Optimizing Automatic Traffic Recorders Network in Minnesota

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Diwakar Gupta, Principal Investigator
Department of Industrial and Systems Engineering
University of Minnesota

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16. Abstract (Limit: 250 words)

Accurate traffic counts are important for budgeting, traffic planning, and roadway design. With thousands of centerline miles of roadways, it is not possible to install continuous counters at all locations of interest (e.g., intersections). Therefore, at the vast majority of locations, MnDOT samples axle counts for short durations, called portable traffic recorder (PTR) sites, and obtains continuous counts from a small number of strategically important locations. The continuous-count data is leveraged to convert short-duration axle counts into average-annual-daily-traffic counts. This requires estimation of seasonal adjustment factors (SAFs) and axle correction factors at short-count locations. This project focused on developing a method for estimating SAFs for PTR sites. The continuous-count data was grouped into a small number of groups based on seasonal traffic-volume patterns. Traffic patterns at PTR sites were hypothesized by polling professional opinions and then verified by performing statistical tests. PTRs with matching seasonal patterns inherited SAFs from the corresponding continuous-count locations.

Researchers developed a survey tool, based on the analytic hierarchy process, to elicit professional judgments. MnDOT staff tested this tool. The statistical testing approach was based on bootstrapping and computer simulation. It was tested using simulated data. The results of this analysis show that in the majority of cases, three weekly samples, one in each of the three seasons, will suffice to reliably estimate traffic patterns. Data could be collected over several years to fit MnDOT's available resources. Sites that require many weeks of data (say, more than five) may be candidates for installation of continuous counters.

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Prepared by:

Diwakar Gupta
Xiaoxu Tang
Department of Industrial and Systems Engineering
University of Minnesota

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EXECUTIVE SUMMARY

Accurate estimation of traffic volume is important for a variety of reasons, such as budgeting, traffic planning, speed enforcement, and roadway design. The raw data consists of axle counts, which come from either continuous-count, also known as automated traffic recorders (ATR) sites or weigh-in-motion (WIM) sites, or short-count locations, also known as portable traffic recorder (PTR) sites. There are relatively few ATR locations and most traffic counts come from short-count locations. In order to convert axle counts from PTR locations into average annual daily traffic (AADT) estimates, MnDOT needs to calculate seasonal adjustment factors (SAFs) and axel correction factors (ACFs) for each PTR location.

MnDOT's current method for estimating SAFs consists of the following steps. MnDOT uses Ward's clustering algorithm (Ward, 1963) to group ATR data into 12 clusters based on weekday 48-hour count period proportions of AADT (usually 12 in each month) for each ATR/WIM site for the months of year of the typical count season (April through October). Only a few (four or five) of the resulting clusters produce monthly adjustment factors that resemble historical cluster factors. ATR/WIM sites in other clusters are not used to produce adjustment factors except to adjust counts taken on the same road within a reasonable distance from a given site. Each cluster with factors resembling past factors sets and containing a similar roster of ATRs/WIMs is then labeled by its key characteristics, e.g., high weekends and high summer. Independent of this clustering, each PTR site is placed in a group, and each group is attached to either a single ATR or a cluster of ATRs based on professional judgment regarding the similarity of characteristics. Each PTR site in the group inherits the SAFs of the cluster to which this group is attached. Upon knowing SAFs for a PTR site, short-term axle counts are converted to AADT counts.

University of Minnesota researchers approached the problem from a different angle and proposed an alternative methodology for categorizing the traffic patterns and calculating the seasonal adjustment factors (SAFs) for portable traffic recorder (PTR) sites. This methodology for estimating SAFs uses seasonal traffic volumes and includes an approach to quantify professional judgment.

Researchers prepared the raw data provided by MnDOT using reasonable exclusion of abnormal data. Imputation procedures were then used to compile available data into a dataset with 39 ordered weeks. By analyzing this ATR data, we established a pattern identification method that could be used to group PTRs. A traffic pattern is defined by two components: the weekday traffic volume (referred to as "weekdays"), and the ratio of weekend traffic volume to weekday traffic volume (referred to as "weekend/weekday ratio"). Each component has three attributes. Specifically, for each ATR station, the weekday traffic volume can be categorized as average (A), high (H), or low (L) relative to the average traffic volume across three seasons at that station. Similarly, the weekend to weekday ratio can be categorized as either the same, or high, or low based on pre-determined thresholds. It is possible to categorize traffic into more categories, depending on the degree to which traffic is more or less than the average of three seasons. In this proof-of-concept exercise, we kept the number of categories small for clarity of exposition.

According to the above-mentioned scheme, if a station's traffic pattern is deemed AHA on weekdays, then that means the traffic volume in spring, summer and fall is, respectively, average, high, and average, relative to the average of weekday traffic across all three seasons at that station. Similarly, the SHS weekend traffic means that the weekend daily traffic relative to weekday daily traffic is the same in spring and fall, but high in summer. PTR stations that are located along routes taken by weekend recreational traffic in summer months may exhibit this seasonal pattern. Because data are not collected from PTR sites during winter, we do not consider the winter season in this analysis. That is, the seasonal pattern is categorized only for three seasons: spring, summer, and fall.

Based on the results obtained, the most common seasonal traffic pattern is AHA weekday and LLL weekend/weekday, followed closely by AHA weekday and HHH weekend/weekday. The third common pattern is AAL weekday and LLL weekend/weekday. Sixteen to 19 stations each exhibit one of the top three patterns. The forth pattern, AHA weekday and SHS weekend/weekday has a total of five stations. The remaining patterns typically apply to only one or two stations. After identifying these patterns, we calculate the SAFs and the associated confidence intervals (if possible) for each pattern.

The results produced by our methodology are not directly comparable to the AADT adjustment factors for short duration weekday traffic volume counts currently in use. In contrast with the existing method, the alternative methodology defines the traffic pattern at the seasonal level. There are over 20 patterns identified in this alternative methodology, whereas there are only five cluster groups used in the existing method. Furthermore, the high and low volumes are defined differently in the two methodologies. Segmenting at the seasonal level may result in more informative and accurate SAF estimates.

A critical step in the methodology requires analysts to obtain professional judgment regarding the traffic patterns of PTR sites. Analysts must utilize this information to validate the pattern identification method proposed. To that end, researchers designed a survey tool to automate the process of collecting county engineers' opinions regarding the traffic patterns of PTR sites. The survey is programmed within Excel and implements an analytic hierarchy process (AHP) methodology to analyze the survey participants' responses. We emphasize that the survey does not collect opinions about the absolute volume of traffic at any given site. This is the case because we will use the volume information from sampled data (either 48 hours or a week) and extrapolate it using assigned SAFs to obtain the seasonal volumes and overall AADT. Thus, there is no need to ask the respondents about their estimate of total volume in each season.

The survey focuses on the top five patterns identified from our ATR data analysis. These patterns cover 80% of the ATR stations. Each remaining pattern only has a small number of ATR stations. For those patterns, using SAFs estimated from ATR data may be too noisy. The survey contains a total of 10 questions. Each question asks the user to compare two traffic patterns at a time and indicate which pattern is more likely to represent the true traffic pattern at the selected PTR site. The survey is also programmed with several options for the user to review the pattern indicated by current answers, manually change the answer to the question that most-likely causes inconsistency in the respondent's answers, or let the program automatically make the change to meet the consistency requirements.

A separate ATR-data-based survey is also created for training and testing purposes. Two MnDOT participants have so far completed the training survey. However, due to the very limited amount of data, it is not possible to identify all of the potential problems that one might encounter if this survey tool were adopted for widespread use. Although there is no reason to believe that this approach will not be successful in the field, more testing will be beneficial. The researchers conjecture that future deployment of this method will benefit from the presentation of background materials and training sessions to county engineers.

Finally, researchers carry out a simulation exercise that analyzes the sample-size requirements for desired estimation accuracy at short-count sites. Specifically, researchers propose a simulation methodology that samples and bootstraps continuous-count data to create data records as if they were collected from PTR sites. This approach is illustrated with three sets of attributes: (1) total volume by season, (2) weekend volume by season, and (3) heavy commercial volume by season. Three levels are defined for each attribute, namely, high, average, and low. A traffic pattern is a combination of levels for spring, summer, and fall. The most common pattern is AHA – average attribute level in spring and fall, and high in summer.

For each sample size (in terms of weeks), we carry out a simulation with 200 iterations and track the correctness of the identified pattern. The percent of correct classification among the 200 iterations is calculated and treated as classification accuracy for that sample size. We aggregate the station level simulation results obtained and calculate the percentage of stations that show a classification accuracy rate of no less than 50% for each sample size. The results are obtained for all stations individually and subsequently for the three subsets of stations by seasonal traffic pattern. This analysis enables the identification of the minimum sample size that meets two thresholds for each attribute – the thresholds are the sample sizes needed for a minimum 50% of stations to reach a 50% accuracy rate. For most sites, accurate volume estimates can be obtained with three weeks of short-count data – one week for each season. We also carry out additional analysis to demonstrate the robustness of our findings. These findings also indicate that when developing annual short-count plans, MnDOT may choose to collect additional data during seasons that are not represented in the historical data. This does not appear to be the case at the present time.

The simulation technique is used to simultaneously validate the professional judgment and to identify the traffic-volume pattern. This technique requires more data than what is currently available or collected. If this approach is adopted, future data collection may be spread over multiple years to avoid excessive effort in any given year of traffic count cycles. The work of this project also sets the stage for identifying which PTR sites are likely to benefit the most from more frequent data collection. These sites are also candidate sites for conversion to ATR systems.

CHAPTER 1 : INTRODUCTION

1.1 Background

The state of Minnesota has many thousands of centerline miles of roadways (website: Roadway Data Fun Facts) for recent statistics. These roadways have different traffic volumes and types of traffic. Minnesota Department of Transportation's (MnDOT's) Transportation Data & Analysis (TDA) section is responsible for developing estimates of traffic volumes, measured in terms of average annual daily traffic (AADT) counts, vehicle miles traveled (VMT), and heavy-commercial average annual daily traffic (HCADT) counts. Traffic data are submitted to the Federal Highway Administration (FHWA) and drive budgeting, speed enforcement, and traffic planning decisions. Correct estimation of traffic volume and type is therefore an important task. It is also a challenging task because of the large number of roadways and the prohibitive cost of placing sensors to continuously count traffic on all roadways.

Raw data on traffic counts, vehicle class, and weight information comes from three sources. These are referred to as weigh-in-motion (WIM) sites, automatic traffic recorder (ATR) sites, and portable traffic recorder (PTR) sites. WIM sites record volume, class and weight, ATR sites record volume and class, and PTR sites primarily record volume. Only a few selected PTR sites have class counts (to be explained in more detail later). The WIM and ATR sites are also referred to as continuous-count locations and PTR sites are also referred to as short-count (usually 48 hours) locations because at the former sites, sensors record traffic information all the time so long as they are operational. In contrast, at the PTR sites, traffic information is sampled for a limited period of time, usually 48 hours, which happens approximately every two to six years. The state of Minnesota has 15 WIM sites, 70 ATR sites, and more than 32,500 PTR sites.

In a strategy that is rooted in statistical clustering, MnDOT identifies patterns of traffic from WIM and ATR data, and then uses professional judgment to determine which PTR sites have matching traffic pattern. The short-count data from PTR sites is extrapolated to the entire year with the help of seasonal adjustment factors (SAFs) derived from the matching continuous-count sites. No attempt is made to measure vehicle weights at PTR sites. MnDOT's scheme uses professional judgment to group PTR sites into groups such that each group is attached to either a single or a cluster of ATR sites. Recall that ATR clusters are obtained using a statistical clustering algorithm.

The key research question that this project tries to answer is the following. Is there an alternate/better way to utilize the continuous-count data, and infrequently sampled short-count data to develop accurate estimates of traffic volumes? Is there an approach that will make the process of incorporating professional judgment more systematic and accurate? How often should MnDOT sample data from short-count sites? Note that in order to collect data at short-count sites, MnDOT needs to set up a portable recorder at that site, which consumes resources and time of state employees. Therefore, it is important to consider the feasibility of recommended alternate approaches.

An alternate methodology should be amenable to future efforts aimed at some big picture issues as well. Is Minnesota using the right number of continuous-count sites? Where will it help to locate additional continuous counters?

There are several papers in the transportation research literature that address the question of the placement of traffic recorders at traffic intersections, splits and merges (see, for example, Bianco et al. 2001, Bianco et al. 2006, and Sayyady et al. 2013). In that stream of work, the aim is to use the minimum number of recorders by utilizing flow balance to reduce measurement requirements, i.e., the fact that total traffic in must equal the total traffic out. The problem addressed in this project is quite different. We do not ask whether the location of traffic recorders is appropriate. Rather, we are concerned with leveraging continuous-count data to provide accurate estimates of traffic volumes at all short-count sites. From a broader perspective, our research question concerns the appropriateness of short counts for estimating traffic volumes. Our results demonstrate that this is largely true, although MnDOT will need to collect more short-count data than its current practice.

1.2 Research Objectives

This project tackled the <u>first step</u> in a three-step approach. The three steps are (i) identify potential ATR location sites by studying whether seasonal adjustment and axle correction factors (SAFs and ACFs) can be estimated well for each short-count site from current data, (ii) use economic development pattern to identify additional locations whose traffic flows may not be well understood from the current configuration of ATRs, and (iii) develop an optimization model to determine where best to locate ATRs among the feasible sites identified in steps (i) and (ii) subject to budget constraints.

During the execution of the project involving the first step, it was discovered that short-count data are collected too infrequently for the vast majority of PTR sites to make it possible to perform the analysis initially conceived. Therefore, the project was amended to include two additional goals. In the first goal, the research team used simulation methodology to bootstrap WIM/ATR data to create pseudo-PTR data. This data could be used instead of actual multiple observations from short-count sites to identify whether a particular site's pattern can be estimated from the recommended methodology. In the second goal, the research team developed an approach to quantify professional judgment, which is an integral part of the current and recommended methodology for estimating traffic volumes. We provide an overview of our methodology next.

1.3 Methodology - Overview

MnDOT's current method uses Ward's clustering algorithm to group ATRs into clusters. The user is able to select an arbitrary number of desirable clusters. Then, TDA staff, qualitatively group these clusters into five larger clusters for which they can assign interpretable labels, e.g., high weekends and high summer.

There are two issues with this approach. First, although the initial clustering is based on statistical methods, the final grouping, which is used to derive SAFs is not. This makes the process ad-hoc. Second, the initial clustering is based on traffic volume fluctuations, relative to the daily average volume, by month and day of week, at each station. However, the goal of SAF estimation is to determine seasonal factors. Therefore, it makes more sense to directly group stations by seasonal volumes, without the need to first cluster based on daily volume changes.

Our approach fixes the problems identified above in a straightforward manner. We group ATRs based on the ratios of seasonal traffic volume patterns. The grouping could be done based on other attributes as well, e.g., vehicle class distribution. However, the approach has been tested so far for volume-based grouping. In our approach, a traffic pattern is defined by two components: the weekday traffic volume (referred to as "weekdays"), and the ratio of weekend traffic volume to weekday traffic volume (referred to as "weekend/weekday Ratio"). Each component has three attributes. Specifically, for each ATR station, the weekday traffic volume can be categorized as average (A), high (H), or low (L) relative to the mean traffic volume across the three seasons at that station. Similarly, the weekend to weekday ratio can be categorized as either the same, or high, or low based on pre-determined thresholds.

According to our scheme, if a station's traffic pattern is deemed AHA on Weekdays, then that means the traffic volume in spring, summer and fall is, respectively, average, high and average, relative to the average of weekday traffic across all three seasons at that station. Similarly, the SHS weekend traffic means that the weekend daily traffic relative to weekday daily traffic is the same in spring and fall, but high in summer. Because data are not collected from PTR sites during winter, we do not consider the winter season in this analysis. The seasonal pattern is categorized only for three seasons: spring, summer, and fall.

The results of our analysis reveal that a small number of patterns are sufficient to cover the vast majority of ATR stations. We then use professional judgment to ascertain which traffic pattern best describes each PTR station. Our approach does not require pre-grouping of PTRs for the purpose of SAF calculation. We also develop a methodology to test whether the hypothesized pattern by professionals is statistically supported by the historical data available for that PTR site.

Our analysis either confirms professional judgment or identifies conflicts. In the latter case, more data should be collected to improve confidence in the identified pattern. However, if professional judgment and identified pattern based on available PTR data match, then we use the data from all ATRs with that pattern (e.g., AHA weekdays and SHS weekend) to calculate the SAFs along with their confidence intervals. It is relatively easy to consider a subset of relevant ATRs for identifying actual SAFs. For each PTR site, we also calculate the size of data needed to identify seasonal patterns within a reasonable degree of accuracy. Those sites that require significant amount of additional data to be collected for pattern identification could be considered as candidates for future deployment of ATRs.

To streamline and automate the process of obtaining input from professionals, we developed a survey tool for collecting professional opinions. Once the professional judgment results are gathered, we compare them with the results obtained from a simulation exercise for each PTR site. When conflicts occur, either professional judgment needs to be modified (e.g., more experts polled), or more data needs to be collected to reach a conclusion about the true traffic pattern. The overall approach as described above is illustrated in Figure 1.1.

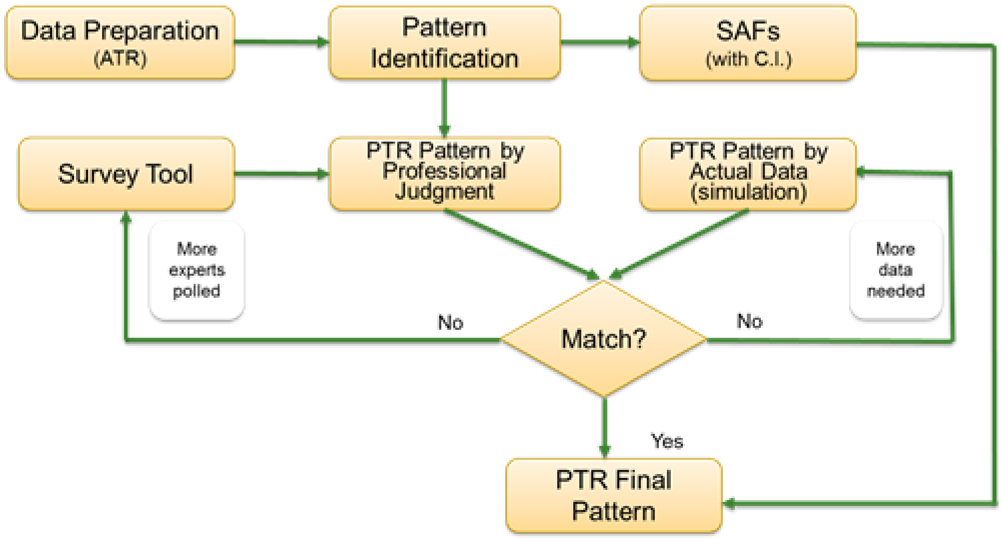


Figure 1.1 Overall Approach

This document contains details of our approach and its assessment. We believe that our approach provides a viable alternative to the method currently used. It provides MnDOT a consistent methodology, rooted in simple logical arguments, which can help make the process transparent to those that use traffic estimates produced by the TDA. The research team believes that this methodology is also applicable to other states that need to estimate traffic on a large number of roadways with different traffic patterns.

1.4 Report Organization

The remainder of the report is organized in the following manner. Chapter 2 describes the pattern identification method that can be used to group PTRs. These groupings are then used to calculate the SAFs. Chapter 3 documents the development of a survey tool that is used to automate the process of collecting professional opinions regarding the traffic pattern of a given PTR site. Chapter 4 discusses a methodology, based on computer simulation, which provides estimates of sample-size requirements for desired estimation accuracy at short-count sites. Chapter 5 concludes the report. Technical and supporting materials are presented in the Appendices.

CHAPTER 2 : SEASONAL ADJUSTMENT FACTORS

2.1 Introduction

The chapter focuses on the estimation of SAFs. We develop a general methodology that categorizes the ATRs into groups and identifies a seasonal traffic pattern for each group. A SAF and associated confidence interval (as applicable) is then calculated for each pattern.

Whereas the methodology does not require that parameters be set to particular values, it is illustrated using specific choices of parameters in this chapter. Specifically, we study the attribute of total volume, categorize its pattern based on two components (weekday and weekend/week ratio), and establish three different levels to characterize each component. However, this methodology can be readily applied to other attributes (e.g., class or weights) and/or alternative attribute levels.

Compared to the current clustering method employed by MnDOT, our pattern identification methodology is intuitive and straightforward to implement. It also avoids the problem of finding qualitative descriptions of properties of count locations that belong to the same cluster. We start with an intuitive classification and then determine which station belongs to which traffic pattern. Our method would make it easier to assign PTRs to clusters of ATRs that are deemed to have a similar seasonal variation in traffic according to the selected attribute.

The remainder of the chapter describes our general methodology and presents the results obtained for the total volume attribute. Section 2.2 discusses the pattern identification methodology. Section 2.3 delivers the seasonal pattern results for the ATR stations. On the basis of the identified patterns, section 2.4 reports the SAFs and associated confidence intervals for groups of ATR stations with the same pattern. Section 2.5 offers concluding remarks for this chapter.

2.2 Overall Methodology

Our overall methodology consists of two steps: pattern identification and SAF calculation.

2.2.1 Pattern Identification

The attribute we chose is total volume and we are interested in volume variation across the four seasons – spring, summer, autumn, and winter. In our approach, a traffic pattern in terms of volume is defined by two components: the weekday traffic volume (referred to as “weekdays”), and the ratio of weekend traffic volume to weekday traffic volume (referred to as “weekend/weekday Ratio”). MnDOT provided the following bookends for defining seasons, weekday, and weekend.

- Spring: April, May
- Summer: June, July, August
- Fall: September, October, November
- Winter: December, January, February, and March
- Weekday: Wednesday and Thursday

- Weekend: Friday, Saturday and Sunday

Anticipating implementation considerations, it was determined that Monday and Tuesday would be needed following the weekend for field work necessary to redeploy equipment for the next weekday/weekend data collection period. Thus, Monday and Tuesday volumes are excluded, and only Wednesday and Thursday are treated as weekdays. The above definition of seasons may not divide data such that each season will consist of full weeks of data. Thus, we slightly modified the start/end of seasons to obtain data that were compatible with our preparation process (details of the procedures are presented in Appendix A). Based on the year of 2012, we match each season to labels consisting of week numbers, such that each season contains the following weeks.

- Spring: Week 14 – Week 22
- Summer: Week 23 – Week 35
- Fall: Week 36 – Week 48
- Winter: Week 49 – Week 52, and Week 1 – Week 13

Because our analysis serves the purpose of providing results for PTR and no data are collected at PTR stations in winter, we restrict our attention to spring, summer and fall, and only keep the corresponding 39 weeks of data.

