FINAL TECHNICAL REPORT FOR TASK A: TRUCK LOADS AND FLOWS

WA-RD 320.3

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16. ABSTRACT

This study describes the analysis of truck volume data collected by the Washington State Department of Transportation (WSDOT) over four and one half years, from 1988 through 1993. The primary objectives of this research were to: investigate the patterns in truck volumes at various locations in Washington State; determine whether seasonal factors can be developed and applied to short-duration truck volume measurements to better estimate average annual conditions; develop procedures for routinely calculating and applying these values in Washington; develop an easy procedure that other states can use to create their own seasonal factoring process, and produce a guidebook that explains this process and lists the necessary steps clearly and concisely.

This report presents the findings for all but the last of these objectives. This last objective is met in another report.

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Truck Flows and Loads for Pavement Management

FINAL TECHNICAL REPORT FOR TASK A: TRUCK LOADS AND FLOWS

by

Mark E. Hallenbeck
Director

Soon-Gwam Kim
Research Assistant
University of Washington

Washington State Transportation Center (TRAC)
University of Washington, JD-10
University District Building
1107 NE 45th Street, Suite 535
Seattle, Washington 98105-4631

Washington State Department of Transportation
Technical Monitor
David Thompson
Manager, Transportation Data Office

Prepared for

Washington State Transportation Commission
Department of Transportation
and in cooperation with
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CHAPTER 1

INTRODUCTION

Truck information has been an important part of traffic data collection since the development of modern roadway design procedures. Truck volume and load estimates play vital roles in the design and maintenance of roadway geometrics, pavement depths, and bridges. As the nation's highway system ages, the estimation of existing and future levels of truck traffic is becoming more important.

Unfortunately, until the widespread availability of inexpensive microprocessors in the early 1980s, the cost of collecting significant amounts of truck volume and weight information was beyond the staff and funding resources of state agencies. As a result, states collected only small quantities of truck volume and load information, and the little information that was collected yielded little or no understanding of patterns of truck volumes and weights on the nation's highway system.

This study describes the analysis of truck volume data collected by the Washington State Department of Transportation (WSDOT) over four and one half years, from 1988 through 1993. The majority of the data for this project were collected using 4-bin vehicle length classifiers at 23 sites and weigh-in-motion (WIM) scales at three sites. For a limited number of analyses, data from another 16 WIM sites were also available. (These sites were installed during the study, and could not provide a complete calendar year dataset for use in the project. However, data were available for examining weekday/weekend patterns, the axle correction factor, and other analyses that required use of all of FHWA's 13 vehicle classes.)

PROJECT OBJECTIVES

The primary objectives of this research were

- to investigate the patterns in truck volumes at various locations in Washington State,

- to determine whether seasonal factors can be developed and applied to short-duration truck volume measurements to better estimate average annual conditions,
- to develop procedures for routinely calculating and applying these values in Washington,
- to develop an easy procedure that other states can use to create their own seasonal factoring process, and
- to produce a guidebook that explains this process and lists the necessary steps clearly and concisely.

EXPECTED PROJECT BENEFITS

The expected benefits from the project are as follows:

- WSDOT will gain a better understanding of the truck traffic patterns occurring in the state.
- WSDOT will learn how its permanent counting data can best be used to improve annual truck estimates.
- A new methodology will help other states develop similar systems, given their individual count programs and truck patterns.
- The estimation of national trends in trucks' use of highways will be significantly advanced.

PROJECT BACKGROUND

Several previous studies have looked for patterns in truck volumes and weights across the nation. A 1982 FHWA effort, "Highway Performance Monitoring System, Vehicle Classification Case Study," relied on four short-duration counts (one per season) performed at 139 sites in five states to examine volume patterns. Another study, "Development of a Statewide Traffic Monitoring Program Based on the Highway Performance Monitoring System," explored procedures for creating seasonal factor

groups for short-duration volume counts as part of the HPMS system within a statewide traffic counting program. The results of this study became the original "FHWA Traffic Monitoring Guide" (which has since been revised and republished), and they have been expanded and improved upon by states such as New Mexico, where a thorough examination of the volume factoring process was recently completed.

A study by the state of Minnesota (Dahlin and Harter) looked at the variability of 3S2 truck traffic at four permanent WIM sites in Minnesota. This study increased many traffic data professionals' understanding of the variability inherent in truck volumes and weights. The Minnesota study also showed that, for Minnesota, the use of "traditional" automobile factoring procedures for calculating and applying seasonal factors to short-duration truck counts was inappropriate and often led to increased error in the estimation of average annual truck volumes.

