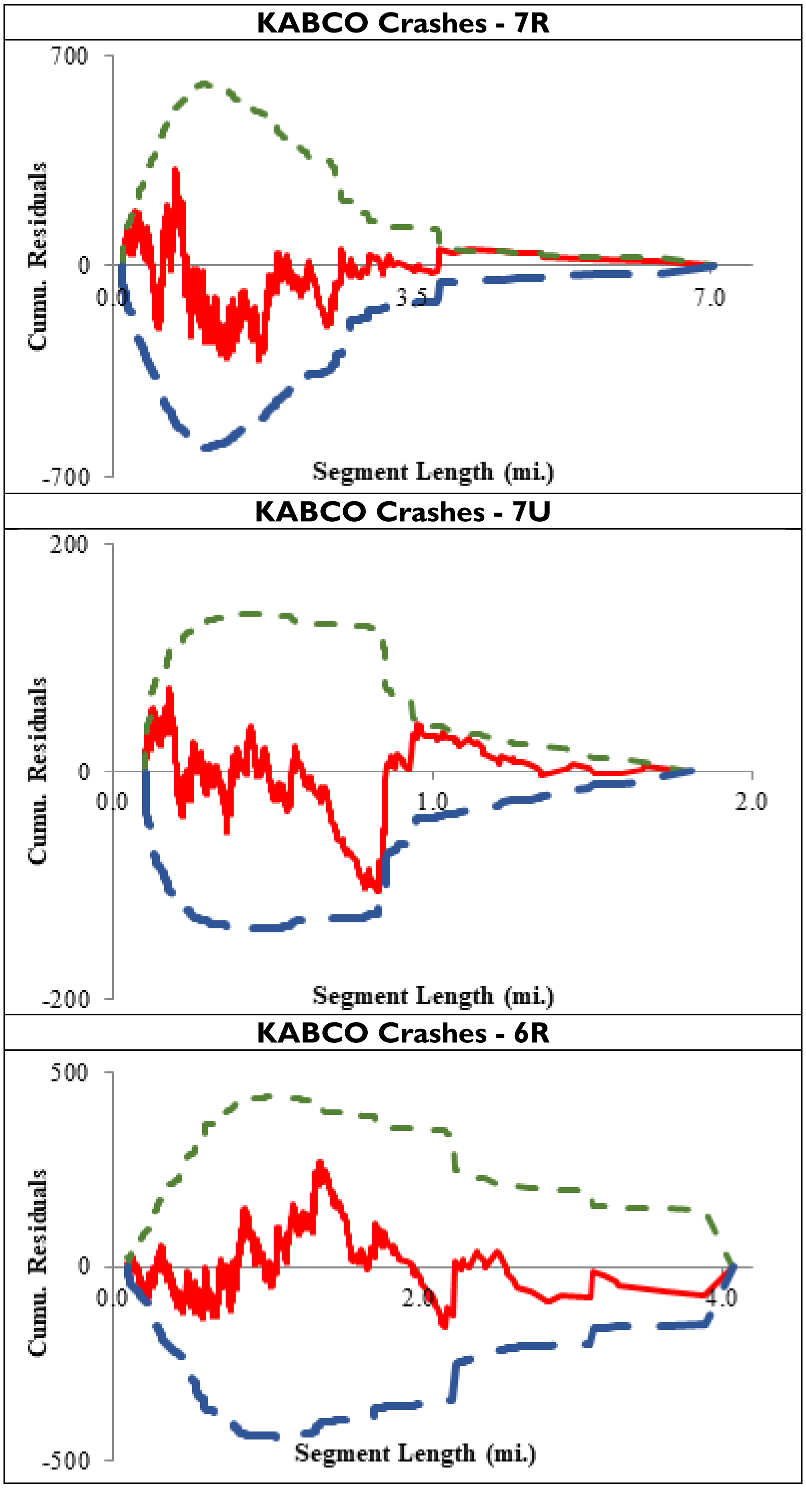

Figure 16. Graph. Cumulative Residuals vs. Segment Length.