It may be practically appropriate to consider only three levels of volume within each season. Specifically, for each ATR station, the weekday traffic volume can be categorized as average (A), high (H), or low (L) relative to the mean traffic volume across the three seasons at that station. For example, if we want to determine whether station 26's spring total volume is high/average/low, we compare station 26's spring total volume with the mean of station 26's spring, summer, and fall total volumes. Formally, we define the attribute value to be:

- High if the volume is greater than the mean plus one standard deviation.
- Average if the volume is within plus/minus one standard deviation range of the mean.
- Low if the volume is smaller than the mean minus one standard deviation.

Similarly, the weekend to weekday ratio can be categorized as either the same, or high, or low based on pre-determined thresholds. Examining this ratio will provide insights into the relationship between weekend and weekday traffic volumes and the resulting impact on the SAFs as they are applied to weekday-only short duration counts.

Formally, the levels for categorizing the weekend to weekday ratio are defined to be:

- High if the ratio is greater than $1+c$.
- Same if the ratio is within $1-c$ and $1+c$.
- Low if the ratio is smaller than $1-c$.

where c represents the deviation of weekend traffic volume relative to weekday volume. This parameter is the cutoff used to determine the attribute level and, therefore, the choice of its value may potentially impact the results of the analysis. For illustrative purpose, the analysis proceeds by setting c equal to 5% and presents the results following the same procedures as applied to prior analyses. An additional set of results for $c=10\%$ is reported in Appendix B.

This scheme uses six letters to describe each pattern. If a station's traffic pattern is deemed AHA on weekdays, then that means the traffic volume in spring, summer and fall is, respectively, average, high and average, relative to the average of weekday traffic across all three seasons at that station. Similarly, the SHS weekend traffic means that the weekend daily traffic relative to weekday daily traffic is the same in spring and fall, but high in summer. Because data are not collected from PTR sites during winter, we do not consider the winter season in this analysis. Therefore, the seasonal pattern is categorized only for three seasons: spring, summer, and fall.

Upon classifying ATR stations in this way, we would obtain a cluster that conforms to an intuitive seasonal pattern. This exercise could be repeated for every attribute of interest, allowing classification of each PTR into different groups, depending on the attribute of interest. The thresholds for categorizing the attribute values into different levels could also be easily adjusted based on professional judgment.

2.2.2 SAF Calculation

Now the ATR stations are categorized into a number of groups according to their identified seasonal traffic patterns. Next an SAF and associated confidence interval will be calculated for each pattern with the following procedure:

- For each ATR station, calculate average daily volume across all years. Note that all weekdays (Monday through Friday of an entire year) are included for the purpose of calculating annual average daily traffic. This is justified on the basis that SAF will be used to predict annual average daily volume across all days of the week. However, it is easy to modify the calculation to exclude Monday and Tuesday if deemed necessary.

- For each ATR station, calculate average Wednesday/Thursday/Weekend volume for each month.

  Derive the following ratio using the results obtained from the previous two steps:

$$\text{Ratio} = \frac{\text{Average daily volume across all years}}{\text{Averge Wed/Tur/Weekend daily volume in the specific month}}$$

  SAF = the average of the ratios (obtained in the last step) across the stations with the same weekday+weekend/weekday ratio pattern.

- Confidence interval calculation:

For each weekday+weekend pattern, based on the ratios calculated using the formula above for all stations in this pattern, calculate two-sided t-interval with confidence level 1-α=95% for a population mean μ based upon a sample of n ratios with a sample mean of $\overline{x}$ and a sample standard deviation s:

$$\mu \in \left(\overline{x} - \frac{s * t_{\alpha/2,\mathrm{n}-1}}{\sqrt{n}}, \overline{x} + \frac{s * t_{\alpha/2,\mathrm{n}-1}}{\sqrt{n}}\right),$$

where $t_{\alpha/2, n-1}$ is the critical point. Note that C.I. is not applicable for the patterns with only one station. The blank cells in Table 2.2 and Table 2.3 correspond to those instances.

2.3 Seasonal Traffic Pattern Results

We apply the methodology to the prepared dataset and identify the seasonal traffic pattern results for the ATR stations. These results are reported in Table 2.1. The most common seasonal traffic pattern is AHA weekday and LLL weekend/weekday, followed closely by AHA weekday and HHH weekend/weekday. The third common pattern is AAL weekday and LLL weekend/weekday. The top three patterns have many observations, each with 16 to 19 stations. The fourth pattern, AHA weekday and SHS weekend/weekday has a total of five stations. The remaining patterns typically apply to only one or two stations.

Looking at the weekday component alone, the most common pattern was AHA, followed by AAL. In terms of the weekend/weekday ratio, the majority of the stations (41 stations) have the pattern of LLL, with the weekend traffic volume consistently lower than the weekday volume across all seasons. The second common pattern is HHH with 18 stations in this category, followed by SHS with 6 stations. The remaining patterns do not have more than three stations each. It is also worth noting that there is only one station falling into the SSS category.

Table 2.1: Seasonal Traffic Pattern Results

Pattern		Number of Stations	Stations
Weekday	Weekend/ Weekday		
AAL	LLL	16	101, 212, 303, 309, 326, 329, 341, 351, 384, 390, 405, 410, 422, 425, 458, 460
AAL	LSL	1	388
AAL	LSS	1	386
AAL	SHS	1	179
AAL	SLS	1	420
AHA	HHH	17	26, 29, 51, 170, 175, 187, 191, 197, 200, 204, 208, 219, 220, 221, 222, 223, 382
AHA	HHS	1	227
AHA	LHS	1	55

AHA	LLL	19	28, 33, 36, 199, 305, 315, 321, 335, 336, 342, 352, 354, 359, 365, 381, 400, 402, 407, 464
AHA	LLS	1	110
AHA	LSL	2	31, 225
AHA	SHH	1	214
AHA	SHS	5	34, 35, 164, 211, 213
AHA	SSS	1	210
ALA	LLL	1	8
HAA	LLL	3	56, 301, 389
HAA	LSH	1	353
LAA	HHH	1	188
LAA	HHL	1	218
LAA	LLL	2	54, 209
LAA	LSS	1	198

2.4 SAF Calculation Results

This section reports the results of the calculated SAF and associated confidence interval (if applicable) for each pattern. However, since several patterns contain only one observation, for which it is not possible to calculate the confidence interval. For these instances, the confidence interval cells are left blank in the tables. The entire data are presented in two tables because they do not fit in a single table. Each table presents a subset of patterns. In the heading, after identifying each pattern, we list the number of stations that exhibit that pattern in parentheses.

Table 2.2: SAFS for Weekday+Weekend/Weekday Ratio Pattern (Part 1)

Month	**Day of Week**	AAL LLL (16)	AAL LSL (1)	AAL LSS (1)	AAL SHS (1)	AAL SLS (1)	AHA HHH (17)	AHA HHS (1)	AHA LHS (1)	AHA LLL (19)	AHA LLS (1)	AHA LSL (2)
April	Wednesday	0.91	0.97	0.99	0.95	0.97	1.27	1.12	1.10	0.95	1.04	0.99
	C.I.	0.90-0.92					1.15-1.38			0.93-0.96		0.89-1.09
	Thursday	0.90	0.95	0.94	0.93	0.96	1.13	1.01	1.05	0.92	1.01	0.96
	C.I.	0.89-0.91					1.05-1.21			0.91-0.93		0.91-1.02
	Weekend	1.07	1.05	1.06	0.98	0.99	1.04	1.03	1.20	1.10	1.14	1.11
	C.I.	1.05-1.10					0.98-1.10			1.07-1.13		0.66-1.56
May	Wednesday	0.87	0.91	0.88	0.92	0.94	1.10	1.05	0.88	0.91	1.00	0.95
	C.I.	0.85-0.88					1.03-1.16			0.89-0.92		0.78-1.12
	Thursday	0.86	0.91	0.87	0.88	0.94	0.96	0.96	0.85	0.88	0.96	0.90
	C.I.	0.84-0.87					0.94-0.99			0.87-0.90		0.67-1.13
	Weekend	1.02	0.98	0.90	0.84	0.98	0.84	0.93	0.87	1.03	1.07	0.94
	C.I.	0.99-1.05					0.79-0.89			1.01-1.06		0.56-1.32
June	Wednesday	0.86	0.89	0.89	0.86	0.94	0.96	0.89	0.82	0.88	0.95	0.87
	C.I.	0.84-0.87					0.90-1.02			0.86-0.90		0.42-1.33
	Thursday	0.84	0.88	0.85	0.82	0.93	0.84	0.78	0.80	0.86	0.90	0.83
	C.I.	0.83-0.86					0.81-0.88			0.84-0.88		0.31-1.35
	Weekend	0.99	0.93	0.85	0.79	0.96	0.74	0.78	0.77	0.99	1.01	0.85

	C.I.	0.96-1.02					0.69-0.78			0.95-1.03		0.33-1.38
July	Wednesday	0.90	0.91	0.92	0.87	0.97	0.92	0.91	0.74	0.89	0.91	0.86
	C.I.	0.88-0.92					0.84-0.99			0.87-0.92		0-1.79
	Thursday	0.87	0.89	0.88	0.82	0.94	0.80	0.80	0.72	0.85	0.85	0.81
	C.I.	0.86-0.89					0.74-0.86			0.84-0.87		0-1.69
	Weekend	1.05	0.94	0.88	0.79	1.01	0.70	0.76	0.69	1.01	0.99	0.83
	C.I.	1.03-1.08					0.64-0.75			0.98-1.05		0.01-1.65
August	Wednesday	0.88	0.94	0.90	1.09	0.94	0.90	0.84	0.80	0.86	0.89	0.86
	C.I.	0.87-0.90					0.83-0.97			0.84-0.87		0.68-1.05
	Thursday	0.87	0.93	0.90	1.24	0.94	0.80	0.77	0.79	0.84	0.86	0.84
	C.I.	0.86-0.89					0.75-0.85			0.83-0.86		0.80-0.88
	Weekend	1.02	0.97	0.90	1.13	0.99	0.67	0.72	0.71	0.97	0.97	0.82
	C.I.	0.99-1.05					0.62-0.73			0.94-1.01		0.55-1.09
September	Wednesday	0.91	0.95	0.94	0.93	0.96	1.07	1.02	0.91	0.90	0.93	0.91
	C.I.	0.89-0.93					1.01-1.14			0.88-0.92		0.58-1.24
	Thursday	0.90	0.94	0.95	0.88	0.95	0.98	0.92	0.87	0.88	0.92	0.84
	C.I.	0.88-0.92					0.94-1.02			0.86-0.90		0.67-1.02
	Weekend	1.06	0.97	0.90	0.87	0.98	0.81	0.90	0.81	1.03	1.00	0.92
	C.I.	1.04-1.08					0.76-0.86			0.99-1.06		0.81-1.02
October	Wednesday	0.94	0.98	0.98	1.08	0.98	1.12	1.01	0.99	0.92	1.00	0.95
	C.I.	0.91-0.96					1.06-1.19			0.91-0.93		0.85-1.05

	Thursday	0.92	0.95	0.95	1.03	0.95	0.99	0.94	0.89	0.90	0.96	0.90
	C.I.	0.90-0.95					0.95-1.03			0.88-0.91		0.54-1.27
	Weekend	1.07	1.04	0.98	1.11	0.99	0.89	0.92	0.96	1.04	1.03	1.01
	C.I.	1.04-1.10					0.84-0.94			1.01-1.07		0.21-1.81
November	Wednesday	0.94	0.97	0.97	0.97	0.94	1.15	1.00	1.13	0.94	0.99	1.02
	C.I.	0.92-0.95					1.06-1.25			0.92-0.96		0.86-1.17
	Thursday	1.00	1.00	0.98	1.01	1.05	1.13	1.03	1.13	0.98	1.12	1.07
	C.I.	0.98-1.02					1.07-1.19			0.96-1.00		1.02-1.12
	Weekend	1.14	1.13	1.13	1.10	1.00	1.01	1.01	1.15	1.11	1.04	1.16
	C.I.	1.11-1.16					0.95-1.08			1.09-1.14		0.65-1.67

Table 2.3: SAFS for Weekday+Weekend/Weekday Ratio Pattern (Part 2)

Month	**Day of Week**	AHA SHH (1)	AHA SHS (5)	AHA SSS (1)	ALA LLL (1)	HAA LLL (3)	HAA LSH (1)	LAA HHH (1)	LAA HHL (1)	LAA LLL (2)	LAA LSS (1)
April	Wednesday	1.41	1.11	1.05	0.94	0.86	1.12	1.10	1.13	0.93	1.02
	C.I.		1.03-1.19			0.80-0.92				0.30-1.55	
	Thursday	1.33	1.03	0.99	0.85	0.85	1.03	1.02	1.06	0.90	0.93
	C.I.		0.95-1.10			0.77-0.94				0.87-0.93	
	Weekend	1.37	1.11	1.11	1.14	1.13	0.99	0.98	1.07	1.19	1.05
	C.I.		0.97-1.26			0.84-1.41				0.74-1.63	
May	Wednesday	1.00	1.01	0.97	0.85	0.82	0.43	1.01	1.06	0.90	0.97

	C.I.		0.96-1.05			0.63-1.01				0.27-1.54	
	Thursday	1.00	0.92	0.92	0.81	0.82	0.59	0.97	0.92	0.88	0.91
	C.I.		0.90-0.95			0.68-0.97				0.66-1.10	
	Weekend	0.91	0.96	0.95	1.04	1.11	0.96	0.93	0.90	1.09	1.00
	C.I.		0.91-1.01			0.72-1.50				0.94-1.24	
June	Wednesday	0.83	0.91	0.86	0.82	0.86	1.00	0.98	1.02	0.87	0.96
	C.I.		0.84-0.97			0.75-0.97				0.11-1.63	
	Thursday	0.77	0.82	0.84	0.90	0.84	0.93	0.93	0.94	0.86	0.90
	C.I.		0.75-0.90			0.75-0.94				0.23-1.49	
	Weekend	0.78	0.78	0.86	1.20	1.12	0.94	0.89	0.84	1.04	0.93
	C.I.		0.66-0.90			0.86-1.37				0.40-1.68	
July	Wednesday	0.75	0.90	0.88	1.05	0.91	1.03	0.99	1.00	0.84	0.94
	C.I.		0.84-0.95			0.81-1.01				0.26-1.42	
	Thursday	0.72	0.81	0.81	1.03	0.87	0.95	0.91	0.87	0.85	0.90
	C.I.		0.74-0.88			0.80-0.94				0.24-1.46	
	Weekend	0.67	0.77	0.86	1.41	1.20	0.97	0.90	0.79	1.05	0.99
	C.I.		0.67-0.87			0.90-1.51				0.84-1.25	
August	Wednesday	0.71	0.87	0.87	0.96	0.88	0.97	0.97	1.00	0.87	0.93
	C.I.		0.81-0.93			0.74-1.01				0.47-1.27	
	Thursday	0.67	0.80	0.80	0.93	0.87	0.89	0.91	0.93	0.83	0.85
	C.I.		0.73-0.87			0.74-0.99				0.47-1.19	

	Weekend	0.63	0.75	0.79	1.32	1.11	0.89	0.87	0.85	0.98	0.90
	C.I.		0.67-0.83			0.92-1.30				0.45-1.51	
September	Wednesday	0.74	0.98	0.91	0.85	0.90	1.07	1.00	0.94	0.84	0.93
	C.I.		0.95-1.01			0.67-1.12				0.50-1.17	
	Thursday	0.75	0.90	0.90	0.77	0.89	1.01	0.93	0.85	0.82	0.89
	C.I.		0.86-0.94			0.66-1.12				0.60-1.05	
	Weekend	0.61	0.88	0.91	1.07	1.12	0.90	0.90	0.93	0.97	0.92
	C.I.		0.84-0.93			0.92-1.33				0.51-1.42	
October	Wednesday	0.94	1.03	0.94	0.83	0.86	1.05	0.96	0.84	0.82	0.87
	C.I.		0.99-1.07			0.76-0.96				0.52-1.11	
	Thursday	0.88	0.94	0.90	0.82	0.84	0.94	0.89	0.80	0.80	0.78
	C.I.		0.91-0.96			0.76-0.92				0.52-1.08	
	Weekend	0.83	0.95	0.95	1.01	1.05	0.89	0.86	0.84	0.97	0.85
	C.I.		0.91-0.99			0.72-1.38				0.95-0.98	
November	Wednesday	1.27	1.06	0.99	0.90	0.88	1.03	0.97	1.02	0.95	0.93
	C.I.		1.00-1.12			0.73-1.03				0-1.94	
	Thursday	1.28	1.06	1.02	1.02	0.96	1.00	0.94	0.99	0.93	0.95
	C.I.		1.02-1.10			0.88-1.04				0.26-1.61	
	Weekend	1.19	1.07	0.96	1.14	1.14	1.04	0.92	1.13	1.22	1.01
	C.I.		1.03-1.12			0.87-1.41				0.38-2.06	

2.5 Conclusion

This chapter describes the development of a complete methodology for estimating SAFs that does not assume volume distribution based on professional judgment. While we illustrate the methodology using total volume attribute, our methodology is quite general and can be applied to any attribute of interest. For this exercise, we define a seasonal traffic volume pattern by two characteristics, weekday and weekend to weekday ratio. We categorize each characteristic into three levels according to pre-determined thresholds, i.e., average, high and low for weekday, as well as same, high, and low for weekend to weekday ratio. Because data are not collected from PTR sites during winter, we do not consider the winter season in this analysis. Therefore, the seasonal pattern is categorized only for three seasons: spring, summer, and fall.

This scheme uses six letters to describe each pattern. If a station's traffic pattern is deemed AHA on weekdays, then that means the traffic volume in spring, summer and fall is, respectively, average, high and average, relative to the average of weekday traffic across all three seasons at that station. Similarly, the SHS weekend traffic means that the weekend daily traffic relative to weekday daily traffic is the same in spring and fall, but high in summer. We then calculate an SAF and its confidence interval for each of the identified traffic patterns.

The results produced by this methodology are not directly comparable to the AADT adjustment factors for short duration weekday traffic volume counts currently in use. In contrast with the existing method, the alternative methodology defines the traffic pattern at the season level. As a result, there are over 20 patterns identified in this alternative methodology, whereas there are only five cluster groups used in the existing method. Furthermore, the high and low volumes are defined differently in the two methodologies. Segmenting at the seasonal level may result in more informative and accurate SAF estimates. It is interesting to note that the most common patterns in Table 2.1 are AHA-LLL and AHA-HHH, which correspond approximately to "high summer weekday, low weekend" and "high summer weekday, high weekend" categories.

CHAPTER 3 : QUANTIFYING PROFESSIONAL JUDGMENT

3.1 Introduction

In Chapter 2, an alternative methodology is developed for categorizing traffic patterns and estimating the SAFs for the PTR sites. In order to use SAFs obtained from ATR data and extrapolate them for the PTR sites, we need to identify the pattern at each PTR site. This step requires professional judgment when seasonal sampling as discussed in Chapter 4 is not possible. To complete this step, we develop a survey tool to automate the process of collecting information from professionals and quantify professional judgment regarding traffic patterns of PTR sites. This information will be used along with the pattern identification method proposed in Chapter 2 (which was based on collected data) to estimate seasonal factors. In this way, our overall approach utilizes both subjective (professional judgment) and objective data.

The survey is programmed within Excel and implements the analytic hierarchy process (AHP) methodology to analyze the survey participant's responses. The remainder of this chapter presents the survey methodology, and analyzes the limited feedback collected from the training survey tool. Section 3.2 documents the survey design methodology with detailed information about relevant attributes, pattern definitions, and survey questions. Section 3.3 briefly describes the separate ATR survey that is created for training and testing purposes. Section 3.4 presents the results based on the feedback collected from the survey respondents. Section 3.5 concludes this chapter. The AHP methodology and theoretical underpinnings of the survey are discussed in Appendix C. Other supporting materials are included in Appendix D and Appendix E. The ATR and PTR survey tools are provided as supplemental items to this report.

3.2 Survey Design Methodology

3.2.1 <u>Overview</u>

A typical user will need to go through the following steps to complete the survey:

1. Once the survey file is open, enable macro if asked.
2. Then a pop-up window will show up, click OK to start the survey.
3. Read the instructions presented in the second row.
4. Proceed according to the instructions.
5. Send back the survey to ptrsurvey15@gmail.com.

The survey is an Excel-based program and has four general components, as illustrated in Figure 3.1. It first asks the user to select a PTR location for which the subsequent responses apply, and then enter his or her personal information. Next, the survey explains the pattern identification method (i.e., how the seasonal pattern is defined, and what criteria are used to categorize the attributes of a pattern) and then describes the common patterns. It is important for the user to understand the criteria correctly, and then apply them to judge the traffic pattern for the chosen PTR site. Although we ask experts to utilize their professional experience to judge the potential traffic pattern, the possible categories of patterns are obtained by analyzing the actual ATR data.

The key part of the survey consists of a series of questions. We focus on the top five patterns identified from our ATR data analysis, because these patterns cover 80% of the ATR stations. Each remaining pattern only has a small number of ATR stations and, therefore, including these into the training survey may introduce noise into the survey results. Each question asks the user to compare two traffic patterns and indicate to what degree one pattern more likely represents the true pattern at the chosen PTR than the other pattern. Note that in this pairwise comparison, if two patterns are both highly likely or both highly unlikely, then the pairwise comparison result should be the same. There are a total of 10 questions. The format selected to construct the questions in a pair-comparison follows the AHP methodology, which we explain in the next section.

It is worth emphasizing that the survey does not collect opinions about the absolute volume of traffic at any given sites. This is the case because we will use the volume information from sampled data (48 hours or a week) and extrapolate it using assigned SAFs to obtain the seasonal volumes and overall AADT. Thus, there is no need to ask the respondents about their estimate of the total volume in each season.

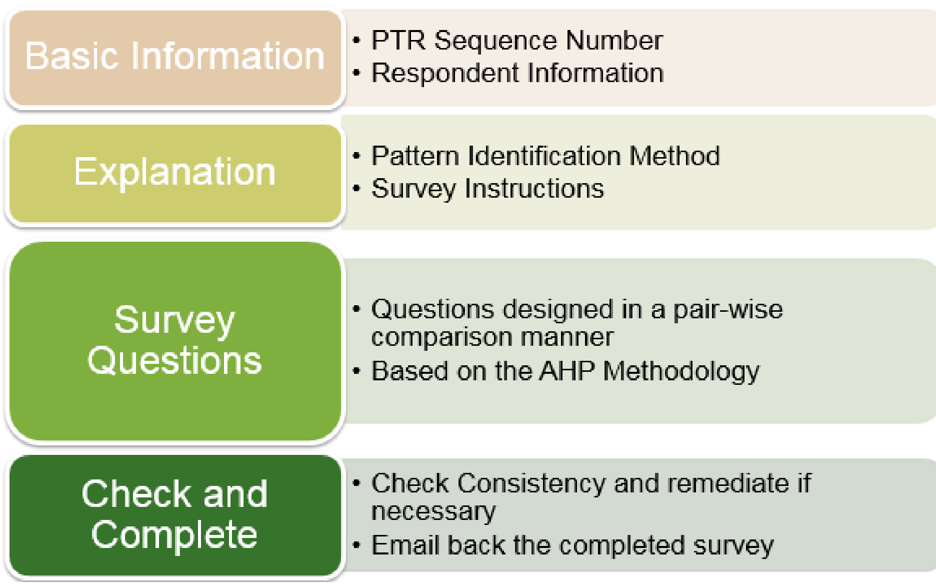


Figure 3.1: Survey Overview

The final step of the survey is a consistency check for the user's responses. Occasionally, the user's responses may indicate a lack of transitivity. For example, if the user thinks pattern A is more likely than pattern B and pattern B is more likely than pattern C. But at the same time, the user considers pattern C to be more likely than pattern A, then the responses are considered "inconsistent". Unless inconsistencies are corrected, no reasonable pattern can be inferred from such responses. The survey has been programmed with several built-in functions for checking the consistency of the answers. If the answers are found to be inconsistent, then the user is offered two choices – fix the inconsistency in the most inconsistent pairwise response by manually changing responses and try again, or allow the program to fix inconsistencies according to a programmed algorithm. The user is strongly advised not to use the automated procedure because that can lead to arbitrary changes to professional judgments. The overall logic of the survey is illustrated in Figure 3.2.