The LTPP program within FHWA has also realized the importance of studying the data available from continuous AVC and WIM counters, and it has committed to analyzing these data to determine their "regional" applications. The collection of large quantities of truck data for the LTPP study has led to a number of efforts to further analyze and refine the collection of truck information, including several unfunded NCHRP efforts and a technical assistance contract to manage the traffic data collection portion of the LTPP study.

Finally, a study parallel to this one is being conducted by the state of Florida to examine the vehicle load patterns recorded by WIM stations across the state. Combining the results of these two studies will provide insight into the total impacts of seasonal variation of truck loads on the nation's highway system.

REPORT ORGANIZATION

This report is organized into five chapters and three appendices. This initial chapter introduces this report, and provides background on the subject of estimating annual truck volumes. Chapter 2 presents the methodology used for each of the analyses

performed for this project, discusses why each analysis approach was taken, and provides a brief overview of those approaches. Chapter 3 discusses the findings that resulted from the project analyses. Chapter 4 addresses the implications of the findings presented in Chapter 3, and the impacts of the findings on the implementation of factoring procedures for improving the estimation of annual truck traffic volume estimates. Chapter 5 summarizes the conclusions developed from the project, and makes specific recommendations for state departments of transportation.

Following the main body of the report are three appendices. The first appendix discusses the use of the decomposition method for developing seasonal adjustment factors at annual traffic recorder sites. The second appendix discusses the regression methodology discussed in Chapter 3, and recommended for further consideration by state agencies in Chapter 5. The final appendix presents additional seasonal pattern figures developed as part of this project, but not referenced directly in the main body of the report.

CHAPTER 2

RESEARCH APPROACH

The analysis work performed as part of this project can be divided into four basic steps. These four steps were completed as part of a seven-task plan. The four analysis steps comprised the following:

- establishing truck volume patterns,
- developing and testing alternative factor groups,
- exploring the impacts and accuracy of different count durations and factoring techniques on annual volume estimates, and
- determining the number of short counts needed for a state's pavement management system.

Each of these tasks is described in more detail below.

ESTABLISH TRUCK VOLUME PATTERNS

This task consumed a major portion of the project effort. To perform this task, the project team examined data from 23 sites equipped with 4-bin length classifiers and 19 sites equipped with WIM scales. Data from the majority of classifier sites were available for three or four complete calendar years. Data from four of the WIM sites were available for over one calendar year, while data from the remaining WIM sites were available for a one-year period, but that period did not run from January through December. In addition, the Idaho Department of Transportation provided a dataset of 4-bin length classification data to the research team for testing the hypotheses developed with the Washington data.

A number of other data items were also collected for each of the permanent data collection sites. These additional factoring included the following:

- functional class of roadway,
- geographic location in the state,
- urban / rural designation,

- proximity to an urban area, and
- subjective description of whether the site was subject to recreational travel patterns.

These factors helped describe the characteristics of each permanent site and were used in the grouping analyses described later in this report.

Because of variation in the length of different vehicles within specific FHWA vehicle classes, Washington's four length classes did not directly relate to the 13 FHWA vehicle classes. In addition, the Washington and Idaho length categories differed. The contents of Washington's four length categories generally included the following vehicle categories:

Bin 1	cars, pick-ups, and short single-unit trucks,
Bin 2	cars and trucks pulling trailers, long single-unit trucks, and RVs,
Bin 3	combination trucks, and
Bin 4	multi-trailer trucks.

The lengths Washington and Idaho used to separate vehicles into the four length categories were as follows:

	State	Minimum Length	Maximum Length
Bin 1	Washington		26 feet
	Idaho		20 feet
Bin 2	Washington	26 feet	39 feet
	Idaho	20 feet	40 feet
Bin 3	Washington	39 feet	65 feet
	Idaho	40 feet	70 feet
Bin 4	Washington	65 feet	115 feet
	Idaho	40 feet	148 feet

Washington State Department of Transportation personnel performed preliminary edits on the Washington data and removed data known to be invalid. These validity checks were done by hand, and relied on rules of thumb developed over time by WSDOT staff. The majority of the data points removed were the result of equipment failure,

although some data were removed when it became apparent that the inductance loop's calibration had drifted, resulting in the misclassification of vehicles. Additional equipment errors were undoubtably present in the data, but determining where and when these errors occur was beyond the scope of this project.