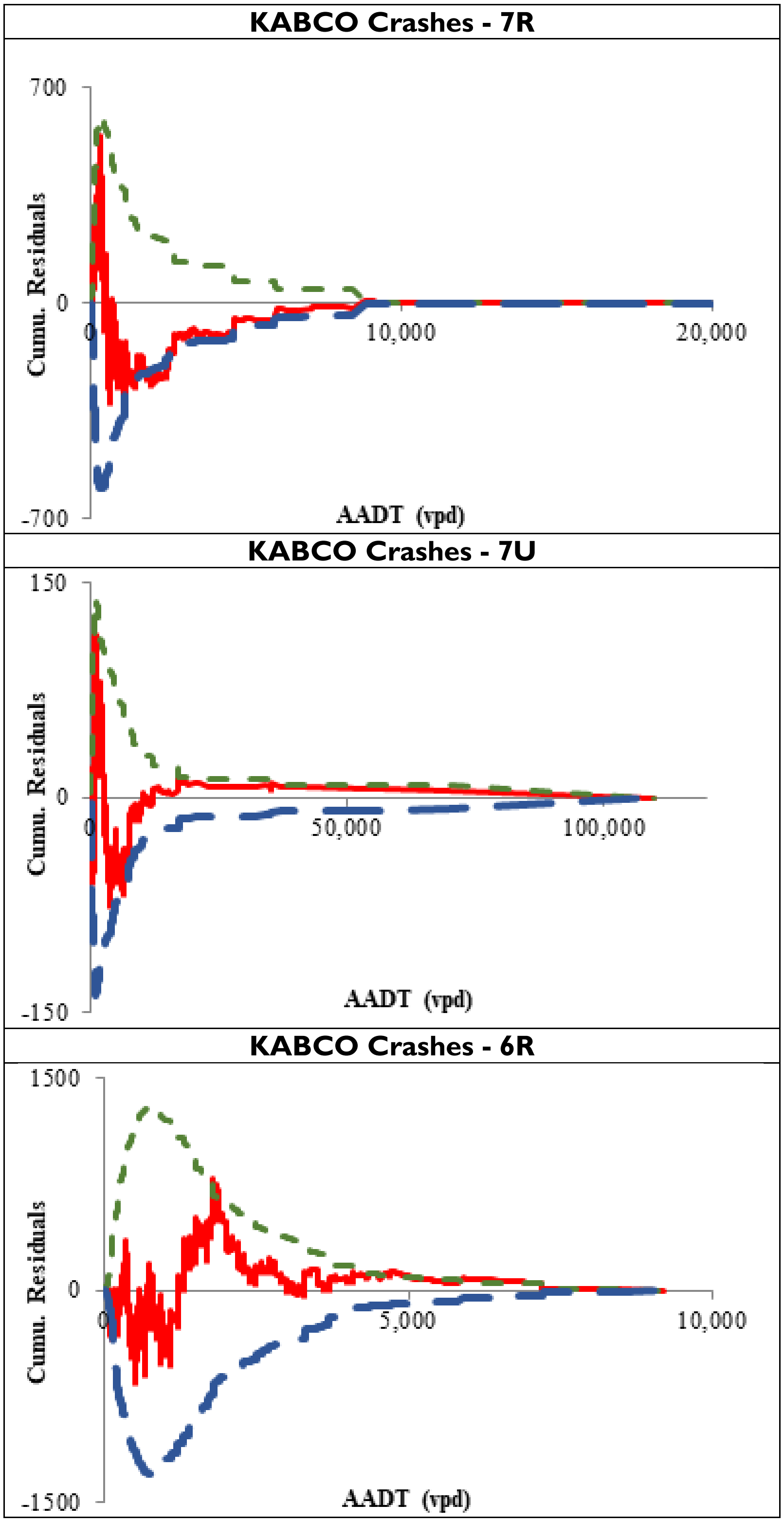

Figure 17. Graph. Cumulative Residuals vs. AADT.

By sorting the data by each variable (AADT, segment length, or any other predictor variable of interest), CURE plots can be created to assess the precision of the functional form of these variables in the model. The CURE plots developed for 6R, 7R, and 7U are mostly within the boundary of two standard deviations.

A.3.3 Sensitivity Analysis

The goal of the sensitivity analysis was to determine the impact of AADT estimation errors on the expected crash frequencies and hence, the final ranking of the study sites. The sensitivity analysis was separately performed for each functional classification and crash severity group (KABCO and KABC). The analysis involved the following steps:

- Step 1: Apply the EB method.
- Step 2: Determine the rank of each segment based on the results obtained from Step 1.
- Step 3: Determine the percentile of the rank of each segment.
- Step 4: Increase the AADT of each segment by 10, 50, 100, 250 and 500 percent by keeping the rest of segments and variables unchanged.
- Step 5: Repeat Steps 1-4 separately for each segment and AADT percent increase. The end result is repeating Steps 1-4 185,930 times = [(3,110 segments in 6R) + (12,386 segments in 7R) + (3,097 segments in 7U)] x (5 AADT percent increases) x (2 crash severity groups).
- Step 6: Calculate the percentile rank change of each segment by comparing the initial rank of each segment (no AADT change) against the rank obtained when AADT was increased by a certain percent.

A.4 RESULTS

Figure 18 through Figure 20 show the distribution of the percentile rank changes for different AADT groups and functional classes in a box-violin plot format. The plots show that higher percent increases in AADT are associated with higher percentile rank changes, as expected. This trend is visible for all functional classifications. However, even the highest percent (500 percent) increase in AADT does not have a significant effect on the expected crash frequencies and therefore, the final segment ranking. In particular, the highest percentile rank changes are on average less than 10 percent in the case of 6R and 7U, and less than 5 percent in the case of 7R. Overall, the plots show that the average percentile rank changes are higher for 6R and 7U compared to those of 7R. Because the traffic volume of most rural local roads is lower than 2,000 vpd, the box-violin plots for higher volumes (greater than 2,000 vpd) are skewed toward lower percentile rank changes. This trend can be partially attributed to the fact that the AADT coefficients (0.035 and 0.034) of the two SPFs developed for 6U (for KABCO and KABC crashes respectively) are significantly smaller than those of the other two functional classifications. Another potential reason that relates to the small AADT coefficients is that the sample size of 7R (12,386) is significantly larger than those of 6R (3,110) and 7U (3,097). Further, the CURE plots of 7R show that the residuals for the AADT range 0-10,000 vpd are not close to zero, indicating that the SPFs may need to be improved. One possible improvement is to divide 7R into subgroups based on geography or roadway/geometric characteristics and develop separate SPFs for each subgroup. Other potential improvements may include changing the form of the SPFs, adding more variables and interaction terms, and changing the objective functions that are used to estimate the parameter estimates.