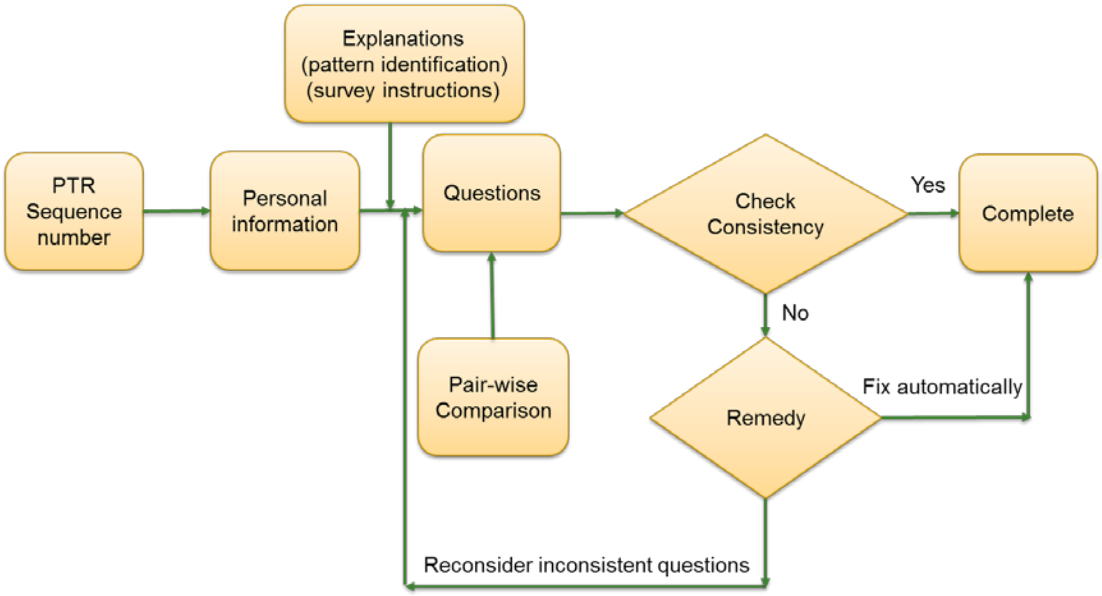


Figure 3.2: Survey Flowchart

3.2.2 <u>Information Collection</u>

The survey starts with instructions explaining the purpose of the survey as well as general steps for completing the survey. Subsequently, the user is asked to provide some basic personal information and enter the sequence number for the PTR (in describing the survey tool, we use PTR throughout. The same explanation applies to the training tool if we replace PTR by ATR, because that program is based on ATR data) site that the user selects to evaluate. The PTR sequence number is a key data field for us to compile and process the responses later. In case the user does not have this information at hand, the survey is programmed with two alternative methods to help the user obtain the PTR number: the PTR location and AADT data (website: Traffic Forecasting & Analysis) from an internal spreadsheet, as well as an online mapping tool (website: MnDOT Traffic Data) from an external link. Additional instructions on how to use the online map to search for the PTR site are provided as supplemental items to the survey (please see the Appendix D and Appendix E). A snapshot of this portion of the survey is included in Figure 3.3.

Personal Information (this is only for research purpose and will be kept strictly confidential):

Name	
Position/Department	/
E-mail address	
Date	**Month:** **Day:** **Year:**

Note that you only need to enter your personal information once, if you choose to complete the survey for multiple PTR sites.

Please enter a PTR site sequence number:

Please use the following options for further information of the PTR site you will be evaluating:

PTR location, direction, Annual Average Daily Traffic (AADT) etc.

Info

Online Map: For more instructions about how to use this map, please see "**Online map instructions.ppt**" file.

MAP

Figure 3.3: Information Collection

3.2.3 Pattern Selection

Next, the survey explains the pattern identification method, based on which the user will evaluate the seasonal traffic pattern of the chosen PTR site. A detailed description of how a pattern is defined and how the attributes are categorized for the pattern is included in the survey.

To minimize the influence of outlier traffic count sites, we focus on the top five common patterns identified in Chapter 2, which make up 80% of the total population of stations. Table 3.1 lists the top five most common traffic patterns identified from the historical data. The last column of the table gives some examples of continuous count locations (ATR/WIM stations) for each pattern. The user can review summary information about any location in each example pattern by clicking on the ATR/WIM ID number. This feature is only available in the Excel-based survey tool. Specifically, it is not available in the training tool.

Table 3.1: Top Five Common Patterns

Pattern #	Weekday	Weekend/Weekday Ratio	ATR/WIM Examples
1	Spring = Average; Summer = High; Fall = Average	Spring = Low; Summer = Low; Fall = Low	28 33 36 199
2	Spring = Average; Summer = High; Fall = Average	Spring = High; Summer = High; Fall = High	26 29 51 170
3	Spring = Average; Summer = Average; Fall = Low	Spring = Low; Summer = Low; Fall = Low	212 303 309 326
4	Spring = Average; Summer = High; Fall = Average	Spring = Same; Summer = High; Fall = Same	34 35 164 211
5	Spring = High; Summer = Average; Fall = Average	Spring = Low; Summer = Low; Fall = Low	56 301 389

3.2.4 Pairwise Comparison

The next step is to show how each survey question is constructed and what is expected from the user in terms of his or her responses. Each of the 10 questions picks two out of the top five common patterns and asks the user to indicate the degree to which one pattern is more or less likely than the other for the chosen PTR site. The rating scale is illustrated in Figure 3.4.

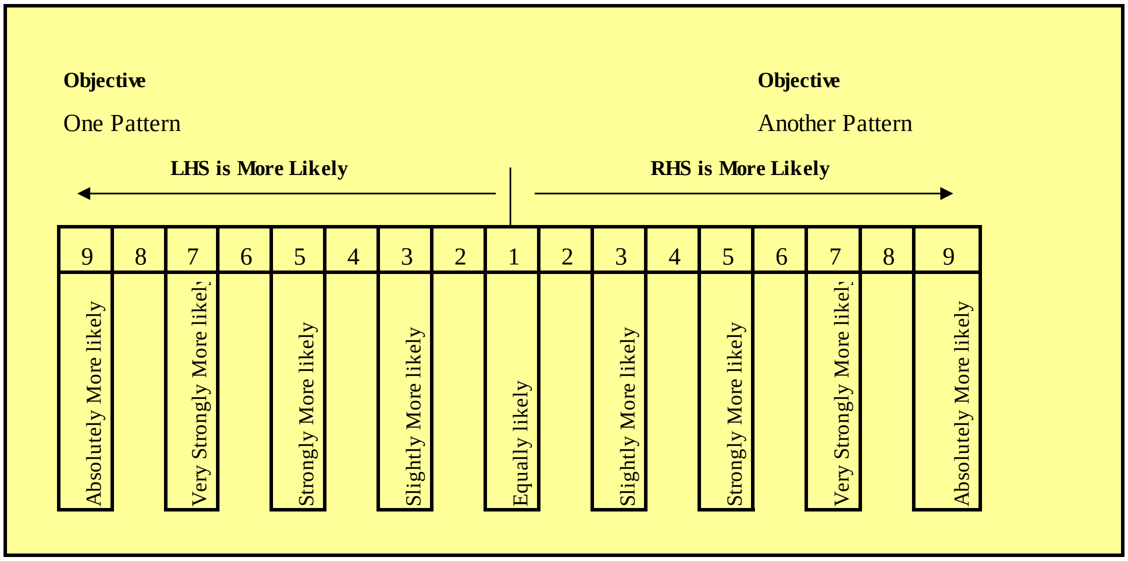
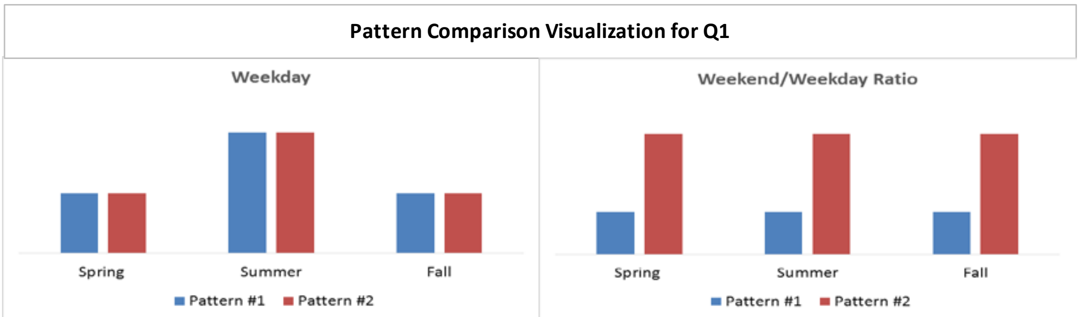


Figure 3.4: Pairwise Comparison Rating Scale

A snapshot of the first question in the survey is included in Figure 3.5 as an example. For this question, a bar graph that compares the two patterns is also provided to help visualize the difference. The remaining nine questions are structured in a similar manner, i.e., each asks the user to perform a pair-wise comparison of a different pair of patterns. Once the user answers a particular question, a green checkmark will appear in front of the question to help the user track progress.

Q1) Thinking about the selected PTR site, do you believe its traffic pattern is more likely to be

Pattern #1:
Weekday: Spring = Average; Summer = High; Fall = Average
Weekend/Weekday Ratio: Spring = Low; Summer = Low; Fall = Low
OR
Pattern #2:
Weekday: Spring = Average; Summer = High; Fall = Average
Weekend/Weekday Ratio: Spring = High; Summer = High; Fall = High



Please rate:

Pattern #1 is More Likely | **Pattern #2 is More Likely**

9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Figure 3.5: First Question in Survey

3.2.5 Review and Check

After the user answers all of the 10 questions, he or she may review the pattern indicated by his or her input. An important task at this stage is the consistency check. The results of the survey will not be meaningful if the responses are not consistent. To implement these tasks, the survey offers the three buttons as shown in Figure 3.6.

The Pattern You Selected | **Check Consistency** | **Fix Automatically**

Figure 3.6: Review and Check Buttons

More specifically, clicking "The Pattern You Selected" button reveals the pattern indicated by the user's responses in a pop-up window. The user may go back and modify answers at any time before submission.

Clicking the "Check Consistency" button will make the program perform a test of consistency of the answers and inform the user whether the consistency requirement is satisfied or not. If the latter occurs, the survey tool will also identify the question number whose answer most likely created the inconsistency. The user may find that the question identified by the program is a reasonable first question to revisit and possibly change his or her answer to. Achieving consistency is an iterative process if the manual approach is taken and the user needs to perform consistency check after each change to verify if such changes are enough, or if additional changes are warranted.

We strongly recommended that users fix their answers manually if consistency is not satisfied. However, the survey tool also offers a “Fix Automatically” option, which allows the program to change the answer to meet the consistency requirements. If this option is chosen, the user needs to perform the consistency check only once. After pressing the “Fix Automatically” button, the user will find that consistency is achieved in all cases.

Whereas the above procedure concludes the process to complete the survey for a single PTR site, the survey tool is designed with the functionality of allowing the user to complete multiple surveys within the same excel file. This can be done by clicking the “Start a New Survey” button. Alternatively, the user may decide to close the current session. In that case, after the user completes all surveys that he or she intends to, click the “Save and Close” button (see Figure 3.7). This will save the responses and exit the excel program. Please e-mail the Excel file with your responses to ptrsurvey15@gmail.com after this step is completed.

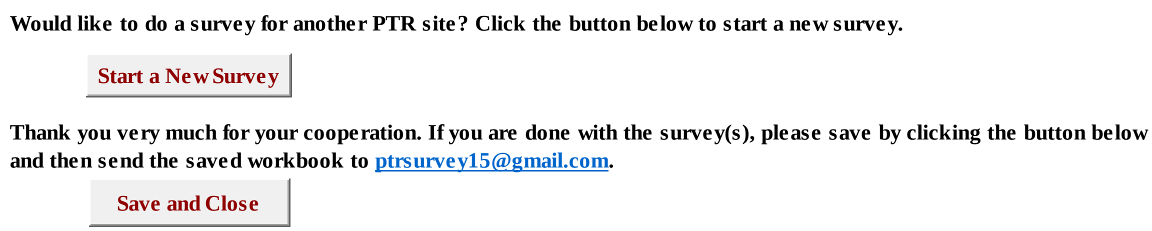


Figure 3.7: Option for Completing Multiple Surveys and Saving the Workbook

3.3 Training Survey

In addition to the PTR survey described above, we have created a separate survey tool with the primary purpose of training the participants on how to use the survey. The feedback provided by the participants also helped us identify areas for potential improvements. Although response to the survey tool has been limited, some changes were made to further enhance the usability of the tool. The training tool is identical to the PTR survey tool except for one variation. The training survey asks the participant to evaluate the traffic pattern at an ATR station as opposed to a PTR site. By design, the responses from the training survey are not intended for pattern identification. Rather, its purpose is to help county engineers become familiar with the survey methodology. Due to its similarity to the PTR survey which is detailed above, we do not reiterate the ATR survey design and will refer the readers to the excel file supplementing this report for the complete survey.

3.4 Survey Results

We submitted the training survey to MnDOT in early June 2015. The training survey was distributed to the TAP members (as opposed to the county engineers) to collect initial responses prior to the target completion date. At the time of writing this report, we received a total of 14 survey responses from two participants. Table 3.2 summarizes the results implied by the survey responses. Participant 1 evaluated a total of five ATR stations, for each of which the C.R. has a value much greater than 0.1, indicating a violation of the consistency requirement. Participant 2 completed a total of seven surveys, the majority of which have consistent answers. There are only two out of the seven surveys with inconsistent responses (with C.R. values fairly close to the threshold). Please note that the participants were explicitly advised to manually fix the inconsistency instead of using the “Fix Automatically” option for this exercise, which is a possible cause for the inconsistent responses received. We also suspect that the participants did not repeatedly perform consistency checks until there were no inconsistencies.

Upon examining the ATR stations selected by the participants, not all of the responses can be used for further analysis. ATR stations 223 and 388 are outside of the original sample compiled for the pattern identification method, as they do not have sufficient historical traffic data (details regarding the exclusion of certain ATR stations from the pattern identification analysis are included in Chapter 2). Additionally, ATR stations 179, 301, and 353, while selected by the participants, do not belong to sub-sample with the top five common patterns on which our survey focuses on. Therefore, by design, the patterns chosen by the participants do not match the patterns identified based on data.

Table 3.2: Pattern by Professional Judgment

Name	ATR	Identified Pattern(#)	Relative priority scores for pattern 1-5 (%)					C.R.
Participant 1	28	1	49.65	3.16	24.50	8.07	14.62	0.43
	51	2	13.51	51.86	7.78	24.05	2.80	0.49
	191	1	51.03	2.82	24.43	7.87	13.83	0.50
	402	2	6.99	30.77	30.04	29.99	2.21	0.68
	353	1	53.27	2.95	22.61	7.76	13.41	0.38
Participant 2	179	1	37.84	7.71	17.13	19.10	18.22	0.18

	204	4	10.88	17.11	9.65	49.60	12.76	0.06
	212	1	37.31	6.90	29.38	10.15	16.26	0.09
	301	1	49.83	5.35	17.68	12.63	14.52	0.19
	223	4	23.60	11.35	8.48	47.03	9.53	0.05
	388	4	20.61	6.41	9.95	46.86	16.17	0.08
	460	5	14.51	7.85	23.08	8.23	46.33	0.07

Once the aforementioned five ATR stations are excluded, we are left with seven survey responses, listed in Table 3.3. Due to the very limited amount of data, we include all of the seven responses for further analysis, although some of these responses do not satisfy the consistency requirement.

Table 3.3: Pattern Comparison: Professional Judgment vs. Data

Stations	**Pattern (#)**	
	By professional judgment	**By actual data**
28	*Weekday: AHA* *Weekend/Weekday Ratio: LLL*	*Weekday: AHA* *Weekend/Weekday Ratio: LLL*
51	*Weekday: AHA* *Weekend/Weekday Ratio: HHH*	*Weekday: AHA* *Weekend/Weekday Ratio: HHH*
191	Weekday: AHA Weekend/Weekday Ratio: LLL	Weekday: AHA Weekend/Weekday Ratio: HHH
402	Weekday: AHA Weekend/Weekday Ratio: HHH	Weekday: AHA Weekend/Weekday Ratio: LLL

204	Weekday: AHA Weekend/Weekday Ratio: SHS	Weekday: AHA Weekend/Weekday Ratio: HHH
212	Weekday: AHA Weekend/Weekday Ratio: LLL	Weekday: AAL Weekend/Weekday Ratio: LLL
460	Weekday: HAA Weekend/Weekday Ratio: LLL	Weekday: AAL Weekend/Weekday Ratio: LLL

As seen in Table 3.3, professionally judged patterns for two ATR stations (highlighted in *Italics*) match those identified based on data. For the majority of the remaining stations, professional judgment is able to match the weekday pattern but shows some discrepancy for the weekend/weekday ratio component. There are several likely causes for the observed discrepancy: insufficient understanding of the attribute definition for the weekend/weekday ratio component, inaccurate judgment for the weekend traffic pattern of the selected ATR station, as well as failure to fully follow the survey instructions. Finally, the current method utilized by MnDOT does not identify patterns based on the ratio of weekend to weekday volumes.

Actions may be taken to address these issues to further improve the quality of the survey responses. We believe that a training session with potential respondents will alleviate the majority of these problems.

3.5 Conclusion

Chapter 2 developed an alternative methodology for categorizing the traffic patterns and calculating the SAFs for PTR sites. However, to map the derived SAFs to the PTR sites, we needed to obtain professional judgment regarding the traffic patterns of PTR sites. This chapter bridges the gap by designing a survey tool to automate the collection of and quantify the county engineers' opinions regarding the traffic patterns of the PTR sites.

The survey is programmed within Excel and implements an AHP methodology to analyze the survey participants' responses. The survey has four major components. It first asks the user to select a PTR location and enter his or her personal information. Next, the survey explains the pattern identification method, i.e., how the seasonal pattern is defined, what criteria are used to categorize the attribute of a pattern, and what the common patterns are. The key part of the survey is a series of questions. We focus on the top five patterns identified from our ATR data analysis and these patterns cover 80% of the ATR stations. Each remaining pattern only has a small number of ATR stations and, therefore, including these into the survey might introduce noise into the survey results. Each question asks the user to compare two traffic patterns at a time and indicate which pattern is more likely to represent the true traffic pattern at the selected PTR site. There are a total of 10 questions. The consistency verification step is programmed as the last component of the survey. The survey offers several options for the user to review the pattern indicated by current answers, manually change the answer to the question that most-likely causes the inconsistency, or let the program automatically make the change to meet the consistency requirement.

A separate ATR survey is also created for training and testing purposes. Two MnDOT participants completed the training survey. However, due to the limited number of survey responses received, it is difficult to comment whether this approach will be successful in the field. The researchers conjecture that future deployment of this method will benefit from the presentation of background materials and training sessions to county engineers.

CHAPTER 4 : SAMPLING EFFORT ESTIMATION

4.1 Introduction

One of the original objectives of this research project is to identify those PTR stations that may be candidates for conversion to continuous count locations. Knowing the PTR sites that may benefit from such conversion will also help us subsequently answer the question whether the number of ATR stations is adequate. We emphasize that it is not the goal of this phase of the project to identify the optimal number of stations. Rather, this phase builds the tools necessary to develop models to answer that question. In this phase, we determine if the current estimates obtained from short counts are reliable. If the current estimates are good in a statistical sense, then it is unnecessary to collect additional data. Otherwise, it may be necessary to consider the cost and benefit of collecting additional data.

This chapter presents a methodology that analyzes the sample-size requirements for desired estimation accuracy at short-count sites. The results of this exercise help estimate the level of effort needed to achieve a particular level of estimation accuracy. At the moment, the methodology is applied to pseudo PTR stations (constructed by sampling from ATR data) because it was not possible to perform experiments at selected PTR sites. However, this approach transfers relatively easily to PTR sites if and when experimental data can be obtained.

We develop a simulation methodology that samples and bootstraps continuous-count data to create data records as if they were collected from PTR sites. We call such data pseudo-PTR-site data. This approach is illustrated with the following three sets of attributes: (1) total volume by season, (2) weekend volume by season, and (3) heavy commercial volume by season. Three levels are defined for each attribute, namely, high, average, and low. Thus, a traffic pattern is a combination of levels for spring, summer and fall.

The analysis continues to use the dataset consisting of 39 ordered weeks' that was compiled for the exercise in Chapter 2. Different from Chapter 2, the analysis of this chapter uses different definitions of weekday, weekend and seasons. The difference occurred because MnDOT staff at first agreed with the standard definition of seasons and later asked researchers to use a different definition. The methodology we explain in this chapter is not affected by the specific definitions of seasons, weekday and weekend. However, the numerical results would be different under a different regime.

The remainder of this chapter proceeds as follows: Section 4.2 describes the overall methodology. Section 4.3 reports the pattern identification results. Section 4.4 illustrates the classification accuracy results. Section 4.5 provides recommendations regarding the sample sizes required for a minimum of 50% of the stations to reach a 50% accuracy rate. Section 4.6 carries out additional analysis to demonstrate the robustness of the conclusions. Section 4.7 concludes. Technical details of the attribute calculations, bootstrapping, and simulation techniques are presented in Appendix F. The complete set of simulation results is included in Appendix G.

4.2 Overall Methodology

To define the seasonal timelines, we start with the common bookends of the four seasons (with some modifications) in terms of calendar days as listed below:

- Spring: March 22 – June 21
- Summer: June 22 – September 21
- Fall: September 22 – December 21
- Winter: December 22 – March 21

We then make adjustment to the timelines to make them more compatible with our data structure. Specifically, in 2012, the first Sunday in spring (as defined by the common definition) fell in thirteenth week in our data. Based on this observation, we can take week 13 as the beginning of the spring season. Furthermore, we match each season with week labels such that each season has 13 weeks as shown below.