For this project, 24 consecutive hours of valid data (midnight to midnight) were required for any data from a site to be used in the later analyses. These 24 hourly records were then aggregated into daily volume estimates by vehicle class. The daily count records served as the primary dataset for the project.

Computational Methodology

The project team calculated volumes by truck class for each site for each average annual day, average weekday for each month, average weekend day for each month, and average day of each month. The results of these calculations are discussed in the following chapter. Additional tables and graphs illustrating these flows are presented in the Appendix.

The researchers calculated average monthly traffic estimates using the methodology recommended in the *AASHTO Guidelines for Traffic Data Programs* (Joint Task Force on Traffic Monitoring Standards, 1992). This algorithm calculates average days of the week for each month (i.e., average Monday, Tuesday, etc.) and then computes the average day for the month as the simple average of those seven average days. These calculations are expressed mathematically as follows:

(1) Monthly Average Days of the Week (MADW)

$$MADW_{ij} = \frac{\left(\sum_{n\varepsilon(i,j)} DT_{n_{ij}}\right)}{N_{ij}} = \frac{\left(\sum_{n=1}^{n_{ij}} DT_{n_{ij}}\right)}{N_{ij}}$$

where

DT	=	Daily Traffic
i	=	1,2,..., 7 (Mon ~ Sun)
j	=	1,2,..., 12 (Jan ~ Dec)
N_{ij}	=	number of i day in j month

(2) Monthly Average Daily Traffic (MADT)

$$MADT_j = \frac{\left(\sum_{i=1}^{7} MADW_{ij}\right)}{7}$$

These computations were repeated for each vehicle category. The computations are the same for each of those categories.

Annual average daily traffic (AADT), by vehicle category, is calculated by first computing the average day of the week for the year for each vehicle category (e.g., the average Monday for the year is the arithmetic mean of the 12 average Mondays for each month). Then the arithmetic mean of those seven values is calculated. These computations can be expressed as follows:

(3) Annual Average Days of the Week (AADW)

$$AADW_i = \frac{\left(\sum_{j=1}^{12} MADW_{ij}\right)}{12}$$

(4) Annual Average Daily Traffic (AADT)

$$AADT = \frac{\left(\sum_{i=1}^{7} AADW_i\right)}{7}$$

Average monthly weekday (Tuesday through Thursday) and weekend (Saturday and Sunday) volumes for each vehicle class for each month were computed for each site as follows:

(5) Monthly Average Weekday Traffic (MAWDT)

$$MAWDT_j = \frac{\left(\sum_{i=2}^{4} MADW_{ij}\right)}{3} \qquad \text{(Tue ~ Thu)}$$

and

(7) Monthly Average Weekend Traffic (MAWET)

$$MAWET_j = \frac{\left(\sum_{i=6}^{7} MADW_{ij}\right)}{2}$$

(The selection of Tuesday through Thursday as the "weekdays" is discussed in Chapter 3.)

The AASHTO methodology has two significant advantages over the traditional methodology of simply averaging the volumes for all days of the month. The primary advantage is that this system accounts for much of the bias caused by missing data. Because the computations treat each day of the week equally, loss of data on one or more weekend days without loss of proportionate weekday data does not skew the monthly value towards weekday travel. (That is, loss of data for a Saturday and Sunday without the loss of data from the following Monday through Friday would bias the monthly average towards weekday travel if all the days of data present in the dataset were simply averaged.)

In addition, this computational process provides a more accurate comparison of travel trends from year to year by correcting for bias that is artificially induced by the changing number of weekdays/weekends present each month. (For example, in 1992, March had 9 weekend days and 22 weekdays, but in 1993 it had 8 weekend and 23 weekdays.) A simple average for the month might show a reduction in travel during March (assuming lower weekend volumes than weekday volumes) when the real travel pattern was identical, and only the ratio of weekdays to weekends had changed.

The primary drawback to the AASHTO computational process is that it complicates the calculation of the error associated with estimates based on partial datasets. The problem arises because the variability associated with the estimate can no longer be computed as the variability of a simple average. For the same reason, it is

difficult to compute the error associated with seasonal factors developed from the monthly averages.

Car versus Truck Volume Patterns

One of the primary objectives of this project was to determine whether truck traffic volumes follow seasonal patterns that are similar to automobile traffic. If trucks are different, are seasonal adjustments specific to each truck class necessary to accurately estimate annual average daily truck volumes?