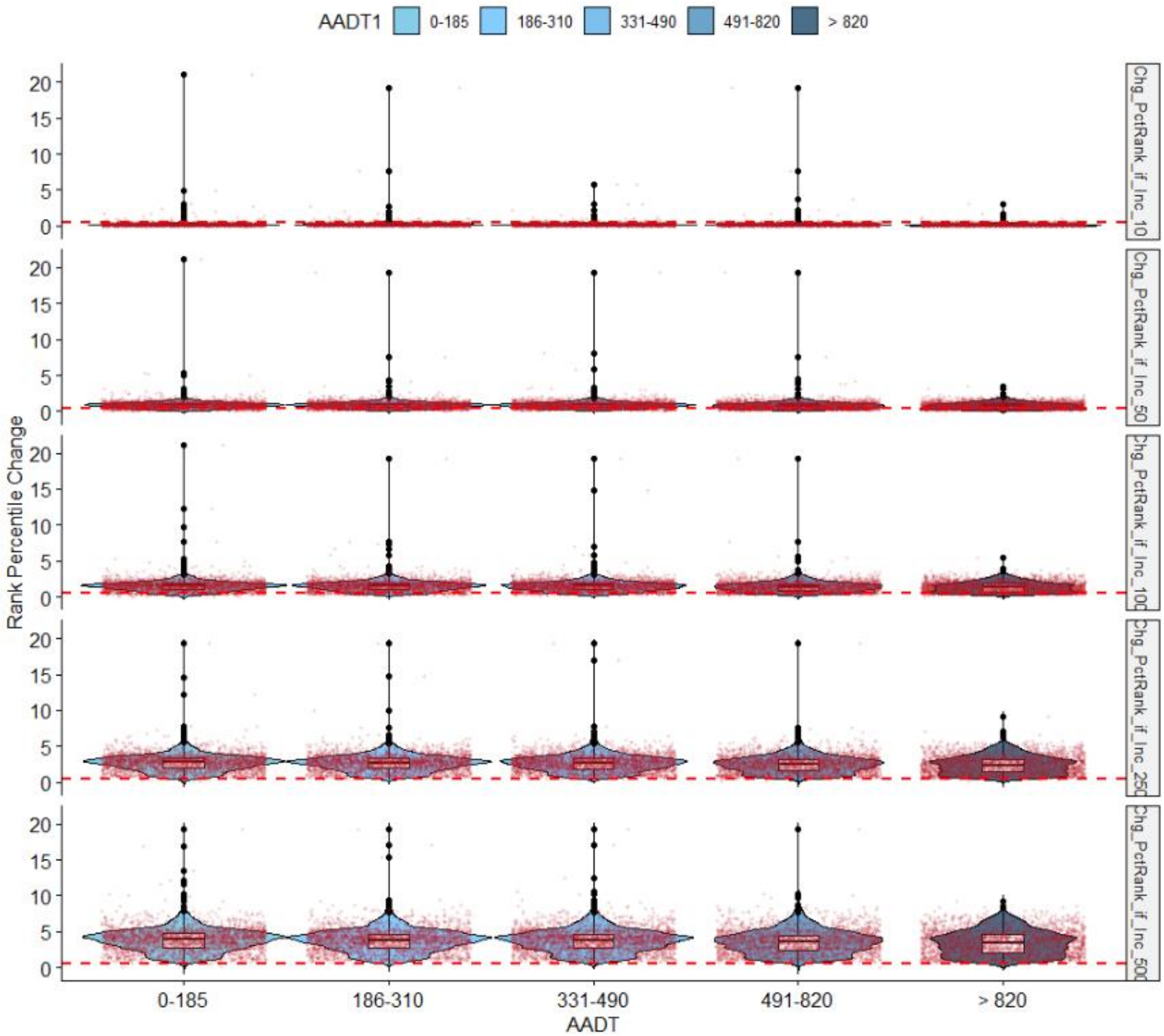

Figure 18. Graph. Percentile Rank Change for Different AADT Groups (7R).

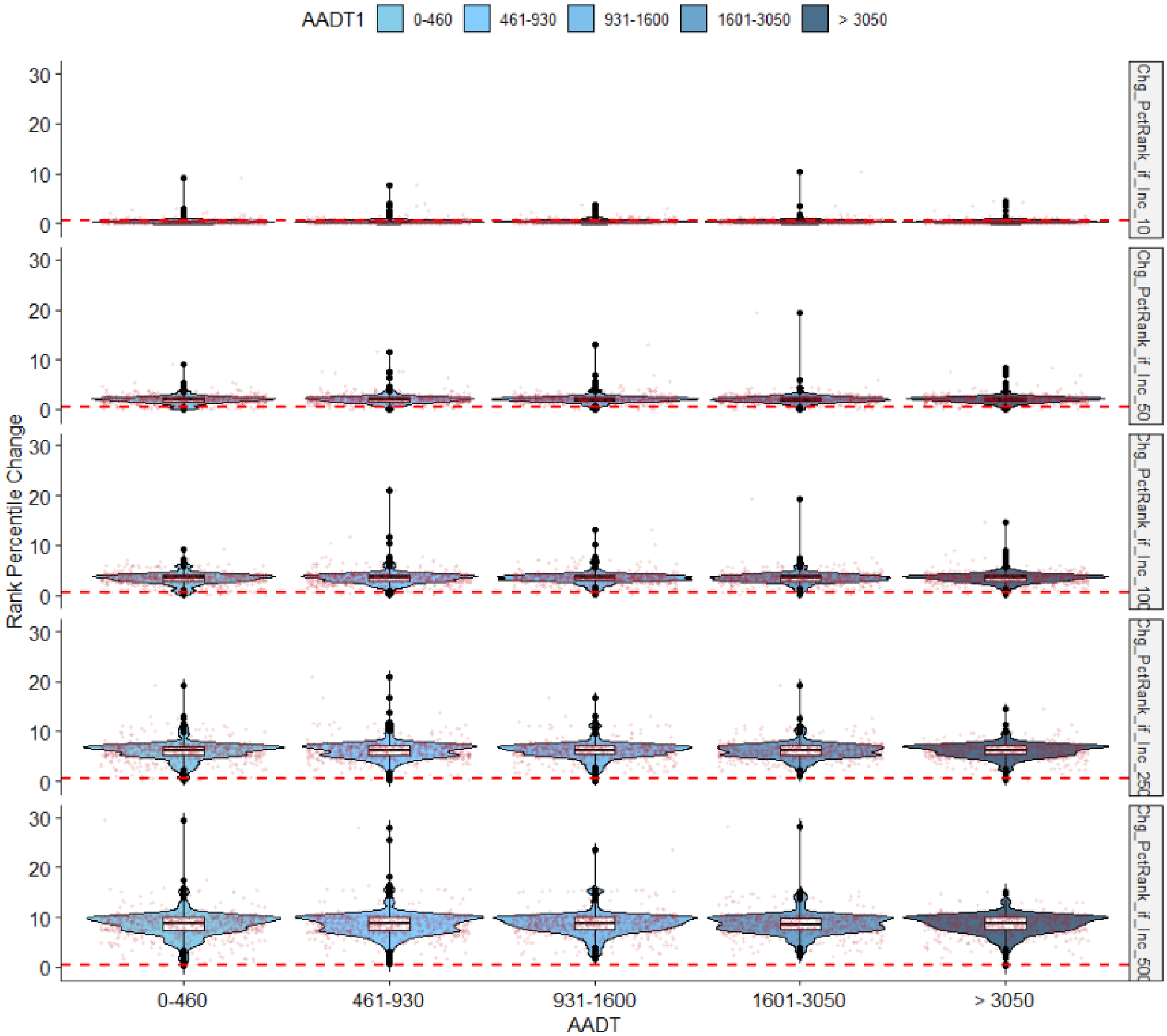

Figure 19. Graph. Percentile Rank Change for Different AADT Groups (7U).