- Spring: Week 13 – Week 25
- Summer: Week 26 – Week 38
- Fall: Week 39 – Week 51
- Winter: Weeks 1 –12, and Week 52

Throughout the analysis in this chapter, the four seasons are identified according to the above definition. The overall approach consists of the following steps, which are also illustrated in Figure 4.1.

1. Prepare data for analysis. The type of data used and the steps involved in cleaning and organizing the data depend on the attribute of interest.
2. Choose attribute levels for each attribute.
3. Determine criterion for assigning labels to each station for each level of the attribute selected.
4. Assign labels.
5. Identify patterns of traffic from ATR data.
6. Simulate data collection from PTR sites with different traffic patterns to determine the size of samples needed to achieve a reasonable classification accuracy.

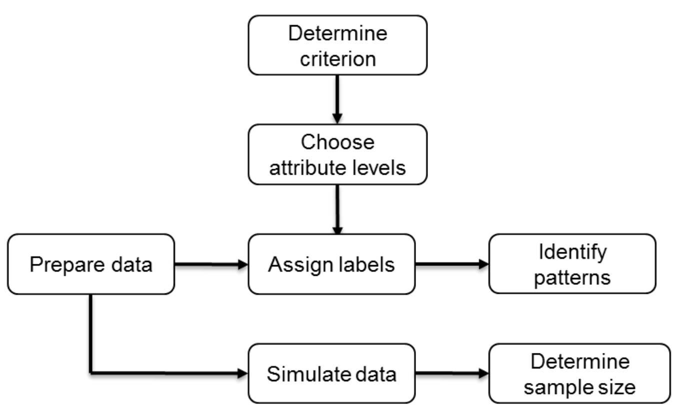


Figure 4.1: Overall Approach

More specifically, we apply the pattern identification method to three sets of attributes: (1) total volume by season, (2) weekend volume by season, and (3) heavy commercial volume by season. The calculations related to *total volume* and *weekend volume* attributes are based on volume data. The calculations of *heavy commercial volume* attributes are based on class data. Within each of the three attributes, we classify traffic pattern into three levels: high, average and low. Three levels were chosen for convenience and simplicity. Step 1 through 5 utilize the same methodology as described in Chapter 2 and will not be discussed in detail here.

Because it would be impractical to collect data frequently from PTR stations, it is necessary to determine the sample size needed for a desired degree of accuracy. In our approach, we sample and bootstrap the ATR data to create pseudo-PTR data for three seasons. Then, we use simulation techniques to test if the identified seasonal traffic pattern would match the true (and known) pattern of the ATR site. For each fixed number of samples taken, we carried out the simulation many times (called iterations), and track the correctness of the pattern classification for each simulation. Classification-accuracy results are reported as a function of the number of samples. The purpose of the simulation exercise is to determine the number of weeks of the short-count data needed to achieve a given level of classification accuracy for a desired proportion of stations

The sample size determination problem can be formulated as follows: for a target level of accuracy rate, select the minimum sample size that could result in a certain proportion of stations reaching the classification accuracy target. This calculation thus takes into account two factors – the classification accuracy for each station, and the proportion of stations that achieve a particular classification accuracy. We selected a 50% classification accuracy threshold and a 50% station accuracy threshold to illustrate our approach in this section. Our methodology can be applied and reworked with different thresholds.

We aggregate the station level simulation results obtained previously and calculate the percentage of stations that show a classification accuracy rate of no less than 50% for each sample size. The results are obtained for all stations and three subsets of stations by seasonal traffic pattern. This analysis enables the identification of the minimum sample size that meets both thresholds for each attribute.

The technical details regarding bootstrapping and simulation techniques are presented in Appendix G. The following sections report the pattern identification results, provide recommendations regarding the sample sizes required for a minimum of 50% of the stations to reach a 50% accuracy rate, and carry out additional analysis to demonstrate the robustness of the conclusions.

4.3 Pattern Identification Results

The pattern identification results obtained for each of the three attributes are presented in Table 4.1, Table 4.2, and Table 4.3, respectively. We use “H” to denote “high” level, “A” to denote “average”, and “L” to denote “low”. A total of six combinations of attribute levels are observed for all attributes. Each combination is referred to as a seasonal pattern. These tables display the pattern identification results by mapping the stations to their exhibited seasonal pattern for each of the attributes.

Table 4.1: Total Volume – Seasonal Traffic Pattern

Pattern	Total Volume			Number of Stations	Stations
	Spring	Summer	Fall		
1	L	A	A	3	33, 53, 188
2	A	L	A	6	8, 101, 212, 341,389,402
3	A	A	L	20	36, 179, 303, 305, 309, 315, 321, 326, 329, 336, 342, 352, 382, 384, 388, 400, 405, 407, 410, 420
4	A	A	H	1	464
5	A	H	A	41	26, 28, 29, 31, 35, 51, 54, 55, 110, 164, 170, 175, 187, 191, 197, 198, 199, 200, 204, 208, 209, 210, 211, 213, 214, 218, 219, 220, 221, 222, 223, 225, 227, 335, 351, 354, 359, 365, 381, 386, 422
6	H	A	A	8	34, 56, 301, 353, 390, 425, 458, 460

As seen in Table 4.1, the most common pattern was AHA, i.e., average volume in spring and fall, and high volume in summer, which is consistent with intuition because both commercial and leisure travel generally increases in summer months. A total of 40 ATR/WIM stations exhibit this seasonal pattern. The second most common pattern is AAL, with 20 stations, which is also consistent with intuition.

Moving on to the results for the weekend volume attribute, while the exact number of stations for each pattern might differ relative to the total volume attribute, the most common pattern is still AHA, followed by AAL.

Table 4.2: Weekend Volume – Seasonal Traffic Pattern

Pattern	Weekend Volume			Number of Stations	Stations
	Spring	Summer	Fall		
1	L	A	A	1	53
2	A	L	A	2	8, 402
3	A	A	L	24	36, 179, 199, 303, 305, 309, 315, 321, 326, 336, 342, 351, 352, 353, 359, 365, 382, 384, 388, 390, 405, 407, 410, 422
4	A	A	H	1	464
5	A	H	A	40	26, 28, 29, 31, 33, 35, 51, 54, 55, 110, 164, 170, 175, 187, 188, 191, 197, 198, 200, 204, 208, 209, 210, 211, 213, 214, 218, 219, 220, 221, 222, 223, 225, 227, 329, 335, 354, 381, 386, 400
6	H	A	A	11	34, 56, 101, 212, 301, 341,389, 420, 425, 458, 460

This pattern remains intact even for the heavy commercial volume – the most common pattern is AHA, followed closely by AAL, although the total number of stations included for this attributed is much smaller. Our analysis shows that seasonal variation can be captured by a small number of patterns by attribute. It is not necessary to use a large number of qualitative labels to describe traffic patterns.

Table 4.3: Heavy Commercial Volume – Seasonal Traffic Pattern

Pattern	Heavy Commercial Volume			Number of Stations	Stations
	Spring	Summer	Fall		
1	L	A	A	7	29, 35, 37, 54, 175, 213, 353,

2	A	L	A	3	39, 197, 382
3	A	A	L	10	31, 34,36, 101, 179, 208, 212, 223, 341, 351
4	A	A	H	6	33, 38, 41, 198, 200, 225
5	A	H	A	15	26, 40, 187, 191, 199, 204, 219, 220, 221, 222, 227, 335, 352, 381, 388
6	H	A	A	1	56

To summarize, the following result is observed across all three attributes: the most common seasonal traffic pattern is AHA, followed by AAL. To provide a high-level summary, we include in Table 4.4 a listing of the count of stations for each pattern across all three attributes. Note that it is not necessary for a station to belong to the same category for different attributes.

Table 4.4: Number of Stations with Different Patterns

Pattern			**Number of Stations with the attributes**		
			Total volume	**Weekend volume**	**Heavy commercial volume**
Spring	Summer	Fall	79 stations in total	79 stations in total	42 stations in total
L	A	A	3	1	7
A	L	A	6	2	3
A	A	L	20	24	10
A	A	H	1	1	6
A	H	A	41	40	15
H	A	A	8	11	1

4.4 Classification Accuracy Results

This section presents illustrative simulation results regarding how the percentage of correct classification changes with increasing sample size for each of the three attributes at the station level. Given the large number of stations, we will only present the results for one station with the most common observed traffic pattern in this report for illustration purpose. The complete set of results is provided in Appendix F. Recall that the most common pattern is “A”, “H”, and “A” for spring, summer, and fall respectively, across all three attributes.

4.4.1 Total Volume

A monotonic increasing relationship between the percentage of correct classification and the number of samples is consistently observed across all stations for the total volume attribute. In the case of Station 28, as shown in Figure 4.2, the percentage of correct classification increases from around 0.6 to 1, as the number of samples varies from 3 to 39. This is consistent with intuition - more sampled weeks lead to increased classification accuracy. The trend appears to be smooth and can be better illustrated by a fitted quadratic curve using the least squares approach.

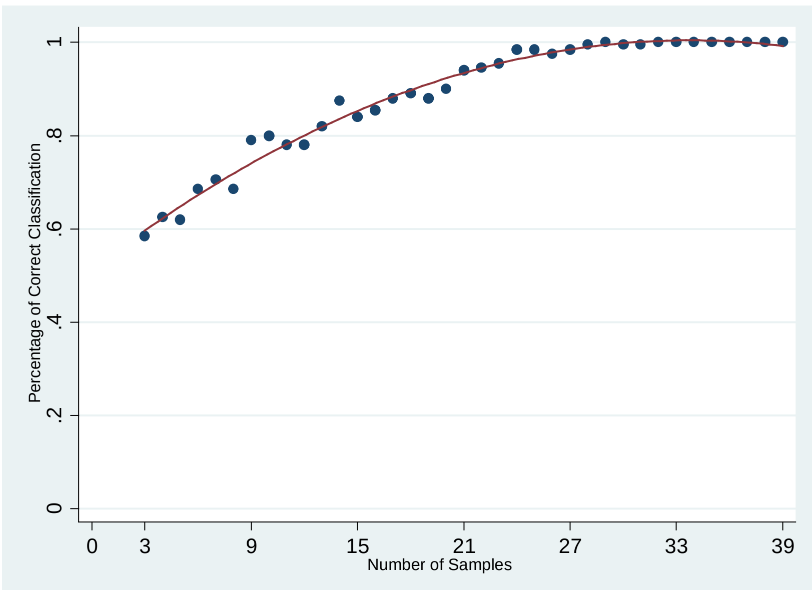


Figure 4.2: Station 28 – number of samples and corresponding percentage of correct classification for Total Volume Attribute

For this station, the marginal increase in classification accuracy, i.e., the slope of the fitted curve, has a diminishing trend as the sample includes more weeks. The same pattern is observed for the majority of the stations with only a few exceptions. For example, stations 8, 110, 188, 204, 208, 464 show an approximately linear relationship, whereas stations 33, 389, 402, and 425 show an increasing slope. These differences might be due to the combination of station-specific characteristics and the randomness within the simulation procedure. Nevertheless, the increasing relationship holds across all stations.

4.4.2 Weekend Volume

As expected, a monotonically increasing relationship has been observed across all stations. Figure 4.3 shows how the percentage of correct classification changes with the sample size for the weekend volume attribute in the case of station 26. For this particular station, the correct classification rate starts at about 0.5 with a 3-week sample and then keeps increasing with increasing sample size, although at a diminishing rate. However, beyond a sample size of 21 weeks, the rate remains largely unchanged with a value very close to 1.

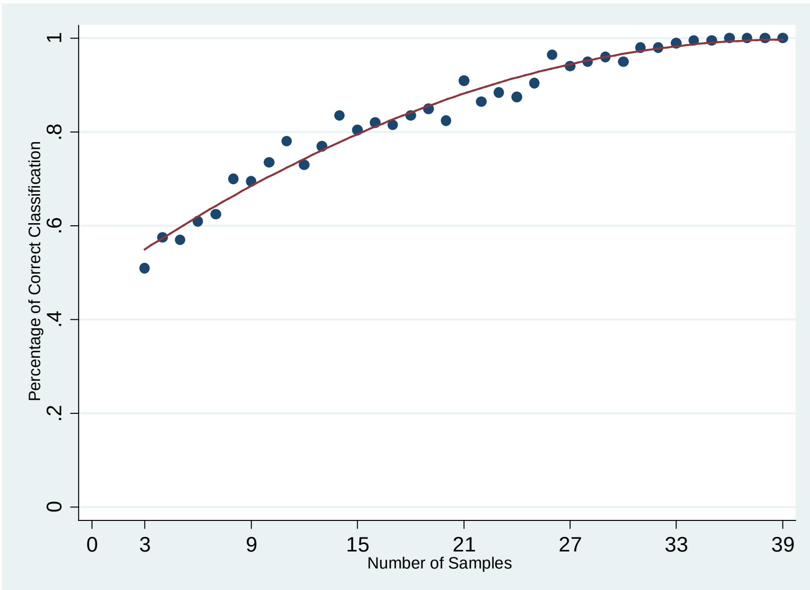


Figure 4.3: Station 26 – number of samples and corresponding percentage of correct classification for Weekend Volume Attribute

A majority of the stations exhibit a similar pattern with a decreasing slope of the fitted curve. Exceptions are stations 28, 33, 101, 188, 199, 208, 212, 221, 225, 301, 309, 326, 341, 351, and 402, that exhibit an increasing slope, and stations 56, 204, 223, 303, and 400 that exhibit a linear relationship. As discussed before, these individual differences might be driven by a variety of factors, such as station heterogeneity as well as the random nature of the sampling and the bootstrapping methods.

4.4.3 Heavy Commercial Volume

As with the previous two attributes, a monotonically increasing relationship has been observed across all stations for the heavy commercial volume attribute. Take station 40 for example. As shown in Figure 4.4, the percentage of correct classification increases from 0.2 to 1, as the sample size increases from 3 to 39 weeks. In contrast with the previous two attributes, over half of the stations, including station 40, display either a constant or an increasing trend of marginal improvement in the classification accuracy, with the remaining stations featuring a diminishing trend. However, this distinct mix could simply be a result of the much smaller number of stations included for this attribute relative to the previous two attributes.

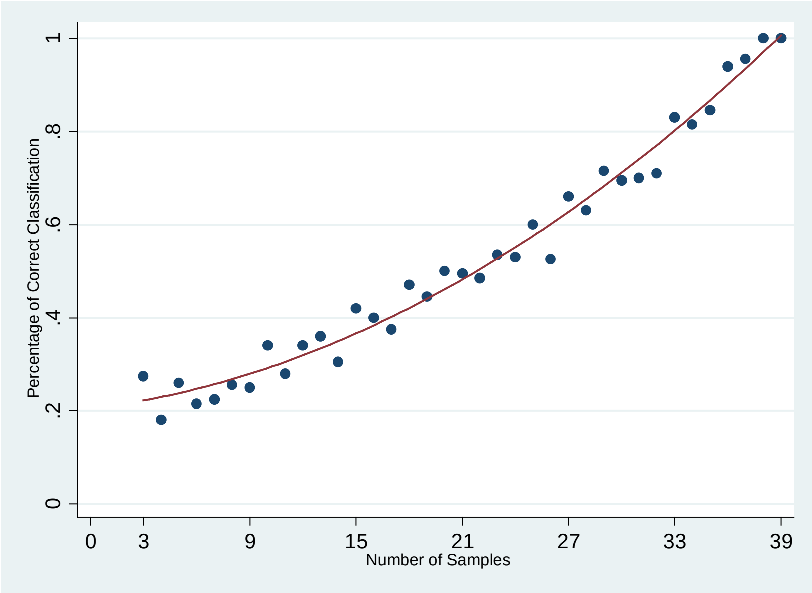


Figure 4.4: Station 40 – number of samples and corresponding percentage of correct classification for Heavy Commercial Volume Attribute

4.4.4 Discussion

We conclude this section with a brief discussion of the results obtained from the above simulation analysis. For each of the three attributes, the classification accuracy rate increases with the sample size. While this general pattern holds across all stations, a fixed sample size would result in different classification accuracy rates among the stations. Thus, to limit the influence of station heterogeneity, the decision with respect to the sample size will be made at a more aggregated level by taking into account all stations. The next section focuses on the determination of the sample size.

4.5 Sample Size Determination Results

4.5.1 Total Volume

Figure 4.5 illustrates the number of samples and the corresponding percentage of stations with a classification accuracy rate of no less than 50% for the total volume attribute. The two variables indicate a generally increasing relationship. The percentage of stations first exceeds the 50% target with a 4-week sample. Therefore, the required sample should have at least four weeks of data. The recommended sample size is highlighted with a diamond shape in the figure.

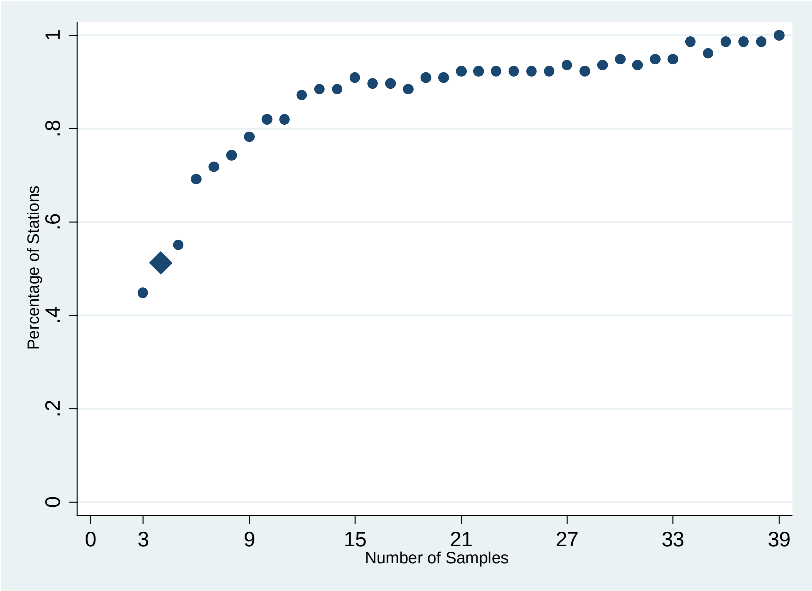


Figure 4.5: Total Volume – number of samples and percentage of stations with a classification accuracy rate ≥ 50%

We next focus on the stations that exhibit the most common traffic pattern, i.e., AHA. There are a total of 41 stations that fall into the category of AHA seasonal traffic pattern. As shown in Figure 4.6, 58.54% of these stations reach a classification accuracy rate of at least 50% when the sample includes three weeks' data. Therefore, the recommended sample size is 3-week, which is identified with a diamond shape in the figure.

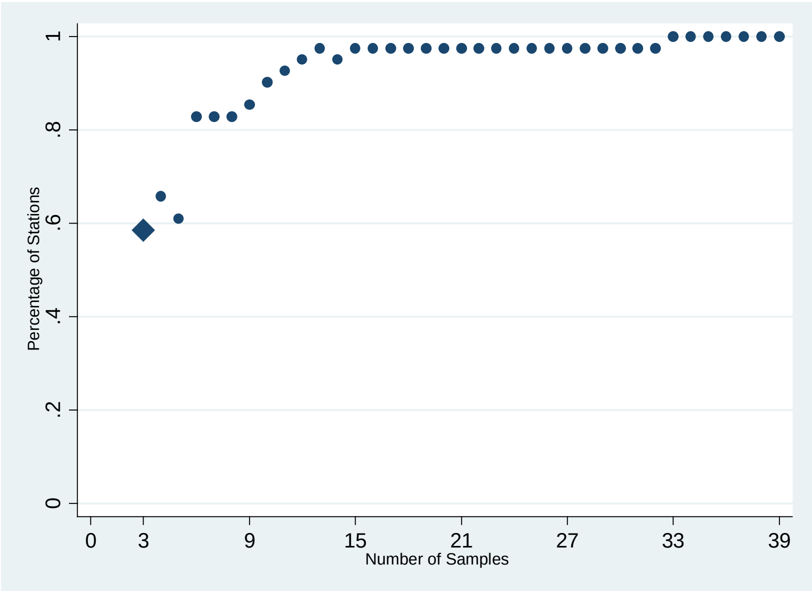


Figure 4.6: Total Volume-AHA – number of samples and percentage of stations showing AHA traffic pattern with a classification accuracy rate ≥ 50%

4.5.2 Weekend Volume

For the weekend volume attribute, there is a positive association between the number of samples and the percent of stations with a classification accuracy rate of no less than 50%. As illustrated in Figure 4.7, the percentage of stations meets the 50% target when the number of samples is 5. Therefore, the sample should include at least 5 weeks of data. This recommended sample size is highlighted with a diamond shape in the figure.

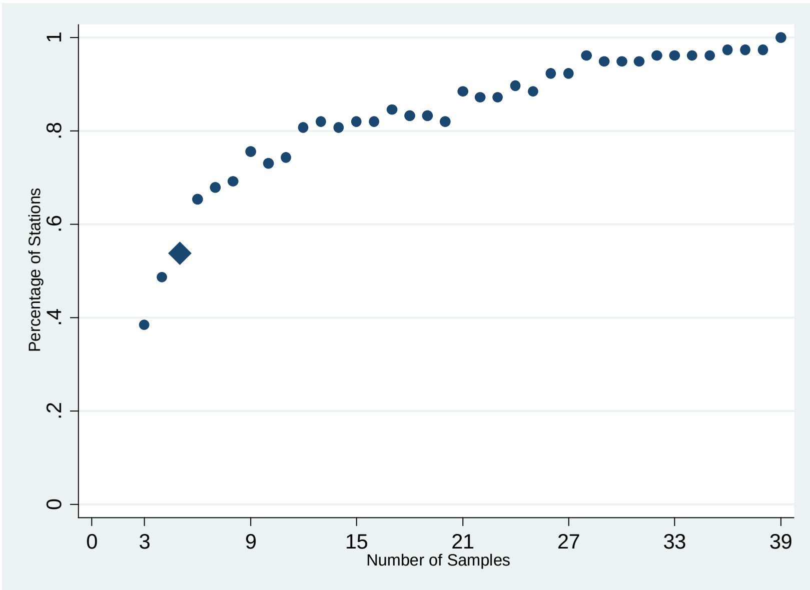


Figure 4.7: Weekend Volume – number of samples and percentage of stations with a classification accuracy rate ≥ 50%

There are a total of 40 stations that fall into the category of AHA seasonal traffic pattern, as previously identified in Section 2.3. Figure 4.8 illustrates the results for this subset of stations. 55% of these stations reach a classification accuracy rate of at least 50% when the sample includes four weeks' data. Therefore, the recommended sample size is 4-week, which is identified with a diamond shape in the figure.