To answer the initial question, the project team plotted the seasonal volume pattern for each of the four length bins. These graphs (see Chapter 4 and the Appendices) showed conclusively that the truck and automobile patterns were significantly different, that truck volumes varied sufficiently through the year, and that some method of seasonal adjustment was necessary to provide valid estimates of average annual conditions.

These initial graphs also revealed that not all truck patterns were similar and that different types of trucks had different seasonal volume patterns. Thus, in order to define necessary seasonal adjustments, the project team first had to examine the various travel patterns within the "truck" category.

13-Bin Versus 4-Bin Classification Schemes

When the Strategic Highway Research Program (SHRP) first introduced its revised traffic data collection plan in the late 1980s, a number of state highway agencies indicated that they would use permanent four-bin or six-bin length classifiers to compute seasonal factors for 13-bin axle classification counts conducted with short-duration, portable traffic counting equipment. This approach to seasonal factoring assumes that vehicles in the 13-bin axle categories follow volume patterns that are similar to the patterns found in the four-bin data. It also assumes that all of the 13-bin truck categories fit cleanly into the length bins (i.e., that the axle bins are simply subsets of the length bins), and that each of the axle-based categories within a length bin follow the same pattern as that length bin. (That is, all of the FHWA categories that would be part of

Length Bin 4 have similar seasonal patterns.) All of these assumptions are also dependent on the length limits selected by each state for its length categories.

To test these theories and to examine the basic issue of variability among truck volume patterns, the seasonal volume patterns of the 13-bin vehicle categories were compared with each other and against the patterns for the four length bins. WIM vehicle records were used to compute 13-bin daily volume records by vehicle class. These records were then used to compute monthly patterns based on the ratio of MAWDT/AADT, and day-of-week patterns based on the ratio of MADW/AADT. As with the four length bins discussed above, these patterns varied from site to site, so the analysis consisted of both comparing volume patterns at pair WIM and 4-bin classifier sites, and comparing volume patterns at all available sites.

The project team assumed that Length Bin 1 = Axle Bins 1, 2 and 3. Length Bin 2 = Axle Bins 4, 5, 6 and 7. Length Bin 3 = Axle Bins 8, 9, 10; and Length Bin 4 = Axle Bins 11, 12, and 13. The project analysis included only the volume patterns of the three truck length bins.

The visual review of classifier operations and the review of vehicle length data from WIM records showed clearly that the above assignment of axle bins to length bins was not perfect. Some overlap existed between the axle and length categories because the two classification methodologies were based on different criteria. This overlap changed for the Washington and Idaho datasets, both because the two states used different length values to separate vehicles and because their software algorithm for differentiating vehicles by axle classification also differed. Despite these limitations, this analysis provided useful results because similar overlap would occur for any state trying to use length classifiers to adjust short-duration, axle-based classification counts.

The project team tested several options for providing a mathematical basis for determining whether two bins are similar. To limit the difficulties caused by widely varying traffic volumes by class, all traffic volumes were normalized by expressing them

as a fraction of the average annual or average monthly traffic (e.g., the average monthly traffic was set equal to 1, days with traffic volumes greater than average were above 1, and lower traffic volumes were some fraction below 1.) Tests of monthly volume patterns used average annual conditions as the normalizing function; tests of day-of-week patterns used average monthly volume as the normalizing value.

With the normalized volumes, the project team was able to use a simple paired difference test to compare sets of patterns. This analysis tool performed better than alternative time series techniques because of strong autocorrelation between the traffic values.

Normalized traffic volumes for two vehicle types were paired from the same site for the same day. One bin's normalized volume was subtracted from the other, and the standard deviation of this difference for all days in a month was then computed. The resulting standard deviation was a very good measure of the distribution of differences between the traffic patterns of the two bins. This same type of analysis tool was also useful for examining the differences in day-of-week patterns within a single truck classification, and for examining the stability of seasonal factors over time.

Weekday Versus Weekend Traffic

Another analysis examined the differences in traffic volumes between weekdays and weekends. This analysis was partly an extension of the analysis of whether different truck classes followed similar travel patterns, and it included investigations of whether all classes of trucks had a specific weekly pattern and whether more truck traffic occurred on specific days of the week.

The analysis for weekday versus weekend traffic was identical to that used in the comparison of 13-versus four-bin data. Estimates of differences were based on the standard deviation of paired, normalized traffic volumes for different days for a single vehicle category.