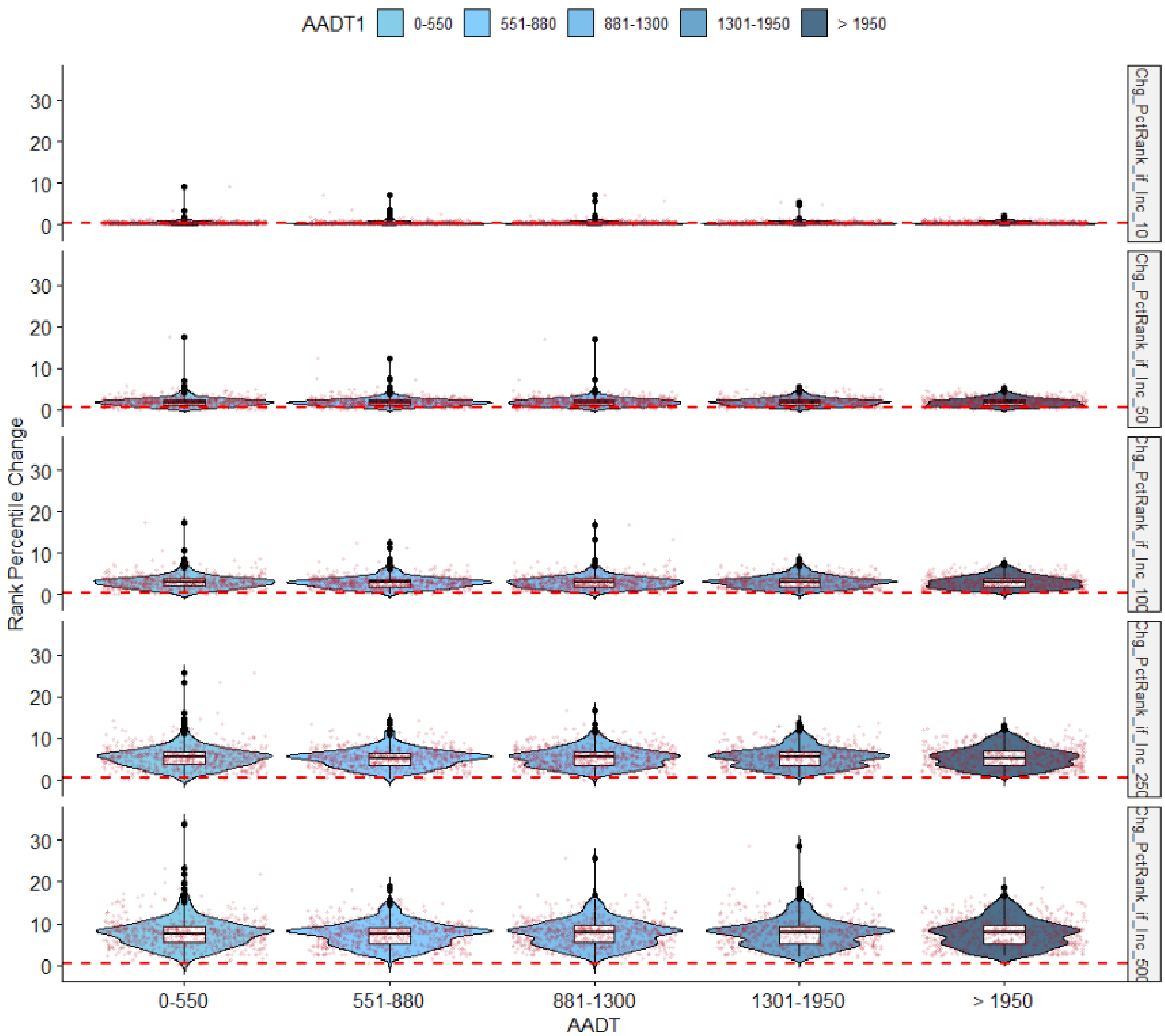

Figure 20. Graph. Percentile Rank Change for Different AADT Groups (6R).

In general, the results show that AADT estimation errors do not significantly affect the expected crash frequencies and the associated percentile rank changes. This is consistent with previous findings reported by Staats.[(3)] Staats performed a similar sensitivity analysis to evaluate how AADT estimation errors can impact the number of predicted crashes that are used in safety analysis (EB method that uses SPFs). The sensitivity analysis included the following steps:

a) Identified all intersections in Kentucky using GIS tools.

b) Classified intersections based on their characteristics (rural or urban roads, number of approaches, unsignalized or signalized, and number of lanes in each direction). The analysis considered intersections where State roads intersect local roads.

c) Estimated predicted average crash frequency using SPFs from the HSM for different types of intersections such as three-leg and four-leg stop-sign controlled intersections. The AADT of the major road of an intersection was obtained from Kentucky's *Highway Information System*, while the AADT of the local intersecting road was estimated from a model.

d) Estimated the expected number of crashes based on the following Empirical Bayes (EB) formula:

$$Expected\ Crashes\ in\ X\ years = Overdispersion\ parameter * N * CMF * X + (1 - Overdispersion\ parameter) * Previous\ crashes$$

Where:

Overdispersion parameter = obtained from the HSM and calibrated for each SPF

N = the number of crashes predicted by the SPF

CMF = crash modification factor (from HSM or CMF Clearinghouse)

X = the number of years

Previous crashes = the number of crashes at the intersection in the past X years

e) Adjusted AADTs using the following equation:

$$Adjusted\ AADT = Estimated\ AADT/(1 + Percent\ Error)$$

Where:

Estimated AADT = AADT generated by a model

Percent Error = maximum percent error (797 percent), minimum percent error (-94 percent), average positive error (134 percent), or average negative error (-38 percent).

f) Revised SPF values using the adjusted AADTs. The EB method incorporated the updated SPF values and used crash data over a 10-year period assuming a CMF of 0.15. Staats estimated that the average crash cost was $54,051.

g) Estimated maximum countermeasure construction cost for each prediction error and intersection, assuming that the benefit-to-cost ratio was equal to five.

h) Calculated percent errors for maximum countermeasure costs between the original AADT, the estimated AADT, and the adjusted AADTs. This range of errors captured the variation in the number of predicted crashes due to different AADT estimation errors.

Staats found that the average AADT estimation errors ranged between 134 percent (overestimated AADTs) to 38 percent (underestimated AADTs). After accounting for the two errors and adjusting the AADT values, the author found that the derived crash prediction errors were much smaller: 28 percent for overestimated AADTs and 22 percent for underestimated AADTs. The maximum AADT estimation error was 797 percent and the lowest was 94 percent. The derived crash prediction errors were 54 percent and 253 percent respectively. In general, the study showed that the AADT errors had a limited impact on the final crash predictions. This happened because the local road AADT only influences the number of crashes predicted by SPFs. However, intersection crash predictions must take into account both SPFs and historical crash rates and the latter have a higher weight in the calculation of the expected number of crashes.[3]

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APPENDIX B – AUTOMATED ESTIMATION OF TRAFFIC VOLUMES USING TRIP GENERATION METHOD

SUMMARY

This appendix presents a traffic volume estimation procedure that incorporates a trip generation method suitable for residential roads with one point of entry (i.e., cul-de-sacs).[1] This method has two advantages over many traditional and non-traditional methods. First, it eliminates the need to carry out traffic counts in the field by yielding time and cost savings. Second, it provides significantly more accurate AADT estimates, particularly on urban local roads where the correlations of Census variables with AADT tends to be weak to negligible. The Virginia (VDOT) first developed this method to manually estimate traffic volumes on secondary local roadways instead of taking short-duration counts in the field.[1] According to VDOT's approach, region and district staff review candidate segments using aerial photos, evaluate roadway eligibility criteria, count the number of houses along residential roads, and use a trip generation equation to estimate traffic volumes.