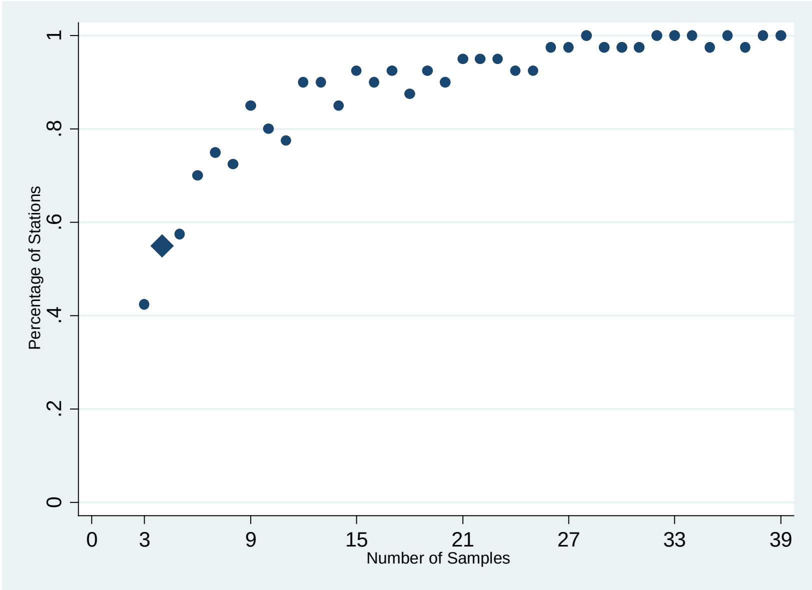


Figure 4.8: Weekend Volume-AHA – number of samples and percentage of stations showing AHA traffic pattern with a classification accuracy rate ≥ 50%

4.5.3 Heavy Commercial Volume

As with the previous two attributes, there is generally a positive association between the number of samples and the percentage of stations with a classification accuracy rate of no less than 50% for the heavy commercial volume attribute.

As illustrated in Figure 4.9, the percentage of stations may exhibit chatter, i.e., a downward spike, which can be seen in this figure at the 8-week sample. Also note that both the 7- and 9-week sample sizes meet the 50% threshold. We recommend a sample size of 9 weeks for stability considerations.

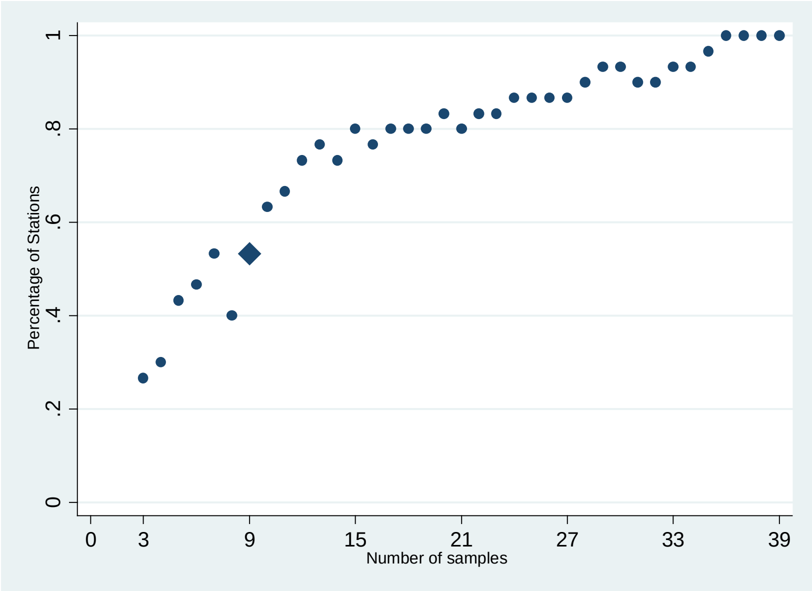


Figure 4.9: Heavy Commercial Volume – number of samples and percentage of stations with a classification accuracy rate ≥ 50%

Among the stations that exhibit the AHA seasonal traffic pattern, 50% of them reach a classification accuracy rate of at least 50% when the sample includes 10 weeks' data. Therefore, the recommended sample size is 10-week, as illustrated in Figure 4.10.

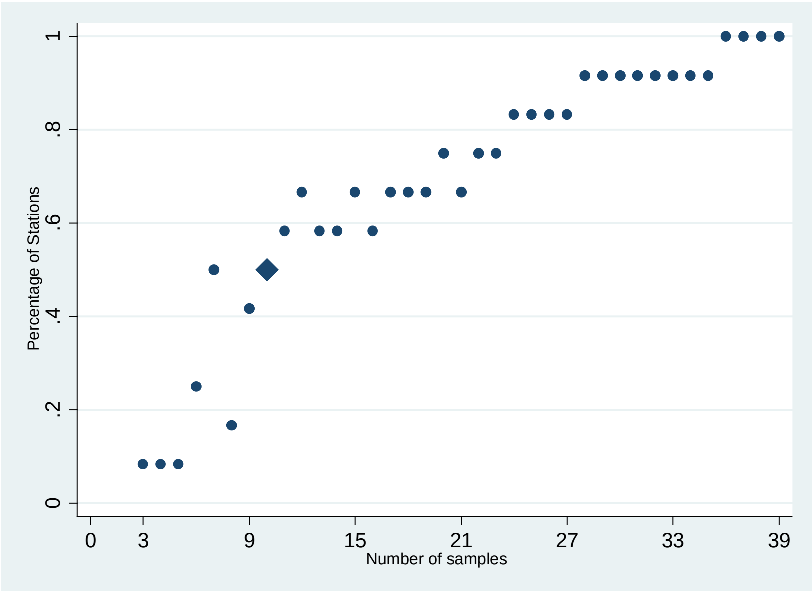


Figure 4.10: Heavy Commercial Volume-AHA – number of samples and percentage of stations showing AHA traffic pattern with a classification accuracy rate ≥ 50%

4.6 Robustness check

A natural question may arise at this point: what if the traffic pattern assigned to a PTR site based on professional judgment is wrong? For example, if a PTR site has a true pattern of AAL but is deemed to be AHA with the sample size selected accordingly, what is the resulting impact on the classification accuracy? To address this question, we perform a robustness check with respect to the classification accuracy of total volume attribute for a randomly selected station 384, for which the seasonal traffic pattern has been identified as AAL.

To illustrate the impact of a misjudged traffic pattern, we carry out a simulation with 200 iterations, track the seasonal traffic pattern resulting from each iteration, and compute the traffic pattern distribution over all iterations for each of the sample sizes between 3 and 39 weeks. This result is provided in Table 4.5, where each cell indicates the percent of 200 iterations that show the traffic pattern in the corresponding column header for the sample size listed for the row. This percentage can be interpreted as the probability of the station being identified as a particular traffic pattern for a certain sample size. The percentages sum up to 1 for each row.

As seen in Table 4.5, the station's true pattern, AAL, is the only pattern that has no zero values and indicates an increasing trend as the sample size increases. ALA, LAA, and AAH patterns are only populated with extremely low values, when the sample size is small and the results can be heavily influenced by the randomness of the simulation method. The AAL pattern consistently has the largest percentage among all patterns for all sample sizes. Even with a 3-week sample, the true pattern AAL is identified as the likely pattern more than twice as often as the next likely pattern AHA.

Table 4.5: Station 384 – Robustness Check Results for Total Volume Attribute

Number of Samples	AHA	AAL	HAA	ALA	LAA	AAH
3	0.24	0.57	0.14	0	0.04	0.01
4	0.16	0.635	0.18	0.025	0	0
5	0.145	0.77	0.065	0.005	0.015	0
6	0.16	0.78	0.06	0	0	0
7	0.11	0.835	0.05	0	0	0.005
8	0.08	0.84	0.075	0.005	0	0
9	0.13	0.85	0.02	0	0	0
10	0.085	0.915	0	0	0	0
11	0.08	0.90	0.02	0	0	0

12	0.075	0.915	0.01	0	0	0
13	0.075	0.91	0.015	0	0	0
14	0.04	0.95	0.01	0	0	0
15	0.045	0.955	0	0	0	0
16	0.01	0.985	0.005	0	0	0
17	0.04	0.96	0	0	0	0
18	0.01	0.99	0	0	0	0
19	0.005	0.995	0	0	0	0
20	0.01	0.99	0	0	0	0
21	0.005	0.995	0	0	0	0
22	0.01	0.99	0	0	0	0
23	0	1	0	0	0	0
24	0.005	0.995	0	0	0	0
25	0	1	0	0	0	0
26	0	1	0	0	0	0
27	0	1	0	0	0	0
28	0	1	0	0	0	0
29	0	1	0	0	0	0
30	0	1	0	0	0	0
31	0	1	0	0	0	0
32	0	1	0	0	0	0
33	0	1	0	0	0	0
34	0	1	0	0	0	0
35	0	1	0	0	0	0

36	0	1	0	0	0	0
37	0	1	0	0	0	0
38	0	1	0	0	0	0
39	0	1	0	0	0	0

In practice, one may continue collecting data until at least our pattern is exhibited in at least 50% of iterations. If, furthermore, this pattern is more likely to be observed upon collecting more data, then one may conclude that the most frequently occurring pattern is also the true pattern.

4.7 Conclusions

This chapter presents a methodology that analyzes the sample-size requirements for a desired estimation accuracy at short-count sites. The results of this exercise help us understand the level of data collection effort that may be required to accurately estimate traffic volume at PTR sites, which should be statistically similar to the ATR sites.

We develop a simulation methodology that samples and bootstraps continuous-count data to create data records as if they were collected from PTR sites. This approach is illustrated with three sets of attributes: (1) total volume by season, (2) weekend volume by season, and (3) heavy commercial volume by season. Three levels are defined for each attribute, namely, high, average, and low.

We compile the continuous-count data from 2010 – 2012 into a dataset consisting of 39 ordered weeks' data, which is used for the traffic pattern identification and simulation exercise. For each sample size, we carry out a simulation with 200 iterations, and track the correctness of the pattern classification. The percent of correct classification among the 200 iterations is reported as a function of the number of samples for each station.

We aggregate the station level simulation results obtained previously and calculate the percentage of stations that show a classification accuracy rate of no less than 50% for each sample size. The results are obtained for all stations and three subsets of stations by seasonal traffic pattern. This analysis enables the identification of the minimum sample size that meets both thresholds for each attribute.

Our recommendations regarding the sample sizes required for a minimum of 50% of the stations to reach a 50% accuracy rate are summarized in Table 4.6. Additional analysis is carried out to demonstrate the robustness of the conclusions.

Table 4.6: Sample Size Recommendations

Attribute	Recommended Sample Size					
	All Stations			**Stations with AHA Pattern**		
Total Volume	4 weeks			3 weeks		
	Spring	Summer	Autumn	Spring	Summer	Autumn
	2	1	1	1	1	1
Weekend Volume	5 weeks			4 weeks		
	Spring	Summer	Autumn	Spring	Summer	Autumn
	2	2	1	2	1	1
Heavy Commercial Volume	9 weeks			10 weeks		
	Spring	Summer	Autumn	Spring	Summer	Autumn
	3	3	3	4	3	3

CHAPTER 5 : CONCLUSIONS AND RECOMMENDATIONS

This research project aims to answer the following questions: Is there an alternate/better way to utilize the continuous-count data, and infrequently sampled short-count data to develop accurate estimates of traffic volumes? Is there an approach that will make the process of incorporating professional judgment more systematic and accurate? How often should MnDOT sample data from short-count sites? To collect data at short-count sites, MnDOT needs to set up a portable recorder at that site, which consumes resources and time of state employees. Therefore, it is important to consider the feasibility of any alternate approaches. An alternate methodology should be able to address some big picture issues as well. Is Minnesota using the right number of continuous-count sites? Which locations are likely to be candidates for locating additional continuous counters?

University of Minnesota researchers approached the problem from a different angle than the approach currently taken by MnDOT and proposed an alternative methodology for categorizing the traffic patterns and calculating the seasonal adjustment factors (SAFs) for portable traffic recorder (PTR) sites. This methodology for estimating SAFs does not assume volume distribution based on professional judgment. The methodology can be applied with different user-specified values of key parameters. In this sense, the methodology is potentially applicable when users specify different attributes and threshold values to label traffic patterns.

We group ATRs based on the ratios of seasonal traffic volume patterns. The grouping could be done based on other attributes as well, e.g., vehicle class distribution. However, the approach has been tested so far for volume-based groupings. In our approach, a traffic pattern is defined by two components: the weekday traffic volume (referred to as “weekdays”), and the ratio of weekend traffic volume to weekday traffic volume (referred to as “Weekend/Weekday Ratio”). Each component has three attributes. Specifically, for each ATR station, the weekday traffic volume can be categorized as average (A), high (H), or low (L) relative to the mean traffic volume across the three seasons at that station. Similarly, the weekend to weekday ratio can be categorized as either the same, or high, or low based on pre-determined thresholds.

The results of our analysis reveal that a small number of patterns are sufficient to cover the vast majority of ATR stations. As shown in the results, the most common seasonal traffic pattern is AHA weekday and LLL weekend/weekday, followed closely by AHA weekday and HHH weekend/weekday. The third common pattern is AAL weekday and LLL weekend/weekday. The top three patterns have a multiple observations, each with 16 to 19 stations. The fourth pattern, AHA weekday SHS weekend/weekday has a total of five stations. The remaining patterns are not well represented with typically only one or two stations for each pattern.

The results produced by this methodology are not directly comparable to the AADT adjustment factors for short duration weekday traffic volume counts currently in use. In contrast with the existing method, the alternative methodology defines the traffic pattern at the season level. We identify more than 20 patterns using the alternative methodology. MnDOT’s methodology allows 12 clusters to be identified, many of which are single, extreme patterns that are not used in the cluster-based SAF calculations. Several clusters with more stations are not used at all if their calculated monthly SAF do not match the historically stable group factors but the individual ATR SAFs are used for PTR sites along the same roadway near the ATR. The proposed technique could allow for a greater degree of ATR/WIM site data inclusion when using three season patterns as the criteria for calculating SAFs and allows for more explicitly defined distinctions between weekday and weekend patterns. Additionally, our method uses thresholds that can be set by the user. MnDOT's current methodology lets Ward's algorithm pick these thresholds to identify clusters. Segmenting at the seasonal level may result in more informative and accurate SAF estimates.

We then use professional judgment to ascertain which traffic pattern best describes each PTR station. Our approach does not require pre-grouping of PTRs for the purpose of SAF calculation. We also develop a methodology to test whether the hypothesized pattern by professionals is statistically supported by historical data available for that PTR site.

A critical step in the methodology requires analysts to obtain professional judgment regarding the traffic patterns of PTR sites. Analysts must utilize this information to validate the pattern identification method proposed in Chapter 3. For this purpose, researchers have designed a survey tool to automate the collection and quantification of county engineers' opinions regarding the traffic patterns of (PTR) sites. The survey is programmed within Excel and implements an analytic hierarchy process (AHP) methodology to analyze the survey participants' responses. A separate ATR survey is also created for training and testing purposes. Two MnDOT participants have so far completed the training survey. However, due to the very limited amount of data, it is not possible to identify all of the potential problems that one might encounter if this survey tool were adopted for widespread use.

Finally, to answer whether the current short-count data can produce reliable predictions and further determine whether some PTR sites can benefit from extended data collection, researchers carry out a simulation exercise that analyzes the sample-size requirements for desired estimation accuracy at short-count sites. Specifically, researchers propose a simulation methodology that samples and bootstraps continuous-count data to create data records as if they were collected from PTR sites. This approach is illustrated with three sets of attributes: (1) total volume by season, (2) weekend volume by season, and (3) heavy commercial volume by season. Three levels, namely, high, average, and low, are defined for each attribute. The most common pattern is AHA – average attribute level in spring and fall, and high in summer. Based on a simulation exercise, we provide recommendations regarding the sample sizes required for a minimum of 50% of stations to reach a 50% accuracy rate and carry out additional analysis to demonstrate the robustness of the conclusions.

The simulation technique is used to simultaneously validate the professional judgment and identifies the traffic volume pattern. This technique requires more data than what is currently available or collected. If this approach is adopted, future data collection may be spread over multiple years to avoid excessive effort in any given year of traffic count cycles. The work of this project also sets the stage for identifying which PTR sites are likely to benefit the most from more frequent data collection and potential conversion to continuous counters.

REFERENCES

Bianco, L., G. Confessore, and P. Reverberi. (2001) "A network based model for traffic sensor location with implications on O/D matrix estimates." *Transportation Science* 35 (1): 50-60.

Bianco, L., G. Confessore, and M. Gentili. (2006) "Combinatorial aspects of the sensor location problem." *Annals of Operations Research* 144 (1): 201-234.

Davison, A. C. and D. V. Hinkley. (1997) *Bootstrap methods and their application. Cambridge Series in Statistical and Probabilistic Mathematics*. Cambridge University Press.

Minnesota Department of Transportation. Internet. Traffic Forecasting & Analysis. (Accessed: May 2013), http://www.dot.state.mn.us/traffic/data/data-products.html

Minnesota Department of Transportation. Internet. Roadway Data Fun Facts. (Accessed: May 2013), http://www.dot.state.mn.us/roadway/data/fun-facts.html.

Minnesota Department of Transportation. Internet. MnDOT Traffic Data. (Accessed: March 2015), http://mndotgis.dot.state.mn.us/tfa/Map

Ross, S. M. (2013) *Simulation*, Academic Press, San Diego, CA.

Sayyady, F, Y. Fathi, G. List, and J. Stone. (2013) "Locating Traffic Sensors on a Highway Network: Models and Algorithms." *Transportation Research Record* 2339: 30-38.

Saaty, T. L. (1994) "How to make a decision: the analytic hierarchy process." *Interfaces* 24 (6): 19-43.

Saaty, T. L. (1990) *Multicriteria Decision Making: The Analytic Hierarchy Process*, RWS Publications, Pittsburg, PA.

Ward, J. H., Jr. (1963) "Hierarchical Grouping to Optimize an Objective Function", *Journal of the American Statistical Association*, 58, 236–244

APPENDIX A

DATA PREPARATION

This appendix details the methods and procedures employed to prepare the data used for applying the pattern categorization methodology and deriving the SAF results presented in Chapter 2. Three types of data were made available to us by MnDOT for this project – continuous monitoring data pertaining to volume and vehicle class (this includes both ATR and WIM stations), continuous monitoring data pertaining to axle and vehicle weight (WIM stations data), as well as volume and class counts for short count locations. While our general methodology can be applied to any of these data types, we focus on the continuous-volume data for this exercise.

We were provided with three years of continuous-count data, from 2010 to 2012. We compile the data into a dataset consisting of 39 ordered weeks' data, which is used for generating the traffic pattern identification and SAF results. The entire data preparation process consists of data cleaning, assembling, and imputation steps, which are discussed in detail below.

Data Cleaning

Within the total volume data, there are periods of time during which traffic was affected by special circumstances. These special circumstances include road construction, detour, sensor malfunction, as well as special events such as sugar beet harvest and hunt openers. MnDOT provided us notes regarding the affected data. Thus, we were able to identify these time periods and have them removed from the dataset.

Additionally, we found that the three years' (2010 – 2012) continuous-volume data contain missing values, abnormal observations, and observations with restriction, all of which require further treatment to ensure a meaningful analysis. It is not uncommon for missing data to occur. They could be due to malfunction and/or recalibration of sensor or controller as well as construction of other sorts. Abnormal observations are identified as days with 0 total daily volume, which typically occur immediately before or after some of the missing data days. Observations with restriction refer to rows of data for which the restriction indicator was set to 1, indicating the traffic flow was affected by construction or other activities. Table A. 1 summarizes time windows, by station number, with abnormal data. Table A. 2 presents similar information for data with restriction, both within the 2010 – 2012 "Continuous Volume" data set. The abnormal data and data with restrictions are excluded from further analysis.

Table A. 1: Summary of Abnormal Continuous-Volume Data from 2010 to 2012

Station	Abnormal-Data Time Windows
103	2012/10/1, 2012/10/2
179	2012/7/9 – 2012/7/31, 2012/10/1 – 2012/10/8
233	2012/12/10 – 2012/12/12

390	2012/8/31, 2012/11/1 – 2012/11/6

Table A. 2: Summary of 2010-2012 Data with Restriction Equal to 1

Station	Data-with-Restriction Time Windows
34	2010/6/1 – 2010/6/30
53	2010/6/7 – 2010/6/13
54	2010/6/14 – 2010/6/30
101	2010/6/1 – 2010/6/30
191	2010/6/1 – 2010/6/30
208	2010/6/1 – 2010/6/30
301	2010/6/1 – 2010/6/30
309	2010/6/1 – 2010/6/30
329	2010/6/1 – 2010/6/30
341	2010/6/1 – 2010/6/30
342	2010/6/1 – 2010/6/30
351	2010/6/1 – 2010/6/30
352	2010/6/14 – 2010/6/27
389	2010/6/1 – 2010/6/30

460	2010/6/21 – 2010/6/30

Many stations are found to have data missing for several days and weeks in continuous blocks of times, as shown in Table A. 3.

Table A. 3: Summary of Missing Continuous-Volume Data (2010-2012)

Station	Missing-Data Time Windows
26	2010/1/1 – 2010/9/30, 2010/11/1 – 2011/3/31, 2011/5/1 – 2012/2/29
29	2010/3/1 – 2010/9/30, 2012/8/6 – 2012/12/31
31	2012/8/6 – 2012/12/31
32	2012/1/1 – 2012/10/31
38	2010/1/1 – 2010/11/30, 2011/1/1 – 2011/3/31, 2011/5/1 – 2012/9/90
39	2010/1/1 – 2010/11/30, 2011/1/1 – 2011/3/31, 2011/5/1 – 2012/9/30
40	2010/1/1 – 2010/11/30, 2011/1/1 – 2011/3/31, 2011/5/1 – 2012/9/30
41	2010/1/1 – 2010/11/30, 2010/12/6 – 2011/3/31, , 2011/5/1 – 2012/9/30
42	2012/1/1 – 2012/9/30
43	2012/1/1 – 2012/9/30
53	2010/9/13 – 2010/9/30,
57	2010/6/1 – 2010/12/31
103	2010/5/1 – 2010/12/31, 2012/1/1 – 2012/9/30
110	2011/1/1 – 2011/3/30, 2011/8/1 – 2012/2/29

179	2012/9/1 – 2012/9/30
188	2012/6/25 – 2012/6/30
227	2010/1/1 – 2010/7/31
228	2012/1/1 – 2012/5/16, 2012/6/1 – 2012/10/31
229	2012/1/1 – 2012/10/31
230	2012/1/1 – 2012/10/31
231	2012/1/1 – 2012/10/31
232	2012/1/1 – 2012/10/31
233	2012/1/1 – 2012/12/9
381	2012/12/31
390	2012/9/1 – 2012/10/30

Assembly Steps

Traffic patterns for missing weeks could not be imputed from available data. Thus, if we were to analyze data for each year separately, it would have meant that for each station many weeks would have had no data at all, leaving only a handful of stations in a particular year for which meaningful analysis could be performed. To mitigate the missing data limitation, we apply an averaging procedure to the three years of data and then compile a complete data set for further analysis. Please note that, for consistency, the same procedure is also applied to the three years of continuous-class data. This averaging procedure is described in detail below.