Stability Of Factors Over Time

Because the four-bin length classifier data set contained up to four calendar years of data at some sites, the project team was able to examine the stability of seasonal factors over time at individual sites. This analysis was performed both visually, using plots of monthly factors, and mathematically, by comparing the deviation of monthly factors from different years.

Stability Of Factors Over Distance on A Route

The project team also examined the stability of seasonal factors over long distances on major truck routes. The intent of this examination was to determine whether factors developed at one point on a road could be used to accurately compute adjustment factors for other points on that same facility many miles away. The roads selected were interstates with high levels of through truck traffic.

Three four-bin length classifiers are located on Interstate 90. These classifiers are located just west of Spokane (on the eastern edge of the state), at Cle Elum (in central Washington), and at Issaquah (just east of the Seattle metropolitan area on the western edge of the state). No large cities exist between the eastern-most site and the western most site, although a number of major highways intersect I-90 in between, carrying a considerable number of additional truck movements to the interstate.

There are five four-bin length classifier sites on Interstate 5, ranging from 70 miles south of the Canadian border to 45 miles north of the Oregon border. Four urban areas are located between the northern- and southern-most classifier sites. These include Olympia, Tacoma, Seattle, and Everett. Three of the sites are in urban locations, one in Seattle, one in Everett, and one in Lacey (just north of the state capitol in Olympia). The other classifier sites are in rural areas north of the Vancouver and Seattle/ Everett metropolitan areas.

The analyses performed included a visual examination of normalized volume patterns, and a review of the differences between normalized average monthly traffic for paired counter sites.

Axle Correction Factor Analysis

The axle correction factor analysis was performed with only the available WIM data (i.e., the 13-bin data). To compute axle correction factors, a single value was assigned to each class to represent the number of axles associated with all vehicles in that class. These values were as follows:

Axle Bin	Number of Axles
Bin 1	2
Bin 2	2
Bin 3	2
Bin 4	2
Bin 5	2
Bin 6	3
Bin 7	4
Bin 8	3.5
Bin 9	5
Bin 10	6
Bin 11	5
Bin 12	6
Bin 13	7

These estimates were slightly conservative, in that many of the vehicles within Bins 4, 7, 10, and 13 included more axles than allocated in this table. However, the appropriate number of axles per category changed with the make-up of each of these classes at different sites, and the total impact of these changes on the true axle correction factor was insignificant in almost all cases. Therefore, to simplify the analysis, the above table was used as a reasonable approximation.

Comparison of the changes in axle correction factors between sites, months, and days of the week followed much the same set of analyses as the comparison of a single vehicle category for each of the analyses described above. The best analysis tools remained the visual comparison of changes in the axle correction factor over time and the use of paired differences tests as a measure of statistical confidence.

The one major difference between the truck volume pattern and axle correction analyses was that the axle correction factor did not have to be normalized by dividing it by the average annual condition. The calculation of the axle correction factor from the vehicle classification data normalized the value, so that all sites had a similar base value (approximately 2.2).

DEVELOPING ALTERNATIVE FACTOR GROUPS

In this task, the research team examined a variety of methods for creating factoring procedures for short-duration truck counts. The intent of this effort was to provide a methodology for using data from a limited number of permanent classifier sites to calculate adjustment factors that could improve estimates of average annual truck traffic computed from short-duration vehicle classification counts. When selecting and testing alternative factoring methodologies, the project team considered the complexity of the techniques, as well as the accuracy and reliability of the alternative factoring methodologies. The results of the analyses included consideration of how state DOTs could implement recommendations from the study, and whether those agencies' staff could reliably operate and maintain the recommended program.

The majority of the work for this task involved determining which of the test sites displayed similar truck volume patterns (and could thus be called a "group"), determining how those groups sites could be differentiated, and calculating the error associated with computing and applying the adjustment factors.

A number of techniques were applied to compute these factor groups. The techniques included

- visually classifying volume patterns,
- multiple linear regression techniques, and
- cluster analyses.

The grouping analysis reviewed truck traffic patterns both between sites and between years to ensure that the factor groupings selected were stable. This analysis also included an examination of the stability of the seasonal adjustment factors at different

points on the same roadway to determine whether a specific roadway could be considered a "group," provided its basic characteristics did not change.