To reduce the time and effort required to manually perform these steps, the research team developed a GIS database that contains electronic footprints of over 100 million buildings in the U.S. Then, researchers used GIS scripts and models to apply trip generation concepts and automate, to some degree, the estimation of traffic volumes. The research team validated the method using permanent and short-duration count data in North Carolina and Vermont, and found that the median APEs are 18.0 percent and 20.0 percent, respectively. These errors are significantly lower than those obtained from many traditional and non-traditional AADT estimation methods.

B.1 OVERVIEW OF VDOT'S TRIP GENERATION METHOD

VDOT estimates traffic volumes on secondary local roadways using a trip generation method instead of taking short-duration traffic counts. The use of trip generation estimates[2] was an outcome of a review process that aimed to reduce data collection costs and achieve manpower savings by establishing a local secondary count program. As part of this program, VDOT provided guidelines[3, 4] to its staff on how to identify eligible traffic links and generate traffic volume estimates using the trip-generation method. For example, roadways that are subject to use of trip generation techniques for traffic volume estimates are those that have one point of entry (e.g., cul-de-sacs), are residential in nature, and have a length of 0.5 mile or less. According to VDOT's secondary program, region and district staff performs several actions that mainly involve:

- Reviewing candidate segments using aerial photos.

- Determining potential development and roadway connectivity.
- Evaluating whether specific criteria are met.
- Documenting the trip generation estimate process used.
- Developing and submitting the estimates to the Central Office–Traffic Engineering Division.

B.2 SELECTION OF TRAFFIC LINKS

VDOT developed criteria and guidance to evaluate sites for the trip generation method.[3, 4] District staff reviews each candidate site using recent aerial images to determine development and roadway connectivity. If VDOT staff can make a determination using aerial photos, VDOT recommends using the trip generation method only for traffic links that meet the following criteria:

- Land use is limited to single-family detached housing (ITE Trip Generation Code 210).[2] For other land uses, it may not be possible to determine the number of dwelling units (or other independent variables) from an aerial photo. In the case of higher-density residential, this limitation also eliminates the need to judge which trip generation code to use, which may also be difficult to determine from an aerial photo. The majority of cul-de-sacs in the Northern Region consist of single-family homes.
- No alternative means of motor vehicle access is available, even by private streets or driveways.
- Unusual land uses are nearby that might cause traffic volumes to differ significantly from the trip generation rates. For example, a Metrorail station may induce more bicycle and pedestrian trips and fewer vehicle trips, or it may induce more vehicular trips if it attracts on-street parking.
- Occasionally, a private street diverges from a VDOT-maintained cul-de-sac. Consideration of these cul-de-sacs for the trip generation method is dependent on meeting all the criteria above, even though the private streets may lead to additional development, as long as the combined length of the public and private streets are less than the 0.5-mile threshold.

District staff retains the flexibility to conduct an actual traffic count on any link that exhibits unusual traffic conditions that do not meet the criteria defined above.

B.3 TRAFFIC VOLUME ESTIMATION

According to VDOT, a simple method of computing traffic volumes for cul-de-sacs is to multiply the total number of households on the cul-de-sac by the trip generation rate. However, this would approximate the volume at the point where the cul-de-sac intersects the connecting roadway. The volume on a cul-de-sac is highest at this point since all trips from the cul-de-sac must pass it. The volume becomes lower toward the bulb because households along the stem typically travel away from the bulb. To capture this trend, the trip generation method estimates the average volume per weekday along the cul-de-sac as follows:

Equation B.1:

$$v = \frac{\sum_{n=1}^{H}(g_n \times d_n)}{L}$$

Where:

v = number of trips per weekday using a cul-de-sac, averaged according to the length of the cul-de-sac.

H = households with driveways on the cul-de-sac.

g_n = number of trips per weekday generated by the n^{th} household.

d_n = portion of the length of each trip to and from the n^{th} household that uses the cul-de-sac, taken as the distance along the cul-de-sac between the n^{th} household's driveway and the end of the stem.

L = length of the cul-de-sac.

Because VDOT uses this process for only one land use type, it considers the same *g* value for every household. VDOT extracts this value from the *Trip Generation Manual*.(2) For single-family detached housing (Code 210), *g* = 9.57 trips per weekday per dwelling unit, according to the 8th edition of the manual. VDOT rounds this rate to 10 trips per weekday for computational ease.

VDOT makes a further distinction between "bulb households," with driveways in the bulb of the cul-de-sac, and "stem households," with driveways in the stem. Trips to and from bulb households typically use the cul-de-sac for approximately its entire length, particularly when considering additional maneuvering in the bulb. Stem household trips typically use the cul-de-sac only from their driveways to the connecting road. Equation B.1 simplified as follows:

Equation B.2:

$$v = g \times \left(H_b + H_s \times \frac{d}{L}\right)$$

Where:

g = 10 trips per weekday per household.

H_b = number of bulb households.

H_s = number of stem households.

The ratio *d/L* is a dimensionless constant since both *d* and *L* are expressed in units of length. It represents the average fraction of the cul-de-sac used by trips to and from stem households. Stem household driveways are assumed to be distributed uniformly along the length of the cul-de-sac, so *d/L* = 0.5. VDOT further simplifies Equation B.2 as follows:

Equation B.3:

$$v = 10 \times (H_b + 0.5H_s)$$

Although it is possible to compute a traffic volume estimate without differentiating between bulb and stem households, VDOT does not do so because it wants to produce estimates that are more accurate. Most cul-de-sacs do not have driveways distributed uniformly along their length. Site plans often distribute driveways more densely in the bulb of the cul-de-sac than along the stem. Likewise, connecting roadways often serve households at the corner of a cul-de-sac resulting in fewer driveways.

VDOT established the following five steps for estimating traffic volumes for eligible traffic links.

Step 1: Draw an imaginary line at the entrance of the cul-de-sac, where it joins the connecting road, and count the number of houses whose primary driveway can only be reached by traveling across the line. For example, on the traffic link shown in Figure 21a, there are nine houses.

Step 2: Draw another imaginary line between the bulb and the stem of the cul-de-sac and count the number of houses whose primary driveway can only be reached by traveling across this line. For example, on the cul-de-sac shown in Figure 21b, there are three houses.

Step 3: Add the results of Steps 1 and 2, and multiply the sum by 5. The calculation in this step is based on Equation (3). For example, from the first two figures, the result is (9 + 3) x 5 = 60.

Step 4: Report the result of Step 3 as the number of trips per day on a spreadsheet provided by the Central Office. Use the letter "M" to indicate that the value resulted from a "manual" estimate rather than a physical count. Also, report the date the estimate was prepared.