1. We assume that the weekly pattern of volume at each ATR/WIM station did not change across 2010, 2011 and 2012. Thus, the average value across years represents a reasonable proxy for any missing data.
2. For the purpose of this analysis, Sunday is assumed to be the first day of week. Thus, the first Sunday in a year marks the start of week 1 of that year, regardless of the calendar day. Each week ends on the following Saturday. Specifically, week 1 of 2010 consists of Sunday,

January 3 to Saturday, January 9, week 1 of 2011 consists of Sunday, January 2 to Saturday, January 8, and week 1 of 2012 consists of Sunday January 1 to Saturday, January 7. Labeling weeks in this manner allows us to match full weeks in each year, and as a result, we have 51 full weeks in 2010 and 52 weeks in both 2011 and 2012.

3. Based on the fully labeled data, we average the data by the day of the ordered week.

Data Imputation

The continuous-volume data in their original format contain hourly records of traffic volume. These hourly records are aggregated to arrive at the daily total volume. We then calculate the average of the daily total volume data for the same day of each ordered week across the three years, and, thus, obtain a whole year worth of daily total volume data. Note that the data will be further aggregated up, first to the week level and then to the season level, for each station. Missing data could exist at any of these levels and, correspondingly, imputation needs to be performed as appropriate. We next describe this procedure.

As a first step, we only retain weeks of data for which we have two or more days of non-missing data. Within each of these weeks, the volume for each missing day, if any, is imputed as the average of the non-missing days. In other words, the total volume for each week is calculated as the sum of non-missing days' volume divided by the number of non-missing days and then multiplied by two (if weekday) or three (if weekend). In cases for which one or more entire weeks are missing, we only keep seasons that have seven or more non-missing weeks and remove the rest. For the retained seasons that have one or more missing weeks, the volume for the missing week is imputed as the average value of the non-missing weeks within the same season. We then add up the weekly total volume within a season to obtain the total volume for each season. Stations that have one or more missing seasons are excluded from the analysis.

APPENDIX B

Pattern Results and SAFs for c=10%

This appendix contains tables with the complete set of results obtained for c = 10%.

Table B. 1: Weekend/Weekday Ratio – Seasonal Traffic Pattern (10% cutoff)

Pattern	Weekend/Weekday			Number of Stations	Stations
	Spring	Summer	Fall		
1	H	H	H	9	26, 51, 175, 187, 191, 204, 220, 222, 223
2	H	H	S	3	197, 200, 208
3	L	L	L	27	8, 28, 33, 36, 54, 101, 209, 212, 301, 303, 309, 315, 321, 326, 336, 341, 351 359, 365, 381, 384, 389, 390, 402, 405, 407, 425
4	L	L	S	5	56, 329, 410, 458, 464
5	L	S	L	1	199
6	L	S	S	2	353, 400
7	S	H	H	1	219
8	S	H	S	6	29, 164, 170, 211, 218, 221
9	S	L	S	3	110, 422, 460
10	S	S	H	1	214
11	S	S	L	1	352
12	S	S	S	19	31, 34, 35, 55, 179, 188, 198, 210, 213, 225, 227, 305, 335, 342, 354, 382, 386, 388, 420

Table B.2: Weekday + Weekend/Weekday Ratio– Seasonal Traffic Pattern (10% cutoff)

Pattern		**Number of Stations**	**Stations**
Weekday	**Weekend/ Weekday**		
AAL	LLL	11	101, 212, 303, 309, 326, 341, 351, 384, 390, 405, 425
AAL	LLS	3	329, 410, 458
AAL	SLS	2	422, 460
AAL	SSS	4	179, 386, 388, 420
AHA	HHH	9	26, 51, 175, 187, 191, 204, 220, 222, 223
AHA	HHS	3	197, 200, 208
AHA	LLL	11	28, 33, 36, 315, 321, 336, 359, 365, 381, 402, 407
AHA	LLS	1	464
AHA	LSL	1	199
AHA	LSS	1	400
AHA	SHH	1	219
AHA	SHS	5	29, 164, 170, 211, 221
AHA	SLS	1	110
AHA	SSH	1	214
AHA	SSL	1	352
AHA	SSS	13	31, 34, 35, 55, 210, 213, 225, 227, 305, 335, 342, 354, 382
ALA	LLL	1	8
HAA	LLL	2	301, 389
HAA	LLS	1	56

HAA	LSS	1	353
LAA	LLL	2	54, 209
LAA	SHS	1	218
LAA	SSS	2	188, 198

Table B. 3: SAFS for Weekday + Weekend/Weekday Pattern -10% cutoff (Part 1)

Month	**Day of Week**	AAL LLL (11)	AAL LLS (3)	AAL SLS (2)	AAL SSS (4)	AHA HHH (9)	AHA HHS (3)	AHA LLL (11)	AHA LLS (1)	AHA LSL (1)	AHA LSS (1)	AHA SHH (1)	AHA SHS (5)
April	Wednesday	0.91	0.92	0.93	0.97	1.37	1.12	0.93	0.99	0.94	1.00	1.22	1.18
	C.I.	0.90-0.92	0.87-0.97	0.87-0.98	0.94-1.00	1.17-1.57	1.08-1.17	0.91-0.95					1.15-1.21
	Thursday	0.89	0.90	0.89	0.95	1.20	1.01	0.91	0.98	0.90	0.94	1.12	1.08
	C.I.	0.88-0.91	0.88-0.93	0.84-0.95	0.92-0.97	1.07-1.34	0.99-1.03	0.89-0.93					1.03-1.12
	Weekend	1.10	1.03	0.99	1.02	1.05	0.96	1.12	1.11	1.13	1.11	1.12	1.14
	C.I.	1.08-1.12	0.94-1.11	0.74-1.23	0.96-1.09	0.94-1.15	0.90-1.02	1.08-1.16					1.02-1.25
May	Wednesday	0.87	0.86	0.84	0.92	1.15	1.05	0.89	0.95	0.90	0.90	1.07	1.05
	C.I.	0.86-0.88	0.74-0.98	0.41-1.27	0.87-0.96	1.02-1.27	0.97-1.12	0.87-0.91					1.02-1.07
	Thursday	0.86	0.87	0.83	0.90	0.97	0.97	0.88	0.94	0.84	0.87	0.93	0.94
	C.I.	0.84-0.87	0.76-0.97	0.43-1.22	0.85-0.95	0.92-1.02	0.93-1.02	0.86-0.90					0.92-0.95
	Weekend	1.05	0.99	0.92	0.92	0.79	0.90	1.06	1.05	0.93	0.99	0.91	0.93
	C.I.	1.02-1.07	0.88-1.10	0.41-1.44	0.81-1.03	0.71-0.87	0.85-0.94	1.03-1.09					0.85-1.01
June	Wednesday	0.86	0.87	0.84	0.89	0.98	0.96	0.87	0.93	0.87	0.83	1.00	0.89
	C.I.	0.84-	0.75-	0.82-	0.84-	0.86-	0.89-	0.84-					0.82-

		0.88	0.99	0.87	0.95	1.10	1.02	0.90					0.96
	Thursday	0.84	0.86	0.85	0.87	0.84	0.86	0.86	0.91	0.83	0.79	0.88	0.80
	C.I.	0.82-0.86	0.79-0.94	0.49-1.21	0.80-0.95	0.77-0.91	0.84-0.88	0.83-0.89					0.75-0.86
	Weekend	1.00	0.98	0.93	0.88	0.69	0.81	1.02	1.05	0.89	0.88	0.79	0.72
	C.I.	0.96-1.04	0.83-1.13	0.74-1.13	0.76-1.00	0.61-0.77	0.77-0.84	0.97-1.08					0.64-0.78
July	Wednesday	0.89	0.91	0.94	0.92	0.92	0.95	0.88	0.95	0.86	0.89	0.91	0.86
	C.I.	0.86-0.91	0.80-1.02	0.69-1.19	0.85-0.98	0.77-1.06	0.92-0.98	0.86-0.91					0.76-0.96
	Thursday	0.86	0.89	0.90	0.88	0.79	0.84	0.85	0.88	0.82	0.83	0.81	0.76
	C.I.	0.84-0.88	0.84-0.95	0.55-1.25	0.81-0.95	0.68-0.90	0.79-0.90	0.83-0.87					0.68-0.83
	Weekend	1.06	1.06	1.03	0.91	0.64	0.79	1.05	1.06	0.89	0.94	0.72	0.70
	C.I.	1.02-1.10	0.95-1.16	0.85-1.20	0.76-1.06	0.56-0.72	0.75-0.84	1.00-1.09					0.64-0.75
August	Wednesday	0.87	0.89	0.92	0.97	0.94	0.90	0.84	0.88	0.83	0.87	0.88	0.81
	C.I.	0.86-0.89	0.82-0.95	0.49-1.35	0.83-1.10	0.82-1.06	0.84-0.97	0.82-0.87					0.66-0.96
	Thursday	0.87	0.90	0.88	1.00	0.81	0.84	0.84	0.87	0.81	0.83	0.82	0.72
	C.I.	0.85-0.99	0.84-0.96	0.25-1.51	0.75-1.25	0.74-0.88	0.81-0.88	0.81-0.86					0.56-0.87
	Weekend	1.02	1.03	0.99	1.00	0.63	0.76	1.00	1.00	0.89	0.92	0.72	0.65
	C.I.	0.98-1.06	0.91-1.16	0.30-1.67	0.84-1.15	0.55-0.71	0.67-0.85	0.96-1.05					0.53-0.77
Sep.	Wednesday	0.89	0.92	0.97	0.94	1.13	0.99	0.89	0.89	0.85	0.92	1.02	0.98
	C.I.	0.88-0.91	0.90-0.95	0.79-1.15	0.93-0.96	1.02-1.23	0.82-1.17	0.87-0.91					0.90-1.06
	Thursday	0.88	0.92	0.96	0.93	1.01	0.95	0.88	0.88	0.80	0.84	0.93	0.89
	C.I.	0.86-0.90	0.87-0.96	0.79-1.13	0.88-0.98	0.95-1.07	0.92-0.99	0.86-0.90					0.85-0.93
	Weekend	1.07	1.02	1.05	0.93	0.75	0.87	1.07	1.01	0.97	0.93	0.83	0.86

	C.I.	1.05-1.10	1.00-1.05	0.96-1.14	0.84-1.02	0.67-0.83	0.73-1.00	1.02-1.12					0.81-0.91
October	Wednesday	0.93	0.93	0.96	1.00	1.19	1.04	0.90	0.93	0.91	0.90	1.07	1.03
	C.I.	0.90-0.96	0.79-1.08	0.63-1.30	0.92-1.09	1.10-1.29	1.02-1.07	0.89-0.92					1.01-1.06
	Thursday	0.91	0.94	0.97	0.97	1.04	0.95	0.89	0.89	0.90	0.89	0.95	0.94
	C.I.	0.88-0.95	0.79-1.09	0.83-1.10	0.91-1.03	0.97-1.11	0.89-1.00	0.87-0.90					0.90-0.99
	Weekend	1.09	1.03	1.04	1.03	0.87	0.89	1.07	0.99	1.11	0.94	0.90	0.94
	C.I.	1.06-1.12	0.93-1.12	0.89-1.19	0.93-1.13	0.77-0.97	0.84-0.94	1.02-1.11					0.90-0.99
Nov.	Wednesday	0.92	0.95	0.98	0.96	1.25	0.98	0.92	0.91	1.00	0.98	1.15	1.10
	C.I.	0.91-0.94	0.87-1.03	0.44-1.52	0.94-0.99	1.09-1.40	0.84-1.11	0.90-0.94					1.03-1.16
	Thursday	0.98	1.03	1.04	1.01	1.18	1.04	0.97	1.09	0.97	0.97	1.15	1.09
	C.I.	0.96-1.00	0.92-1.13	0.98-1.10	0.96-1.05	1.08-1.29	0.94-1.14	0.93-1.01					1.00-1.19
	Weekend	1.15	1.10	1.10	1.09	1.00	0.98	1.13	0.99	1.15	1.12	1.04	1.09
	C.I.	1.12-1.18	1.05-1.15	0.65-1.54	0.99-1.19	0.87-1.13	0.94-1.02	1.10-1.16					1.00-1.18

Table B. 4: SAFS for Weekday+Weekend/Weekday Pattern -10% cutoff (Part 2)

Month	**Day of Week**	AHA SLS (1)	AHA SSH (1)	AHA SSL (1)	AHA SSS (13)	ALA LLL (1)	HAA LLL (2)	HAA LLS (1)	HAA LSS (1)	LAA LLL (2)	LAA SHS (1)	LAA SSS (2)
April	Wednesday	1.04	1.41	0.96	1.03	0.94	0.85	0.87	1.12	0.93	1.13	1.06
	C.I.				1.00-1.06		0.59-1.11			0.30-1.55		0.59-1.53
	Thursday	1.01	1.33	0.93	0.97	0.85	0.84	0.89	1.03	0.90	1.06	0.98
	C.I.				0.95-0.99		0.61-1.06			0.87-0.93		0.44-1.51

	Weekend	1.14	1.37	1.06	1.07	1.14	1.17	1.03	0.99	1.19	1.07	1.02
	C.I.				1.03-1.11		0.13-2.22			0.74-1.63		0.57-1.46
May	Wednesday	1.00	1.00	0.91	0.96	0.85	0.86	0.74	0.43	0.90	1.06	0.99
	C.I.				0.93-0.98		0.44-1.28			0.27-1.54		0.74-1.24
	Thursday	0.96	1.00	0.88	0.91	0.81	0.85	0.76	0.59	0.88	0.92	0.94
	C.I.				0.89-0.93		0.53-1.18			0.66-1.10		0.57-1.30
	Weekend	1.07	0.91	0.99	0.95	1.04	1.19	0.96	0.96	1.09	0.90	0.97
	C.I.				0.92-0.98		0.17-2.21			0.94-1.24		0.53-1.40
June	Wednesday	0.95	0.83	0.88	0.89	0.82	0.86	0.85	1.00	0.87	1.02	0.97
	C.I.				0.87-0.92		0.32-1.41			0.11-1.63		0.81-1.13
	Thursday	0.90	0.77	0.85	0.84	0.90	0.86	0.82	0.93	0.86	0.94	0.91
	C.I.				0.82-0.87		0.44-1.27			0.23-1.49		0.76-1.07
	Weekend	1.01	0.78	0.91	0.87	1.20	1.17	1.03	0.94	1.04	0.84	0.91
	C.I.				0.83-0.91		0.34-1.99			0.40-1.68		0.64-1.18
July	Wednesday	0.91	0.75	0.85	0.90	1.05	0.92	0.89	1.03	0.84	1.00	0.97
	C.I.				0.86-0.94		0.45-1.40			0.26-1.42		0.64-1.30
	Thursday	0.85	0.72	0.82	0.84	1.03	0.88	0.86	0.95	0.85	0.87	0.91
	C.I.				0.80-0.87		0.53-1.23			0.24-1.46		0.88-0.93
	Weekend	0.99	0.67	0.91	0.86	1.41	1.27	1.07	0.97	1.05	0.79	0.95
	C.I.				0.81-0.92		0.56-1.97			0.84-1.26		0.39-1.51
August	Wednesday	0.89	0.71	0.89	0.88	0.96	0.86	0.91	0.97	0.87	1.00	0.95

	C.I.				0.85-0.90		0.29-1.43			0.47-1.27		0.69-1.21
	Thursday	0.86	0.67	0.86	0.83	0.93	0.85	0.90	0.89	0.83	0.93	0.88
	C.I.				0.81-0.85		0.34-1.36			0.47-1.19		0.51-1.25
	Weekend	0.97	0.63	0.91	0.83	1.32	1.14	1.05	0.89	0.98	0.85	0.89
	C.I.				0.78-0.88		0.41-1.87			0.45-1.51		0.75-1.03
Sep.	Wednesday	0.93	0.74	0.93	0.96	0.85	0.85	0.99	1.07	0.84	0.94	0.97
	C.I.				0.93-0.98		0.38-1.32			0.50-1.17		0.47-1.46
	Thursday	0.92	0.75	0.91	0.90	0.77	0.84	0.99	1.01	0.82	0.85	0.91
	C.I.				0.88-0.92		0.38-1.31			0.60-1.05		0.62-1.20
	Weekend	1.00	0.61	1.02	0.92	1.07	1.14	1.09	0.90	0.97	0.93	0.91
	C.I.				0.89-0.95		0.18-2.10			0.51-1.42		0.83-0.99
October	Wednesday	1.00	0.94	0.97	0.98	0.83	0.86	0.87	1.05	0.82	0.84	0.92
	C.I.				0.96-1.00		0.34-1.38			0.52-1.11		0.39-1.45
	Thursday	0.96	0.88	0.93	0.92	0.82	0.84	0.85	0.94	0.80	0.80	0.83
	C.I.				0.90-0.93		0.44-1.23			0.52-1.08		0.11-1.55
	Weekend	1.03	0.83	1.04	0.97	1.01	1.12	0.93	0.89	0.97	0.84	0.85
	C.I.				0.94-1.00		0.19-2.04			0.95-0.98		0.79-0.91
Nov.	Wednesday	0.99	1.27	0.99	1.01	0.90	0.86	0.94	1.03	0.95	1.02	0.95
	C.I.				0.98-1.04		0.40-1.32			0-1.94		0.69-1.21
	Thursday	1.12	1.28	0.99	1.03	1.02	0.94	0.99	1.00	0.93	0.99	0.95
	C.I.				1.00-1.05		0.69-1.20			0.26-1.61		0.91-0.98

	Weekend	1.04	1.19	1.16	1.07	1.14	1.20	1.03	1.04	1.21	1.13	0.97
	C.I.				1.03-1.11		0.52-1.87			0.38-2.06		0.40-1.53

Note: 1) A number of confidence intervals have end points with a value of zero, as shown in the table. All of these values were originally derived to be negative but reset to zero for practical considerations. 2) Wherever there is only one observation for a pattern, confidence intervals cannot be calculated, and, thus, the corresponding cells are not populated in the table.

Appendix C

Analytic Hierarchy Process

The design of the survey questions and the method for analyzing the responses are based on the analytic hierarchy process (AHP) (Saaty 1990, Saaty 1994). This appendix provides a high-level discussion of this approach and explains how it is applied to construct the survey questions.

AHP is a theory rank ordering complex alternatives through pairwise comparisons. It relies on the judgments of experts to derive priority scales. These scales measure intangibles and professional judgments. The comparisons are made using a scale of absolute judgments that represent by how much more one element dominates another with respect to a given attribute. However, the judgments may be inconsistent. Therefore, how to measure inconsistency and improve the judgments when possible, is an important component of the AHP methodology.

The basic AHP consists of three main operations: pairwise comparison, priority analysis, and consistency verification. Each of these is discussed in more detail below.

Pairwise Comparison

A pairwise comparison approach is used to seek the user's rating of relative likelihood between each pair of patterns. AHP breaks down the problem of obtaining ranks across multiple entities into a process of comparing entities in pairs to judge which of each entity is preferred, or has a greater amount of some desirable property. Pairwise comparisons are easier. AHP also allows similar decomposition across attributes. After obtaining expert responses, the rankings can be combined to obtain an overall raking of all entities.

In our case, there are a total of 5 patterns considered. We pick two out of the five patterns at a time and ask the user to indicate to which extent the user thinks one pattern is more likely than the other pattern for a given PTR site. This results in "5-choose-2" or 10 pairwise comparisons.

To have a quantitative measure of the comparisons, we need a scale of numbers that indicates the likelihood of the absolute amount by which one pattern is dominant over the other pattern. Table C. 1 exhibits the scale.

Table C. 1: Measurement Scale

Score	**Definition**	**Explanation**
1	Equal likelihood	Both patterns are equally likely
3	Weak likelihood of one over another	Experience and judgment slightly favor one pattern over another
5	Strong likelihood	Experience and judgment strongly favor one pattern over another

7	Very Strong or one demonstrated likelihood	Experience and judgment very strongly favor pattern; its dominance is demonstrated in practice
9	Absolute likelihood	Evidence favoring one pattern over another is of the highest order
2, 4, 6, 8 are intermediate/compromise values between adjacent values. Rational values are used when changes are necessary to ensure consistency.		

Next, we need to construct a matrix based on the pairwise comparison responses, also known as the response matrix. An example is illustrated in Table C.2. Please note that the generation of the response matrix and the further analysis performed around it are implemented with the help of a "behind-the-scene" program within our excel survey tool. The user does not see these computations.

We will now explain the response matrix. The dimension of the matrix is determined by the total number of patterns we consider as possible candidates. In our example, we consider the top five patterns and, therefore, have a 5×5 matrix. Each element aij in the upper diagonal response matrix is the likelihood comparison score for each pair – pattern i and pattern j. For example, a13, the third cell of the first row records the user's response regarding the likelihood of pattern 1 versus pattern 3. This cell in Table C.2 has a value of 7, meaning pattern #1 is 7 times more likely than pattern #3. Note that the order of the two patterns matters. Each element in the Lower diagonal is the reciprocal value of the upper diagonal. i.e., element $a_{ji} = 1/a_{ij}$. Diagonal elements are always 1.

Table C. 2: Pairwise Comparison Matrix Example

Pattern	1	2	3	4	5
1	1	2	7	9	5
2	1/2	1	3	4	2
3	1/7	1/3	1	2	1
4	1/9	1/4	1/2	1	2
5	1/5	1/2	1	1/2	1

For an n×n matrix needed by n patterns, we need n*(n-1)/2 comparisons. Since we consider five traffic patterns, we need 10 pair-wise comparisons and thus a total of 10 questions for the survey.

Priority Analysis

The next step is to perform the priority analysis based on the response matrix. Priority scores are determined by the eigenvector corresponding to the principal eigenvalue λ_{max} of the matrix of pair wise comparisons. There are also other methods for calculating the relative priorities, which are not discussed within this report. Next, the sum of priority scores is normalized to 1. Table C.3 lists the normalized priority scores calculated for the response matrix shown in Table C.2.

Table C. 3: Priority Scores Example

	1	2	3	4	5
p_j	0.52	0.23	0.09	0.08	0.08

$$\lambda_{max} = 5.27$$

The pattern that has the largest relative priority score is the most likely pattern. In this example, pattern 1 with the largest priority score value of 0.52 is the most likely pattern. Note that we also obtain the relatively likelihood of all other patterns.

In the case of the PTR survey, the specific application of the above-described method to determine the pattern implied by the user's answers depends on the number of responses we receive for each PTR site. If we only get 1 response for a specific PTR site, the final pattern is the one that has the highest score. If there are multiple responses for the same PTR site, we calculate a weighted-average priority score for each pattern and select the one with the highest weighted score.

Consistency Verification

The methodology described assumes the transitivity of the user's answers to the 10 questions. For example, if pattern #1 is considered 3 times more likely than pattern #2, pattern #2 is considered twice as likely as pattern #3, and pattern #1 is considered 6 times more likely than pattern #3, then this user's answers satisfy the transitivity condition and are referred to as "consistent" within this methodology.

However, inconsistency occurs when relative scores do not capture true rankings of patterns, in which case the methodology will not work properly. As a result, a crucial step is to confirm that the answers do not violate transitivity. In what follows, we offer a high level description of the technical steps needed to verify the consistency. Essentially, the verification method calculates a consistency ratio and compares its value to a threshold value of 0.1.