The site description characteristics listed earlier in this chapter (i.e., functional class of roadway, geographic location), along with vehicle volumes, were used as the independent criteria against which the factor groups were compared. The independent variables were selected from variables that were readily available for all roadway sections in the state, and those that were likely to have a significant relationship to the type and pattern of truck traffic present.

Comparing Variation Between Alternative Groups

The most significant problem for this analysis was how to determine which stations fit as a "group" (that is, had the same basic traffic pattern, so that their traffic patterns would be differentiated only by normal random variation) and which sites exhibited truly different patterns. Once this initial problem was solved, the characteristics that caused sites to fall within specific groups had to be defined (that is, which variables determined which group a site belonged to if a permanent counter was not present at that site).

The ratio of MAWDT/AADT was used as the primary factor for measuring seasonal variation at a site. Other measures of seasonal variation based on the ratios of MAWET/AADT and MADT/AADT were secondary. The computation of these measures is described earlier in this chapter.

Twelve monthly factors (i.e., the ratio of MAWDT/AADT for each month of the year) were calculated for each data collection site for each year. When 12 monthly factors are grouped into a single pattern, each of those 12 factors is important. For example, six of the 12 months at two sites may be closely related, but the remaining 6 months may be poor matches. An alternative grouping may yield mediocre matches for all 12 months, but none of those matches is "bad." Determining which of these two groupings is better is difficult.

If a state could control when counts were made, the group with six months of good fit would be preferable to the group with 12 months of mediocre fit. (Counts would be taken only during the six months of good fit.) However, in most cases, states have relatively little control over when many counts can be taken. Counts are taken primarily when staffing resources are available and when the counting equipment can work properly. Thus many counts may be taken when temporary labor is available and weather conditions allow placement of portable axle sensors. Rather than attempt to determine which months were most important to have good seasonal factor fit, the researchers chose to weigh each of the 12 months equally.

Criteria Selection

To measure the "goodness of fit" between sets of 12 seasonal factors, two basic tests were analyzed. The first computed the **Mean Standard Deviation** (MSD) for the specified group.

(8) MSD is computed as

$$\overline{sd} = \frac{\sum_{j=month}^{J} sd_j}{J}$$

$$= \left[\sum_{j=1}^{J} \left[\frac{\sum_{i=1}^{I} (MADF_{ij} - \overline{MADF}_j)^2}{I} \right] \right]_J$$

where

i (= member in a group)	=	1, 2, ..., I
j (= labeled month)	=	1, 2, ..., J

$$MADF_{ij} = \frac{MADT_{ij}}{AADT_i}$$

$$\overline{MADF}_j = \frac{\sum_{i=1}^{I} MADF_{ij}}{I}$$

This term is the average of the 12 standard deviations, computed for the factors for each month at each site in the group.

The second value used to measure the quality of fit within a group is the **Mean Absolute Difference** (MAD), which is computed as follows:

(9) MAD

$$|\overline{D}| = \frac{\sum_{j=1}^{J} |\overline{D}_j|}{J}$$

$$= \frac{\left[\sum_{j=1}^{J} \left\{ \frac{\sum_{k=1}^{K} |D_{kj}|}{K} \right\} \right]}{J}$$

where k (= element in a set of paired combination of group member) = $1, 2, \ldots, k$

K = the number of paired elements in the group

$|D_{kj}|$ = $|MADF_{k1j} - MADF_{k2j}|$

= absolute difference in k pair and j month

This computation is similar to the MSD, but it does not weigh the magnitude of the difference as heavily as does the MSD computation. However, it does provide an easily understood value, since 100 * MAD equals the average percentage difference in the pattern of a group. (Note that the sign of the error is ignored when this average percentage difference is computed.)

The problem with both of these statistics is that neither of them has been commonly used in prior work on traffic, and thus neither has selection criteria associated with it. That is, there are established criteria in the field of statistics to determine how large a sample is needed to meet a specific precision guideline when a simple sample is

taken. Unfortunately, this application does not involve a simple sample, but instead incorporates 12 separate samples (one for each month).

Rather than simply using the best, worst, or average point to represent the 12-point sample, the project team used a visual technique to determine the range of MAD and MSD values that would indicate whether groups of sites belonged together. In the selected technique, they plotted graphs of the monthly factors for various groups of stations. At the same time, the statistics for MAD and MSD were computed for those groups. The graphs and statistics were then compared to determine whether the statistics matched consistently with the visual interpretation of "good" groups versus "bad" or "mediocre" groups.