Step 5: Periodically send the spreadsheet back to CO-TED to import it into the traffic monitoring system. This occurs at least once per year. The results are reported in annual publications.

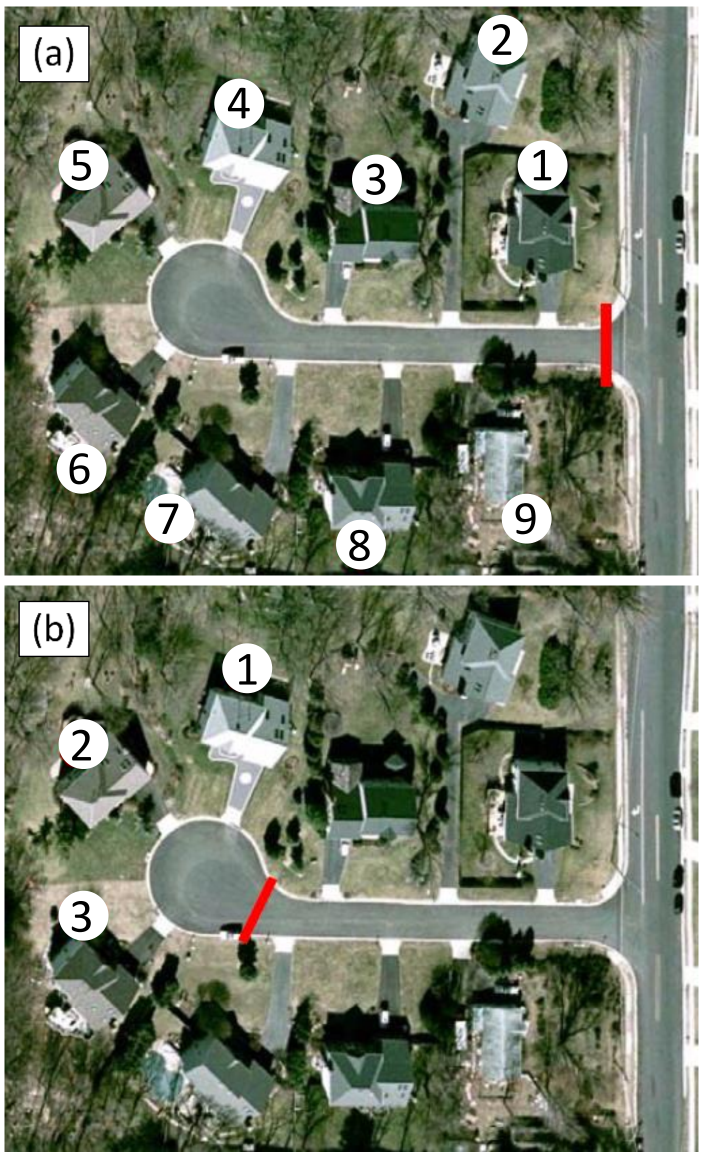

Figure 21. Screenshot of Map. Examples: (a) Step 1; (b) Step 2. Photo Courtesy VDOT Northern Region[48, 49]

VDOT provides its staff with additional aerial photos (Figure 22) and estimation examples to highlight differences between links that have different roadway and geometric characteristics.

Figure 22. Screenshot. Examples: (a) Fariba Drive; (b) Pine Knot Drive. Photo Courtesy VDOT Northern Region.[48,49]

The first three steps of the traffic volume estimation process result in the following:

<u>Figure 22a:</u>

Step 1: 17 houses.

Step 2: 4 houses.

Step 3: (17 + 4) x 5 = 105 trips per day.

<u>Figure 22b:</u>

Step 1: 38 houses.

Step 2: 17 houses.

Step 3: (38 + 17) x 5 = 275 trips per day.

Figure 22a shows a simple case of a traffic link that consists of a bulb and a stem. In Figure 22b, the cul-de-sac has two private-street connections through the bulb, taken into consideration in Step 2, and two connections along the stem. Distribution of the connections along the stem is relatively uniform along the cul-de-sac's length, so the trip generation computation is valid.

B.4 COST AND OTHER CONSIDERATIONS

In general, the cost to generate traffic volume estimates is significantly lower than collecting field data. Some Districts apply the trip generation method in-house, while others hire a temporary service contractor. As of February 2016, a typical hourly rate of these contractors ranged between \$20 and \$30 per hour. Depending on the complexity and the number of the houses along a roadway link, VDOT staff or its contractors spend between 15-30 minutes to generate a traffic volume estimate for one link.

Most contractors are responsible for both conducting counts in the field using portable traffic equipment and generating traffic volume estimates using the trip generation method. Some Districts ask their contractor(s) not to rely heavily on aerial photos but visit the roadway links of interest and collect necessary information and data in the field. To save time and reduce travel costs, contractors try to do both (i.e., conduct short-duration counts and visit eligible links that are close to the counts) in one trip. Other Districts allow their contractor(s) to apply the trip generation method at the office and ask them to visit the field in case the aerial photos are old, trees cover driveways and houses, and there is significant construction activity in the examined area.

B.5 METHOD AUTOMATION AND VALIDATION

To avoid some of the manual steps described above, particularly those that involve reviewing and extracting data from aerial images, the research team used artificial intelligence methods to develop a geodatabase that contains footprints of over 100 million buildings in the entire country. Figure 23 shows an example of building footprints in a residential area in North Carolina. Table 20 shows the approximate number of buildings by state.

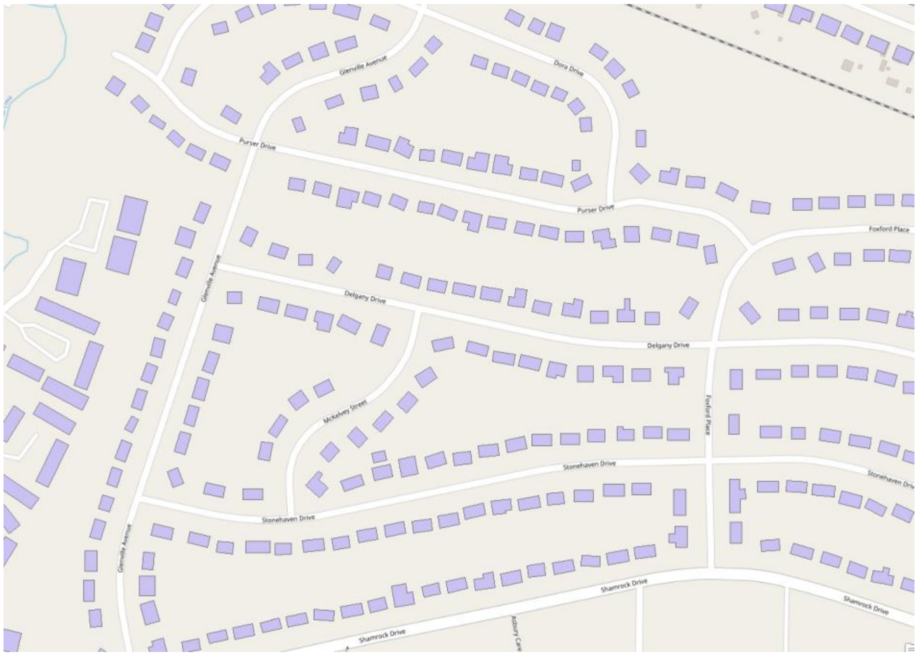

Figure 23. Screenshot. Example of Building Footprints in a Residential Area.