Let λ_{max} denote the principal eigenvalue of the matrix of comparisons. If pair wise comparisons of n alternatives/criteria are consistent, then we must have that $\lambda_{max} = n$. Furthermore, for any $n \times n$ positive reciprocal matrix of this kind, it can be proven that $\lambda_{max} \geq n$.

For each matrix A of pair wise comparisons, the consistency index (C.I.) is defined as:

$$C.I. = (\lambda_{max} - n)/(n-1)$$

and consistency ratio (C.R.) is computed as:

$$C.R. = C.I./R.I.,$$

where R.I. is the random index or the average C.I. of a large number of (positive reciprocal) matrices of the size of A, whose elements are randomly generated ranks, from 1 to 9. R.I. values have been tabulated for matrices of size up to 15.

If C.R. is less than 0.1, the comparisons are considered consistent. Otherwise, one needs to take steps to reduce the level of inconsistency. The inconsistency remedy is explained subsequently.

Inconsistency Remedy

The first step of the inconsistency remedy is to find the differences between aij, the relative importance of i with respect to j, and p_i/p_j, the ratio of corresponding priorities, for each aij. Next, construct the matrix of absolute differences $| a_{ij} - p_i/p_j |$, and apply remedial measures on the elements with largest such differences. Two types of actions are possible.

One of the actions is to simply ask the survey participant to reconsider his (her) answers and to revise selected elements of matrix A until C.R. is less than 0.1. Alternatively, one can either find the eigenvalues of powers of matrix A, or replace selected a_{ij}'s by p_i/p_j, one at a time, until inconsistency reduces to manageable levels. A drawback of this latter procedure is the potential for distortion of natural judgments. It would generally be better to have improved judgments from the participant.

Recall the earlier example. Using the consistency verification method described above, we calculate the following results:

$$\boxed{\begin{array}{l} \lambda_{max} = 5.27 \\ C.I. = 0.07 \\ C.R. = 0.06 \end{array}}$$

Since C.R. is less than 0.1, the consistency is verified and remedy is not needed for this particular example.

The consistency verification step is programmed as the last component of the survey. As described earlier, three options are offered: (1) review the pattern indicated by his/her response, (2) check consistency, and (3) let the program fix the inconsistency automatically. Choosing the button for the second option will trigger the survey tool to run the consistency verification algorithm and inform the user whether the consistency requirement is met, and if not, the algorithm also identifies which question causes the most inconsistency and, therefore, will be a good target for change in the next round. Once changes are made, the user must again perform a consistency check and continue this process until C.R. is less than 0.1. As stated in the instructions for the survey users, it is strongly recommended that the users manually revise their answers to fix the inconsistency issue. However, due to user-friendly considerations, there is also an option offered to allow the survey tool to change the answer to the question that violates consistency.

Appendix D

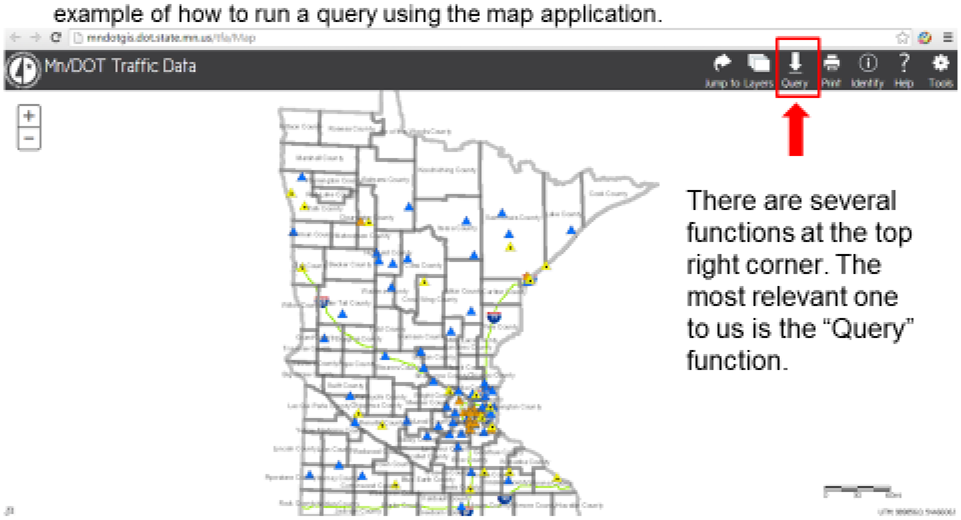
Online Map Instructions for ATR

Instructions:
How to Use MnDOT's Traffic Data Interactive Map

1

Clicking the "MAP" link in the survey will take you to the following website

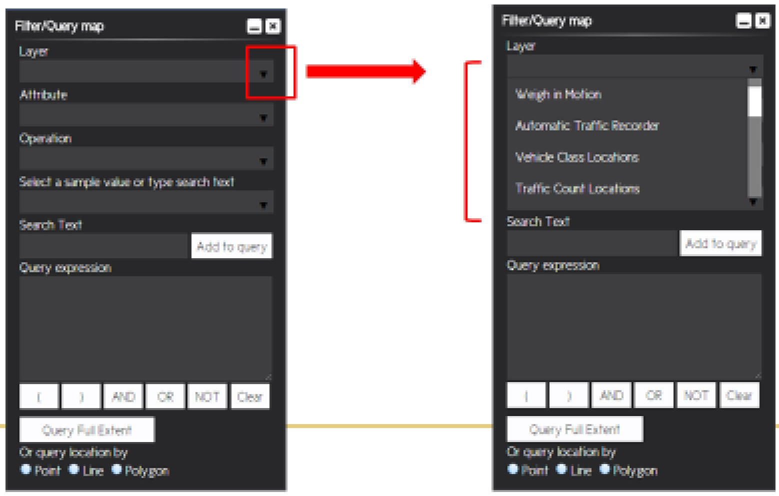
The Mn/DOT Traffic Data is an interactive map that allows you to select where you would like to view data at a larger scale. This presentation walks through an example of how to run a query using the map application.



There are several functions at the top right corner. The most relevant one to us is the "Query" function.

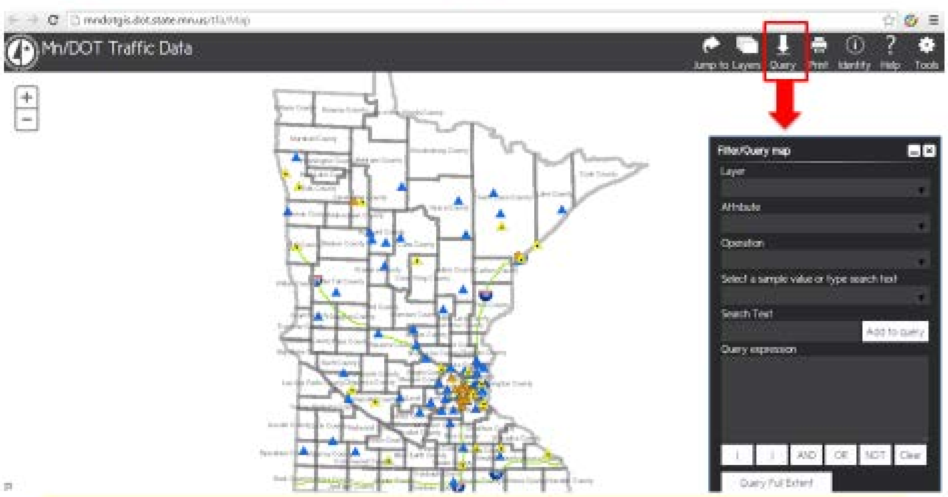
In the Filter/Query Map window, specify the filters to create a query

First click the upside down triangle under “layer” to see the drop-down list. Then choose “Weigh in Motion” or “Automatic Traffic Recorder”



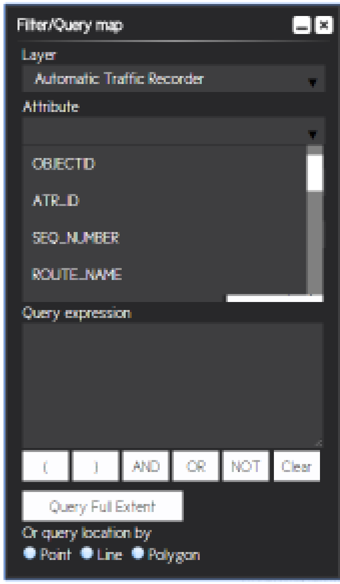
4

Click “Query”, then a pop-up window will appear at the bottom right



3

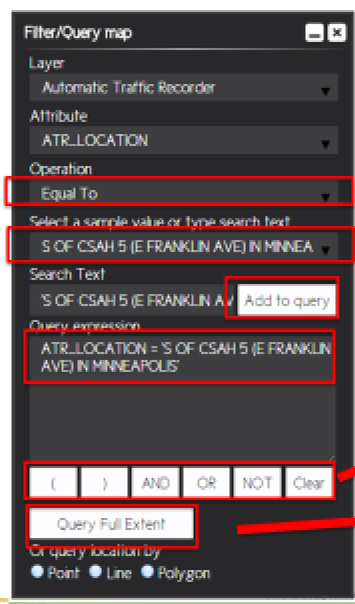
Create a query: Attributes Selection



- There are a list of attributes for you to choose – OBJECTID, ATR_ID, SEQ_NUMBER, ROUTE_NAME, MILEPOST, TRUEMILE, ROUTE_DIRECTION, NUMBER_OF_LANES, COUNTY_NAME, CITY_NAME, etc.
- You can select any attributes to create a query. For this example, we will go with ATR_LOCATION.

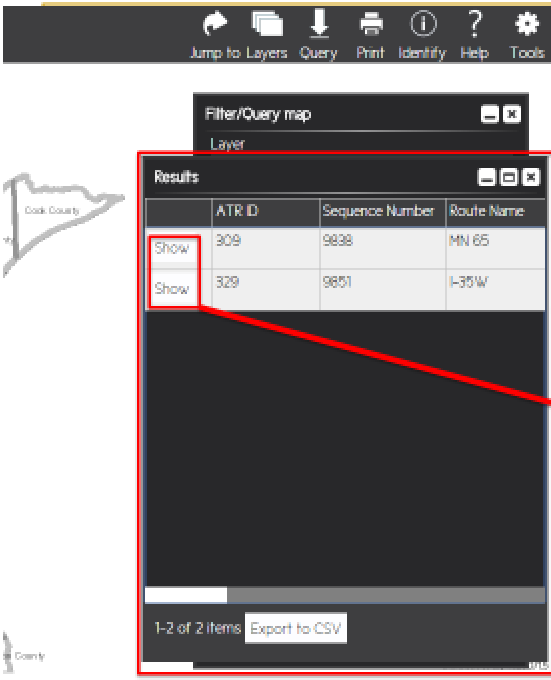
5

Create a query - cont'd



- Select "Equal To"
- Select a location
- Then click "Add to query"
- The query now appears in the "Query expression" box
- Use these operations to reset or add filters
- Click "Query Full Extent" to show results

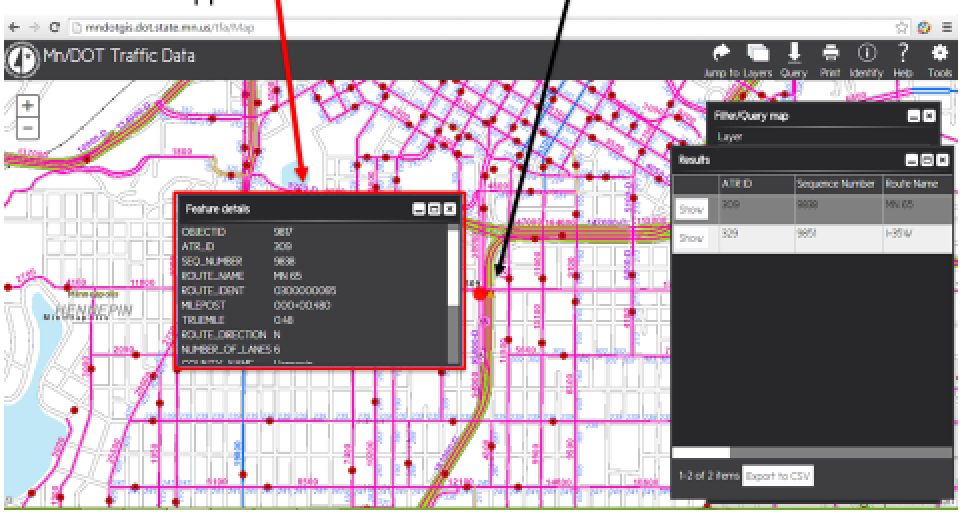
6



- Next, another "results" window will pop up on top of the query window
- In this example, the location we specify happens to have two ATR stations.
- Click the "show" button in front of each result to see the station in the map.

7

- Click the "show" button for ATR 309, the map will zoom in on it. You will see the station highlighted with **a bold red dot**.
Click on the red dot, a window with detailed information about this station appears.



8

Appendix E

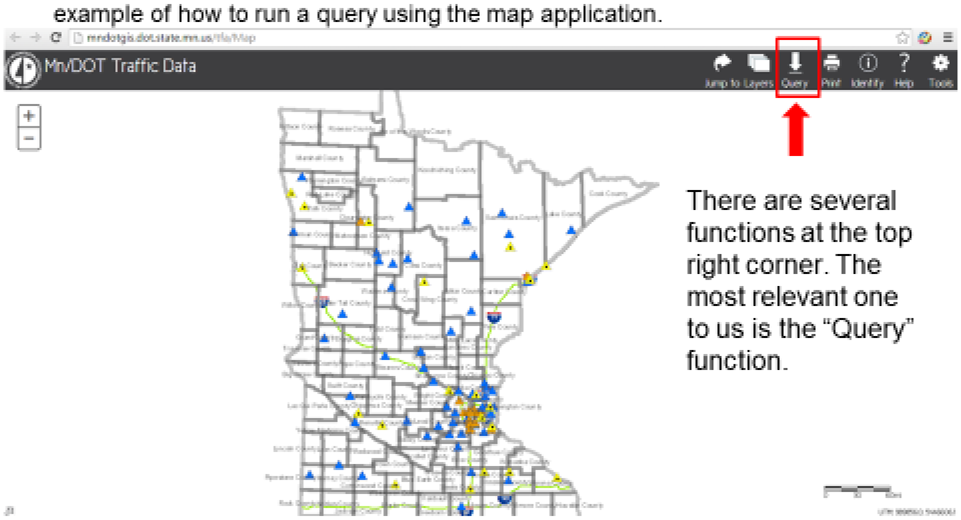
Online Map Instructions for PTR

Instructions: How to Use MnDOT's Traffic Data Interactive Map

1

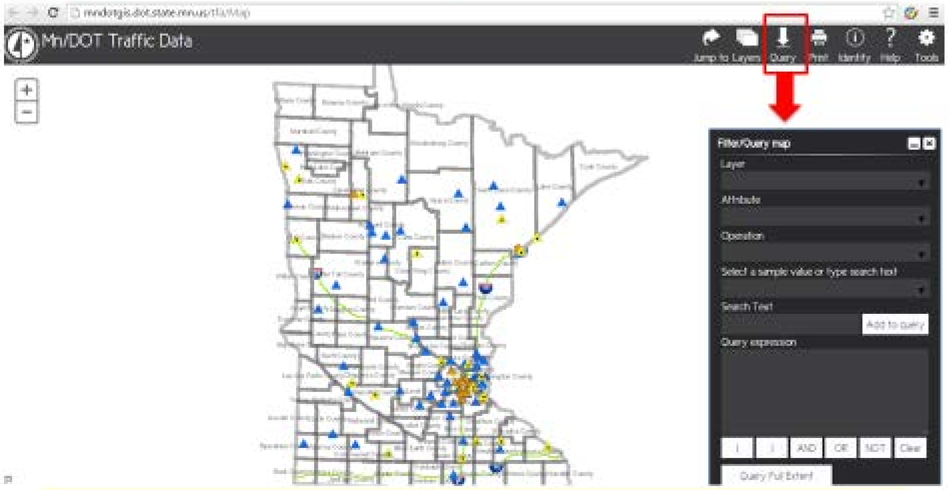
Clicking the "MAP" link in the survey will take you to the following website

The Mn/DOT Traffic Data is an interactive map that allows you to select where you would like to view data at a larger scale. This presentation walks through an example of how to run a query using the map application.



There are several functions at the top right corner. The most relevant one to us is the "Query" function.

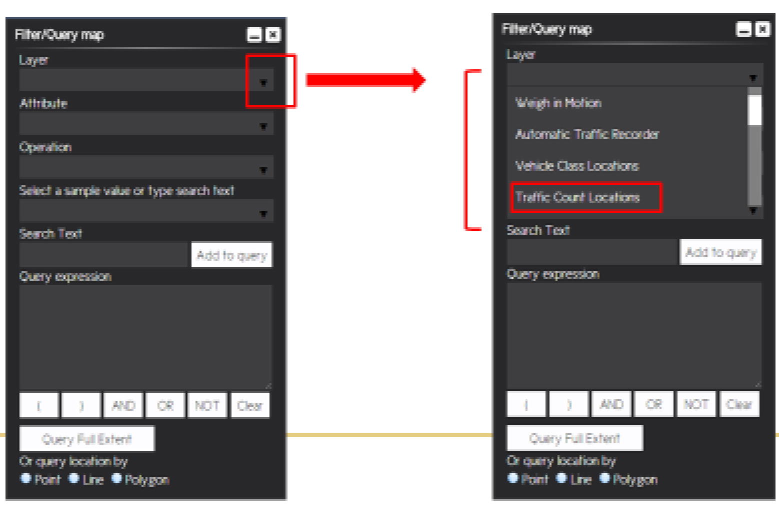
Click “Query”, then a pop-up window will appear at the bottom right



3

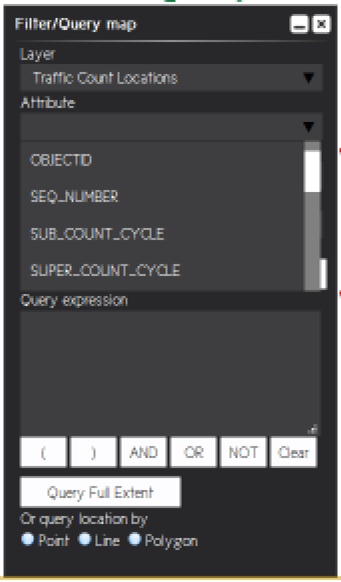
In the Filter/Query Map window, specify the filters to create a query

First click the upside down triangle under “layer” to see the drop-down list. Then choose “Traffic Count Locations”



4

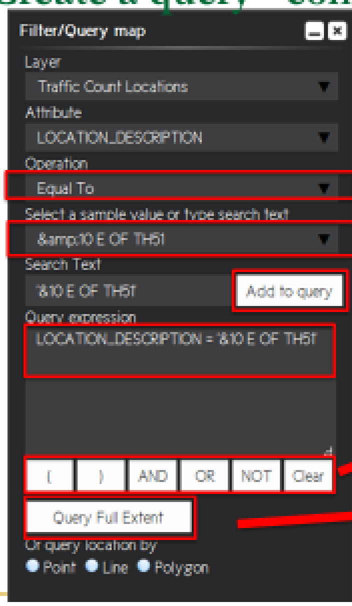
Create a query: Attributes Selection



- There are a list of attributes for you to choose – OBJECTID, SEQ_NUMBER, LOCATION_DESCRIPTION, ROUTE_NAME, COUNTY_NAME, etc.
- You can select any attributes to create a query. For this example, we will go with LOCATION_DESCRIPTION.

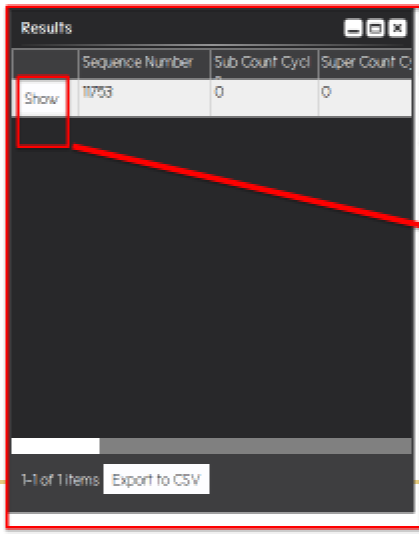
5

Create a query - cont'ed



- Select "Equal To"
- Select a location
- Then click "Add to query"
- The query now appears in the "Query expression" box
- Use these operations to reset or add filters
- Click "Query Full Extent" to show results

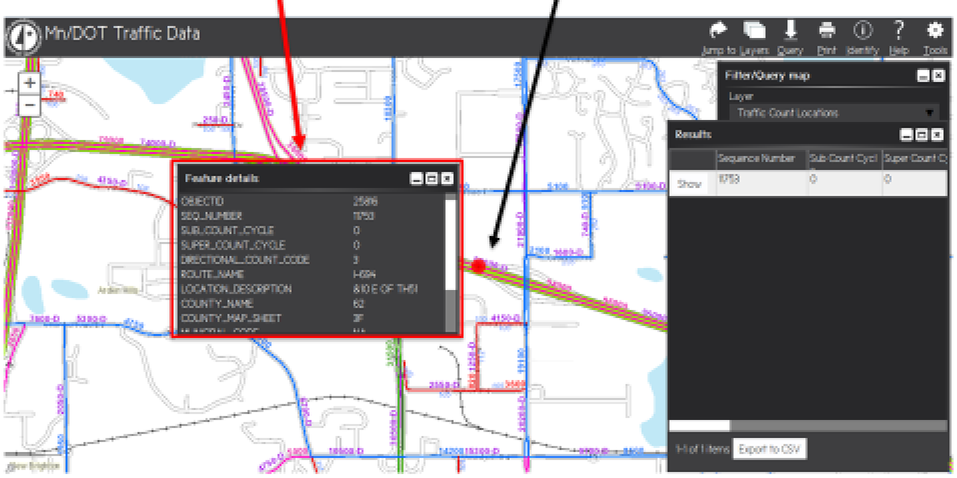
6



- Next, another "Results" window will pop up on top of the query window
- In this example, the location we specify has one PTR site.
- Click the "show" button in front of each result to see the station in the map.

7

- Click the "show" button for PTR 11753, the map will zoom in on it. You will see the station highlighted with **a bold red dot**. Click on the red dot, a window with detailed information about this station appears.



8

Appendix F

Attribute Calculation, Bootstrapping, and Simulation Techniques

This appendix details the calculation of each attribute for all seasons as well as the bootstrapping (Davison, 1997) and simulation (Ross, 2013) techniques.

Attribute Calculation

1. Total volume: The calculation for this attribute uses continuous-volume data, which in their original format contain hourly records of traffic volume. These hourly records are aggregated to arrive at the daily total volume. We then calculate the average of the daily total volume data for the same day of each ordered week across the three years, and, thus, obtain a whole year worth of daily total volume data. Note that the data will be further aggregated up, first to the week level, and then to the season level, for each station. Missing data could exist at any of these levels and, correspondingly, imputation needs to be performed as appropriate. We describe this procedure next.