The project team concluded that when the value of MAD is equal to or below 0.15 (that is, when the average difference between factors is below 15 percent), the patterns of the two stations were very similar. Figures 1, 2, and 3 illustrate groups with these ranges of MAD values.

When MAD ranged from 0.15 to 0.3, the patterns of the two stations were mostly similar, but two or three months tended to display significant differences. These differences were often during the peak travel seasons for specific vehicles. For example, the 4-bin classification (recreational vehicles) had extremely high peaks, and these peaks either may have been timed slightly differently, or the magnitudes of the peaks at these two stations may have been significantly different. MAD values in this range indicated that these groups might be acceptable in most cases, but caution should be used before the group values are applied during peak travel periods. Figures 4, 5, and 6 illustrate groups with these ranges of MAD values.

The final group had MAD values of greater than 0.3. In these cases, there were significant differences between the traffic patterns of the two sites. Figures 7, 8, and 9 illustrate groups with these ranges of MAD values.

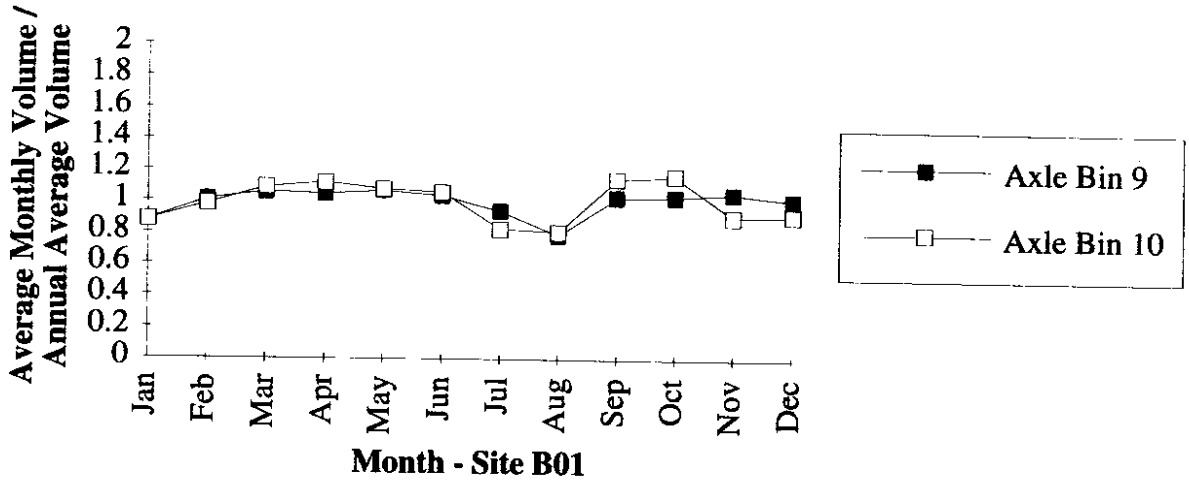

Figure 1. Illustration of Mean Absolute Difference (MAD = 0.065)

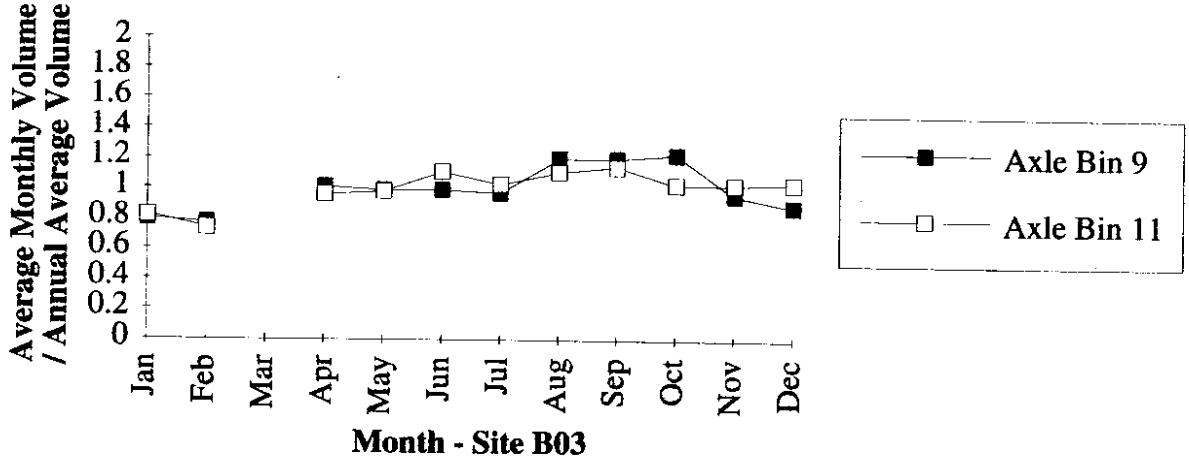

Figure 2. Illustration of Mean Absolute Difference (MAD = 0.078)