Then, researchers developed GIS models and scripts to automatically:

- Determine dangle nodes (i.e., cul-de-sacs) on the transportation network.
- Extract location information (e.g., address) for each building.
- Map every building to the network based on the building address.
- Apply trip generation rules and roadway link eligibility criteria.
- Estimate traffic volumes for eligible links.

The research team used the GIS tools to apply the trip generation method in North Carolina and Vermont. Researchers compared the traffic volumes estimates generated by the trip generation method against permanent and short-duration counts. Figure 24 and Figure 25 show scatterplots between trip generation volume estimates and counts from North Carolina and Vermont, respectively. The validation datasets included 123 counts in North Carolina and 34 counts in Vermont.

Table 20. Number of Electronic Building Footprints by State.

State	Number of Buildings (Millions)	State	Number of Buildings (Millions)
Alabama	2.5	Montana	0.8
Alaska	0.1	Nebraska	1.2
Arizona	2.5	Nevada	0.7
Arkansas	1.5	New Hampshire	0.5
California	10.0	New Mexico	1.0
Colorado	2.1	New York	4.5
Connecticut	1.2	New Jersey	2.5
Delaware	0.3	North Carolina	4.5
District of Columbia	0.1	North Dakota	0.6
Florida	6.5	Ohio	5.0
Georgia	3.5	Oklahoma	2.1
Hawaii	0.3	Oregon	1.8
Idaho	0.5	Pennsylvania	4.5
Illinois	4.5	Rhode Island	0.4
Indiana	3.3	South Carolina	2.2
Iowa	2.0	South Dakota	0.6
Kansas	1.6	Tennessee	3.0
Kentucky	2.4	Texas	9.5
Louisiana	2.1	Utah	1.0
Maine	0.8	Vermont	0.3
Maryland	1.6	Virginia	3.1
Massachusetts	2.0	Washington	3.0
Michigan	4.6	West Virginia	1.0
Minnesota	2.4	Wisconsin	3.1
Mississippi	1.5	Wyoming	0.4
Missouri	3.1	-*	-

* Dashes mean no data (empty cells).

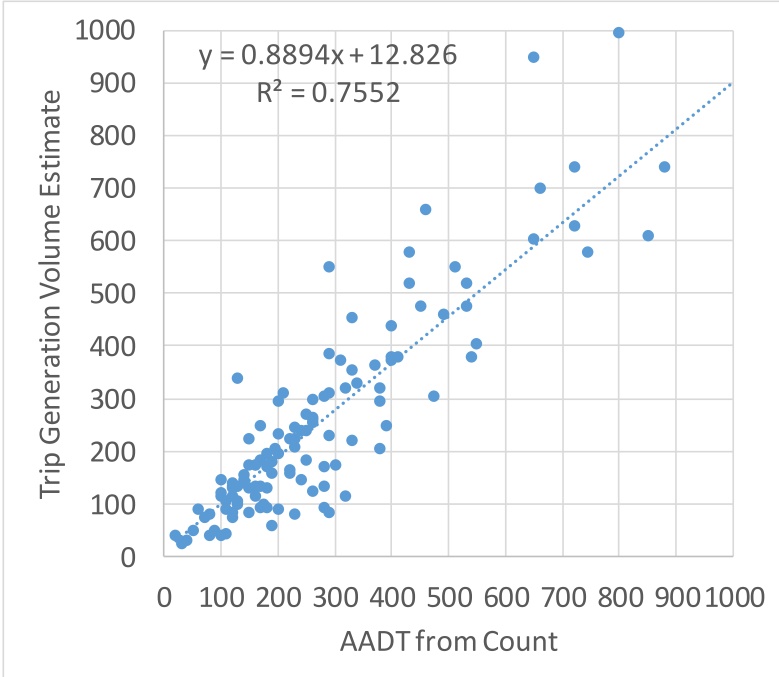

Figure 24. Scatterplot. Traffic Volumes from Trip Generation Method vs. Counts in North Carolina.

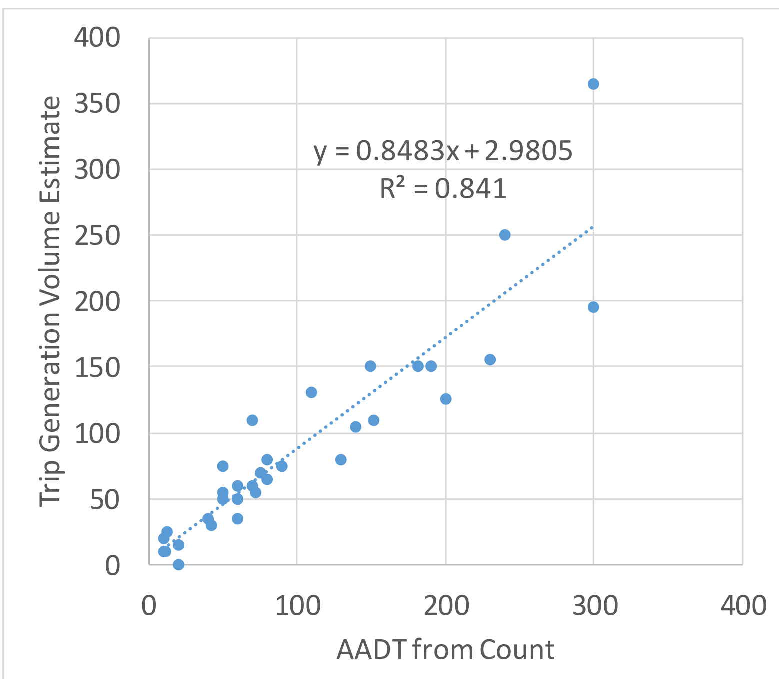

Figure 25. Scatterplot. Traffic Volumes from Trip Generation Method vs. Counts in Vermont.