As a first step, we only retain weeks of data for which we have four or more days of non-missing data. Within each of these weeks, the volume for each missing day, if any, is imputed as the average of the non-missing days. In other words, the total volume for each week is calculated as the sum of non-missing days' volume divided by the number of non-missing days and then multiplied by 7. In cases for which one or more entire weeks are missing, we only keep seasons that have seven or more non-missing weeks and remove the rest. For the retained seasons that have one or more missing weeks, the volume for the missing week is imputed as the average value of the non-missing weeks within the same season. We then add up the weekly total volume within a season to obtain the total volume for each season. Stations that have one or more missing seasons are excluded from the analysis. Table F. 1 contains a list of retained and excluded stations for this attribute.

Table F. 1: Total Volume Data by Station

Category	**Station Number**
Stations with 3 seasons' total volume data (79 stations)	8, 26, 28, 29, 31, 33, 34, 35, 36, 51, 53, 54, 55, 56, 101, 110, 164, 170, 175, 179, 187, 188, 191, 197, 198, 199, 200, 204, 208, 209, 210, 211, 212, 213, 214, 218, 219, 220, 221, 222, 223, 225, 227, 301, 303, 305, 309, 315, 321, 326, 329, 335, 336, 341, 342, 351, 352, 353, 354, 359, 365, 381, 382, 384, 386, 388, 389, 390, 400, 402, 405, 407, 410, 420, 422, 425, 458, 460, 464
Stations with less than 3 seasons' total volume data (15 stations)	32, 38, 39, 40, 41, 42, 43, 57, 103, 228, 229, 230, 231, 232, 233,

2. Weekend volume: The calculation for this attribute uses continuous-volume data but concerns weekends only. Weekend is defined as the time between Sunday 12:00 a.m. to Monday 4:00 a.m. and Friday 4:00 p.m. to Saturday 12:00 a.m. from the same week. Each weekend consists of a total of 60 hours. We calculate the three-year average for each hour of the weekend, and then add up these hourly average values to arrive at the total volume data for each of the 39 ordered weekends.

After obtaining the weekend volume data, we exclude those weekends that have less than 50 hours' data. There should be 60 hour's data in each weekend if no data are missing. However, for a given weekend that has a few (no more than 10) missing hours, the total volume was imputed as average hourly volume during the weekend × 60. We then group the remaining ordered weekends into seasons according to the aforementioned season definition. The stations with less than 6 weekends in any of the three seasons are removed. For stations that remain, the seasonal weekend volumes are imputed as average weekend volume × 13, as there are 13 weekends in a season. Table F. 2 details the retained and excluded stations for the analysis of this attribute.

Table F. 2: Weekend Volume Data by Station

Category	**Station Number**
Stations with 3 seasons' weekend volume data (79 stations)	8, 26, 28, 29, 31, 33, 34, 35, 36, 51, 53, 54, 55, 56, 101, 110, 164, 170, 175, 179, 187, 188, 191, 197, 198, 199, 200, 204, 208, 209, 210, 211, 212, 213, 214, 218, 219, 220, 221, 222, 223, 225, 227, 301, 303, 305, 309, 315, 321, 326, 329, 335, 336, 341, 342, 351, 352, 353, 354, 359, 365, 381, 382, 384, 386, 388, 389, 390, 400, 402, 405, 407, 410, 420, 422, 425, 458, 460, 464
Stations with less than 3 seasons' weekend volume data (15 stations)	32, 38, 39, 40, 41, 42, 43, 57, 103, 228, 229, 230, 231, 232, 233

3. Heavy commercial volume: The calculation for this attribute uses continuous-class data for class labels 8 – 13. The imputation procedure used for this attribute is the same as that used to calculate the total volume attribute. Upon completing the data exclusion and imputation (as appropriate) at the week and season levels, a total of 42 stations are retained for the analysis. Table F. 3 lists the retained and excluded stations.

Table F. 3: Heavy Commercial Volume Data by Station

Category	**Station Number**
Stations with 3 seasons' heavy commercial volume data (42 stations)	26, 29, 31, 33, 34, 35, 36, 37, 38, 39, 40, 41, 54, 56, 101, 175, 179, 187, 191, 197, 198, 199, 200, 204, 208, 212, 213, 219, 220, 221, 222, 223, 225, 227, 335, 341, 351, 352, 353, 381, 382, 388
Stations with less than 3 seasons' heavy commercial volume data (24 stations)	8, 27, 32, 51, 53, 55, 57, 103, 188, 209, 218, 228, 229, 230, 231, 232, 233, 365, 390, 400, 407, 410, 422, 425

Simulation Methodology

In the computer simulation experiment, we sample from the continuous-count data to mimic the actual data collection process. Recognizing that MnDOT is unable to collect short-count data in winter, we sample from a total of 39 ordered weeks' data covering spring, summer, and fall in the simulation process. The relevant data are the 39 ordered weeks' data previously obtained upon performing the procedures outlined in Appendix A. We filter out stations that have missing data to avoid any noise that would otherwise be introduced. The resulting data used for the simulation analysis contains a total of 78 stations for total volume and weekend volume attributes, and 30 stations for heavy commercial volume. These stations are listed in Table F. 4.

Table F. 4: Stations Included in the Simulation Exercise (by Attribute)

Attribute	**Stations Included in the Simulation**
Total Volume or Weekend Volume	8, 26, 28, 29, 31, 33, 34, 35, 36, 51, 54, 55, 56, 101, 110, 164, 170, 175, 179, 187, 188, 191, 197, 198, 199, 200, 204, 208, 209, 210, 211, 212, 213, 214, 218, 219, 220, 221, 222, 223, 225, 227, 301, 303, 305, 309, 315, 321, 326, 329, 335, 336, 341, 342, 351, 352, 353, 354, 359, 365, 381, 382, 384, 386, 388, 389, 390, 400, 402, 405, 407, 410, 420, 422, 425, 458, 460, 464
Heavy Commercial Volume	26, 31, 33, 34, 35, 37, 38, 39, 40, 41, 54, 56, 179, 187, 197, 199, 204, 208, 212, 213, 219, 220, 221, 223, 225, 227, 352, 353, 381, 388

For a given attribute, the simulation process for each station listed in Table F. 4 proceeds according to the following steps. This process is illustrated in Figure F. 1.

1. Determine sampling strategy, for each sample size.
2. Bootstrap samples to create a dataset with 39 weeks of observations.
3. Using the simulated dataset, assign attribute levels and record the seasonal traffic patterns using the method outlined Chapter 3.
4. Repeat Steps 1-3 as many times as the selected number of iterations.
5. Calculate the percentage of correct classification among all iterations.

The correct classification rates are obtained for all of the sample sizes, i.e., from 3 weeks to 39 weeks of data. The results are compiled across all stations to illustrate the relationship between the sample size and the percentage of stations that exhibit a desired level of classification accuracy. This is to identify sample sizes needed to reach a desired level of accuracy. Because the outcome within each iteration (with a fixed number of samples) depends on the actual samples drawn and the randomness introduced during the bootstrapping procedure, the results vary from one iteration to another. Therefore, we measure accuracy by the proportion of stations for which at least 50% of iterations resulted in correct classification.

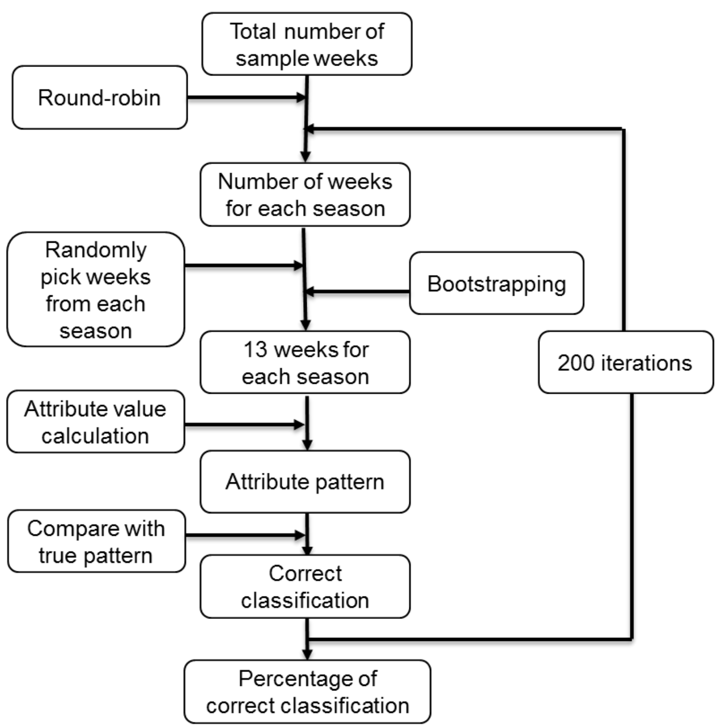


Figure F. 1: Simulation Process

Next, we describe the three key steps of our methodology: sampling, bootstrapping, and pattern identification.

Sampling

The sample size can vary from 3 weeks to 39 weeks, and this step concerns how these weeks of data are selected from the 39 weeks of real data. Specifically, we start with a sample of 3 weeks, one from each season, and then add one more week to the sample for each simulation, until all the 39 weeks of real data are sampled. After the initial sampling of three weeks, we use a round-robin approach to decide the seasons from which additional weeks of data will be picked. For example, in the case of a 5-week sample size, we first take one week from each season, and then add 1 week to spring, followed by 1 more week to summer, thus obtaining a total of 5 weeks in the sample. Within a season, the week number is picked at random without replacement.

Bootstrapping

This step uses a bootstrapping approach to transform the weeks sampled from each season (as obtained in the previous step) into a full season with 13 weeks' records. This step is undertaken to capture the variability within a season, which often cannot be ascertained with a small subset of data.

The procedure applied to bootstrap the sampled data to 13 weeks' data varies depending on the attribute. Suppose we have n weeks of data that have been sampled from a certain season, then for this season we still need to have another (13 – n) weeks of data. For the total volume and heavy commercial volume attributes, we divide the sampled data into two groups, weekdays (Mondays to Fridays) and weekends (Saturdays and Sundays). To create one week of data, we randomly select five days from the weekday group and two days from the weekend group with replacement. This selection is repeated for (13 – n) times to complete the bootstrapping procedure for this season. The whole process is then performed for each season to obtain a total of 39 weeks' data.

For the weekend volume attribute, the bootstrapping is performed at the hourly level, as weekend is defined to be a 60-hour period for the purpose of our analysis. Suppose we have n weekends of data that have been sampled from a certain season, then for this season we still need to have another (13 – n) weekends. In order to generate the data needed, we randomly select 60 hours from the sample with replacement. This selection is repeated for (13 – n) times to complete the bootstrapping for this season. The whole process is then performed for each season to obtain a total of 39 weekends' data.

Pattern Identification

Upon completing the bootstrapping step, we obtain 13 weekly (total/weekend/heavy commercial) volumes for each season. We then apply the method described in Section 2.2 to assign a high, average, or low level to each season. Note that the imputation method utilized for the missing data as described in Appendix A no longer applies here, because the bootstrapped data contain no missing values. We then compare simulated seasonal traffic pattern with the known pattern identified for this station. If they match, the outcome for this simulation run is flagged as "correct", and otherwise as "incorrect". For a given attribute and a given station, we repeat the simulation equal to the maximum iteration index, which was set to 200 in our numerical analysis. For each station, we calculate the percentage of correct outcomes among all simulated outcomes. This percentage is referred to as "percentage of correct classification" and is used interchangeably with "classification accuracy" and "correct classification rate" within this report.

The number of simulations run for each sample size is selected to be 200, because this number is sufficiently large to achieve stable simulation results while keeping the computer program's run time at a practically reasonable level. As an illustration, we plot the results based on 200 and 500 times of simulations for station 199, respectively, in Figure F. 2. It is evident that for each given number of samples, the percent of correct classification generated from 200 versus 500 simulations are essentially the same. Although we do not show additional similar results, this observation was evident for other randomly selected stations as well. Therefore, in subsequent analyses, we use 200 iterations.

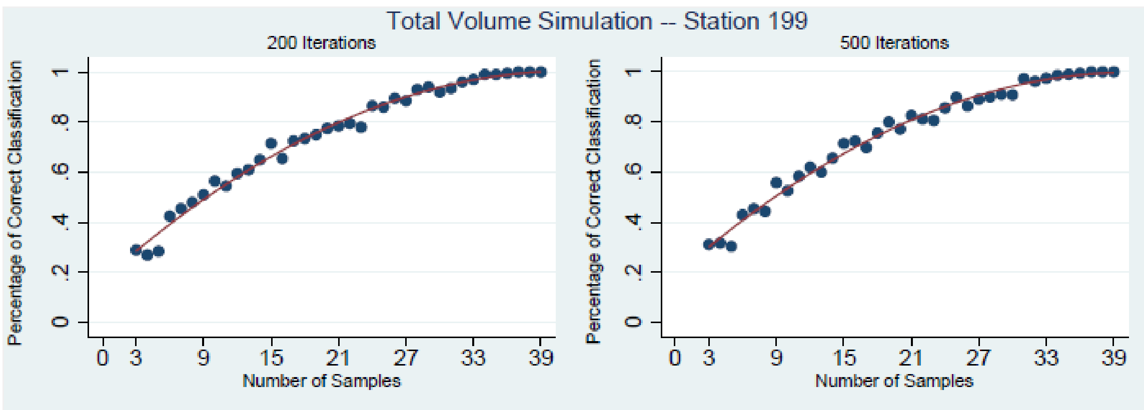


Figure F. 2: Total volume simulation, station 199, 200 vs. 500 iterations

We wish to point out that the correctness of the simulated traffic patterns confirms professional judgment, but the absence of correct conclusion could be, in part, due to the random nature of the simulation methodology, which could produce an incorrect inference. Generally speaking, the more data we sample, the greater the accuracy.

Appendix G

Detailed Classification Accuracy Results

This appendix contains tables with detailed data regarding the percentage of stations that meets a minimum of 50% classification accuracy rate by sample size for each attribute.

Table G. 1: Total Volume – stations with a percentage of correct classification ≥ 50%

Number of samples	Stations with a Percentage of Correct Classification ≥ 50%							
	Total Stations		AHA		AAL		HAA	
	Number	Percentage	Number	Percentage	Number	Percentage	Number	Percentage
3	35	44.87%	24	58.54%	7	35.00%	3	37.50%
4	40	51.28%	27	65.85%	9	45.00%	3	37.50%
5	43	55.13%	25	60.98%	14	70.00%	3	37.50%
6	54	69.23%	34	82.93%	13	65.00%	4	50.00%
7	56	71.79%	34	82.93%	15	75.00%	4	50.00%
8	58	74.36%	34	82.93%	16	80.00%	4	50.00%
9	61	78.21%	35	85.37%	16	80.00%	5	62.50%
10	64	82.05%	37	90.24%	16	80.00%	5	62.50%
11	64	82.05%	38	92.68%	16	80.00%	5	62.50%
12	68	87.18%	39	95.12%	17	85.00%	7	87.50%
13	69	88.46%	40	97.56%	17	85.00%	7	87.50%
14	69	88.46%	39	95.12%	17	85.00%	7	87.50%
15	71	91.03%	40	97.56%	18	90.00%	7	87.50%
16	70	89.74%	40	97.56%	18	90.00%	7	87.50%
17	70	89.74%	40	97.56%	17	85.00%	7	87.50%
18	69	88.46%	40	97.56%	17	85.00%	7	87.50%
19	71	91.03%	40	97.56%	18	90.00%	7	87.50%
20	71	91.03%	40	97.56%	18	90.00%	8	100.00%
21	72	92.31%	40	97.56%	19	95.00%	7	87.50%

22	72	92.31%	40	97.56%	19	95.00%	8	100.00%
23	72	92.31%	40	97.56%	19	95.00%	8	100.00%
24	72	92.31%	40	97.56%	18	90.00%	8	100.00%
25	72	92.31%	40	97.56%	19	95.00%	7	87.50%
26	72	92.31%	40	97.56%	19	95.00%	8	100.00%
27	73	93.59%	40	97.56%	19	95.00%	8	100.00%
28	72	92.31%	40	97.56%	19	95.00%	8	100.00%
29	73	93.59%	40	97.56%	19	95.00%	8	100.00%
30	74	94.87%	40	97.56%	20	100.00%	8	100.00%
31	73	93.59%	40	97.56%	20	100.00%	8	100.00%
32	74	94.87%	40	97.56%	20	100.00%	8	100.00%
33	74	94.87%	41	100.00%	20	100.00%	8	100.00%
34	77	98.72%	41	100.00%	20	100.00%	8	100.00%
35	75	96.15%	41	100.00%	20	100.00%	8	100.00%
36	77	98.72%	41	100.00%	20	100.00%	8	100.00%
37	77	98.72%	41	100.00%	20	100.00%	8	100.00%
38	77	98.72%	41	100.00%	20	100.00%	8	100.00%
39	78	100.00%	41	100.00%	20	100.00%	8	100.00%

Table G. 2: Weekend Volume - stations with a percentage of correct classification ≥ 50%

Number of samples	Stations with a Percentage of Correct Classification ≥ 50%							
	Total Stations		AHA		AAL		HAA	
	Number	Percentage	Number	Percentage	Number	Percentage	Number	Percentage
3	30	38.46%	17	42.50%	10	41.67%	3	27.27%

4	38	48.72%	22	55.00%	12	50.00%	3	27.27%
5	42	53.85%	23	57.50%	15	62.50%	3	27.27%
6	51	65.38%	28	70.00%	16	66.67%	6	54.55%
7	53	67.95%	30	75.00%	17	70.83%	5	45.45%
8	54	69.23%	29	72.50%	19	79.17%	5	45.45%
9	59	75.64%	34	85.00%	18	75.00%	6	54.55%
10	57	73.08%	32	80.00%	19	79.17%	7	63.64%
11	58	74.36%	31	77.50%	20	83.33%	6	54.55%
12	63	80.77%	36	90.00%	19	79.17%	7	63.64%
13	64	82.05%	36	90.00%	20	83.33%	6	54.55%
14	63	80.77%	34	85.00%	21	87.50%	7	63.64%
15	64	82.05%	37	92.50%	20	83.33%	6	54.55%
16	64	82.05%	36	90.00%	20	83.33%	7	63.64%
17	66	84.62%	37	92.50%	21	87.50%	7	63.64%
18	65	83.33%	35	87.50%	21	87.50%	7	63.64%
19	65	83.33%	37	92.50%	20	83.33%	7	63.64%
20	64	82.05%	36	90.00%	19	79.17%	7	63.64%
21	69	88.46%	38	95.00%	21	87.50%	8	72.73%
22	68	87.18%	38	95.00%	21	87.50%	7	63.64%
23	68	87.18%	38	95.00%	20	83.33%	8	72.73%
24	70	89.74%	37	92.50%	23	95.83%	8	72.73%
25	69	88.46%	37	92.50%	23	95.83%	7	63.64%
26	72	92.31%	39	97.50%	22	91.67%	9	81.82%
27	72	92.31%	39	97.50%	23	95.83%	8	72.73%

28	75	96.15%	40	100.00%	23	95.83%	9	81.82%
29	74	94.87%	39	97.50%	23	95.83%	9	81.82%
30	74	94.87%	39	97.50%	23	95.83%	9	81.82%
31	74	94.87%	39	97.50%	23	95.83%	9	81.82%
32	75	96.15%	40	100.00%	23	95.83%	9	81.82%
33	75	96.15%	40	100.00%	23	95.83%	9	81.82%
34	75	96.15%	40	100.00%	23	95.83%	9	81.82%
35	75	96.15%	39	97.50%	23	95.83%	10	90.91%
36	76	97.44%	40	100.00%	23	95.83%	10	90.91%
37	76	97.44%	39	97.50%	24	100.00%	10	90.91%
38	76	97.44%	40	100.00%	23	95.83%	10	90.91%
39	78	100.00%	40	100.00%	24	100.00%	11	100.00%

Table G. 3: Heavy Commercial Volume – stations with a percentage of correct classification ≥ 50%

Number of samples	Stations with a Percentage of Correct Classification ≥ 50%							
	Total Stations		AHA		AAL		LAA	
	Number	Percentage	Number	Percentage	Number	Percentage	Number	Percentage
3	8	26.67%	1	8.33%	1	16.67%	1	20.00%
4	9	30.00%	1	8.33%	2	33.33%	1	20.00%
5	13	43.33%	1	8.33%	4	66.67%	3	60.00%
6	14	46.67%	3	25.00%	3	50.00%	3	60.00%
7	16	53.33%	6	50.00%	3	50.00%	2	40.00%
8	12	40.00%	2	16.67%	2	33.33%	3	60.00%
9	16	53.33%	5	41.67%	3	50.00%	3	60.00%

10	19	63.33%	6	50.00%	5	83.33%	3	60.00%
11	20	66.67%	7	58.33%	4	66.67%	3	60.00%
12	22	73.33%	8	66.67%	4	66.67%	4	80.00%
13	23	76.67%	7	58.33%	6	100.00%	4	80.00%
14	22	73.33%	7	58.33%	6	100.00%	3	60.00%
15	24	80.00%	8	66.67%	6	100.00%	4	80.00%
16	23	76.67%	7	58.33%	6	100.00%	4	80.00%
17	24	80.00%	8	66.67%	6	100.00%	4	80.00%
18	24	80.00%	8	66.67%	6	100.00%	4	80.00%
19	24	80.00%	8	66.67%	6	100.00%	4	80.00%
20	25	83.33%	9	75.00%	6	100.00%	4	80.00%
21	24	80.00%	8	66.67%	6	100.00%	4	80.00%
22	25	83.33%	9	75.00%	6	100.00%	4	80.00%
23	25	83.33%	9	75.00%	6	100.00%	4	80.00%
24	26	86.67%	10	83.33%	6	100.00%	4	80.00%
25	26	86.67%	10	83.33%	6	100.00%	4	80.00%
26	26	86.67%	10	83.33%	6	100.00%	4	80.00%
27	26	86.67%	10	83.33%	6	100.00%	4	80.00%
28	27	90.00%	11	91.67%	6	100.00%	4	80.00%
29	28	93.33%	11	91.67%	6	100.00%	4	80.00%
30	28	93.33%	11	91.67%	6	100.00%	4	80.00%
31	27	90.00%	11	91.67%	6	100.00%	4	80.00%
32	27	90.00%	11	91.67%	6	100.00%	4	80.00%
33	28	93.33%	11	91.67%	6	100.00%	4	80.00%

34	28	93.33%	11	91.67%	6	100.00%	4	80.00%
35	29	96.67%	11	91.67%	6	100.00%	5	100.00%
36	30	100.00%	12	100.00%	6	100.00%	5	100.00%
37	30	100.00%	12	100.00%	6	100.00%	5	100.00%
38	30	100.00%	12	100.00%	6	100.00%	5	100.00%
39	30	100.00%	12	100.00%	6	100.00%	5	100.00%