In the case of North Carolina, the median APE and mean APE were 18.0 percent and 25.3 percent, respectively. In Vermont, the median APE and mean APE were 20.0 percent and 27.0 percent, respectively. These errors are generally lower than those obtained from other traditional and non-traditional methods.

The case study with VDOT and the automation of VDOT's approach by the research team revealed that the use of trip generation estimates minimizes the need to carry out traffic counts on qualified links by yielding time and cost savings. Even if agencies apply the trip generation method manually, it may be cheaper to use state resources and labor than to hire contractors in many cases. Keys to successful application of the trip generation method include a clear implementation plan and specific assignment of roles and responsibilities to different parties within the agency. Developing requirements and guidelines can be a time-consuming process, but the benefits realized outweigh the development effort. Agencies should estimate the cost for generating traffic volume estimates manually or in an automatic fashion, compare it to the cost for conducting and processing short-duration counts, and relate it to the hidden cost of not having data on secondary local roads. Agencies should inform managers and executives on potential cost savings and other benefits achieved through adopting more-efficient procedures such as the one described above.[1]

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ACKNOWLEDGMENTS

FHWA: Marc Starnes (General Task Manager), Stuart Thompson (Former General Task Manager), Steven Jessberger (Panel Member), and Joseph Hausman (Panel Member).

Case study representatives

DVRPC: Scott Brady and Michael Ruane.

NYSDOT: Michael Fay, Robert Limoges, and Regina Doyle.

SEMCOG: Chade Saghir, Delores Muller, and Brian Mohr.

VDOT: John Bechtold, William Dunnavant, Ali Farhangi, Ralph Jones, Donald Logan, and Brett Randolph.

Pilot study representatives

Georgia DOT: Shronica Holland, Robert Binns, Sean Diehl, and LaKenya Rapley.

Montana DT: Becky Duke, Peder Jerstad, Marie Stump, and Don Wark.

Minnesota DOT: Christine Prentice, Darin Mertig, Ian Vaagenes, and Gene Hicks.

North Carolina DOT: Kent Taylor.

New Mexico DOT: Yolanda Duran, Sean Noonen, and John Baker.

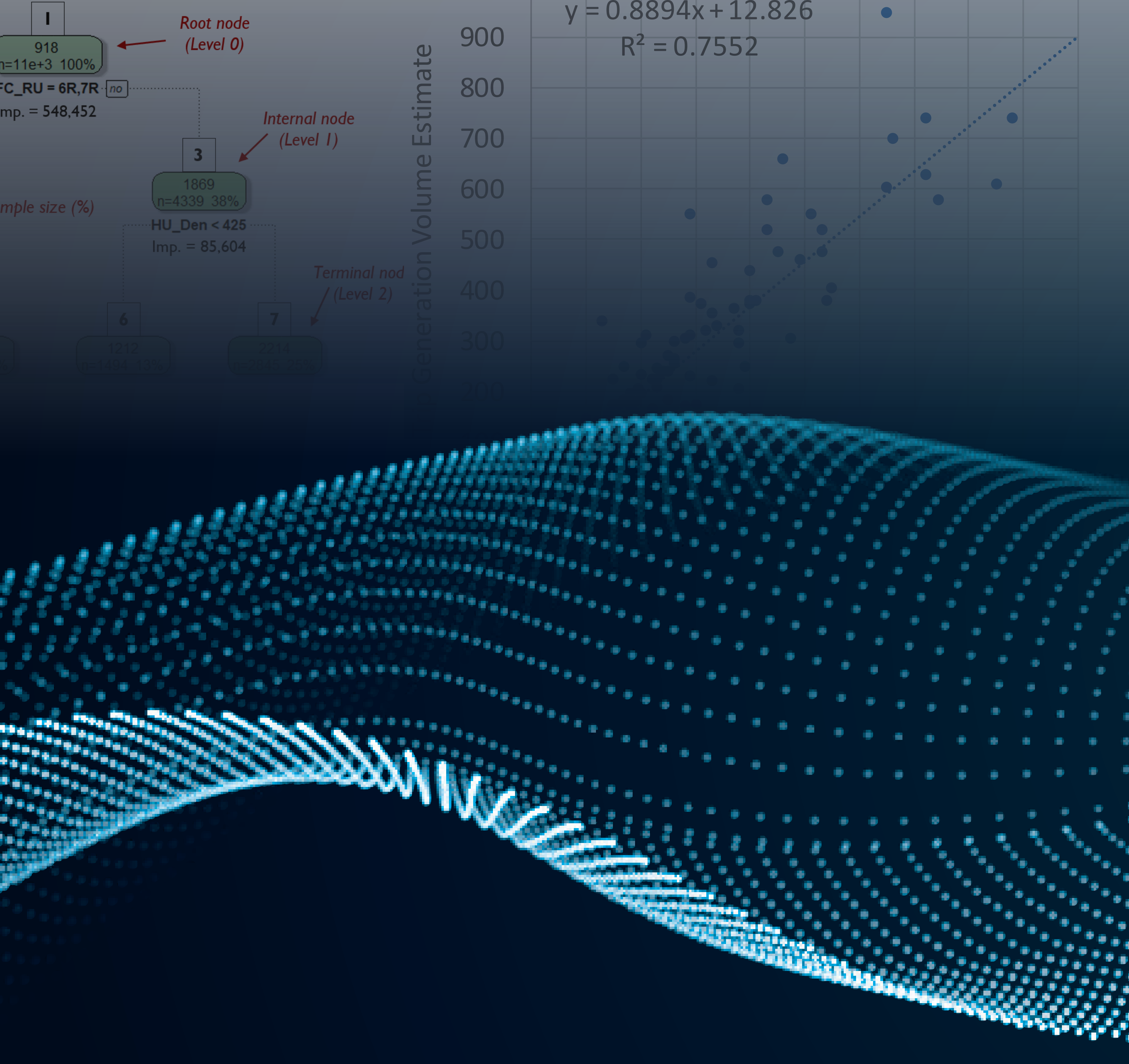
Pennsylvania DOT: Gregory Dunmire and Andrea Bahoric.

Other DOT representatives

Vermont DOT: Maureen Carr and Joshua Schultz.

Texas A&M Transportation Institute researchers: Eun Sug Park, Bobie Guo, Kartikeya Jha, Jose Rivera Montes De Oca, Pete Koeneman, Shawn Turner, Raul Avelar Moran, Sruthi Ashraf, and Steven Venglar.

Cambridge Systematics Inc. researchers: Richard Margiotta, Annita Vandervalk, and Herb Weinblatt.



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Visit safety.fhwa.dot.gov/rsdp

FHWA Office of Safety
Marc Starnes
Marc.Starnes@dot.gov
202-366-2186

FHWA-SA-20-064