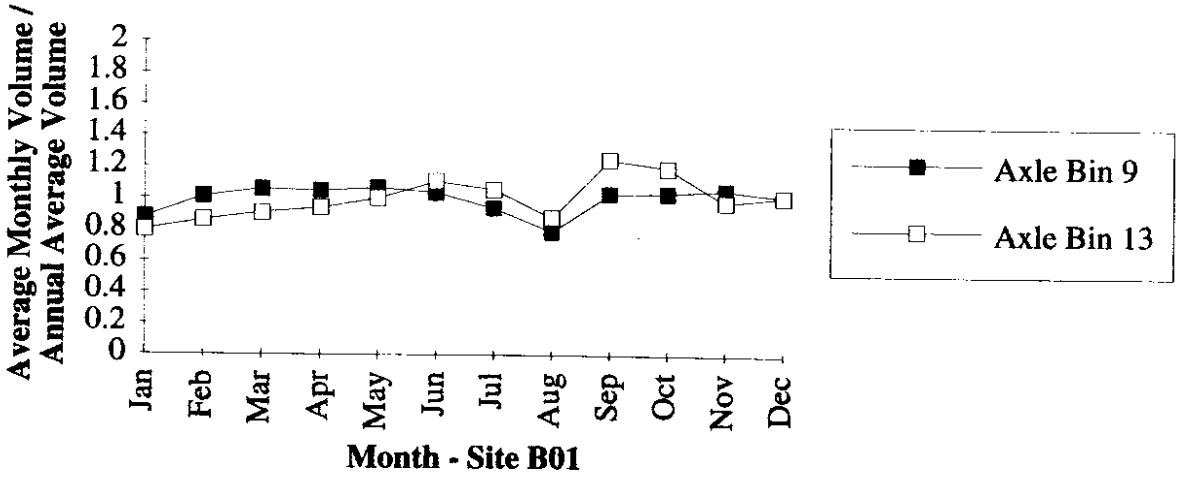

Figure 3. Illustration of Mean Absolute Difference (MAD = 0.11)

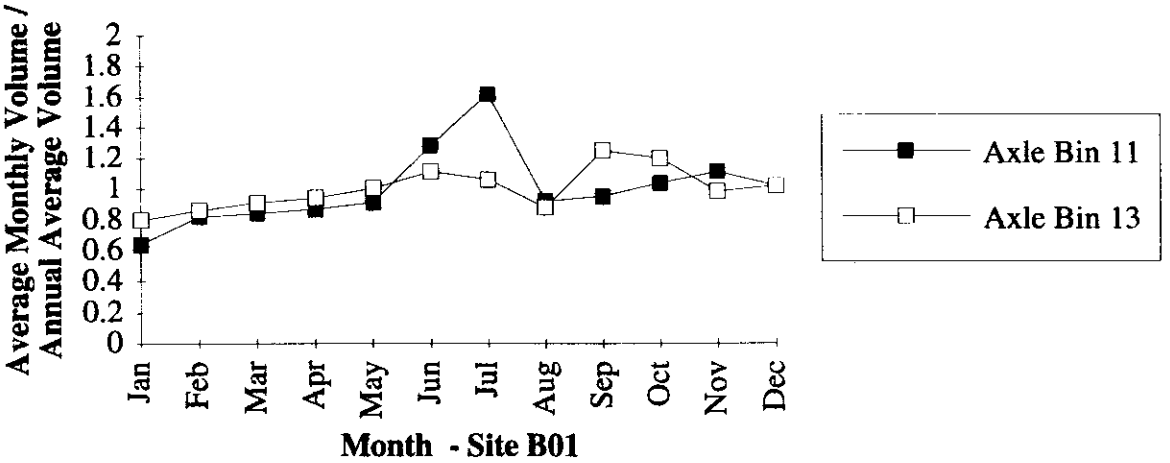

Figure 4. Illustration of Mean Absolute Difference (MAD = 0.15)

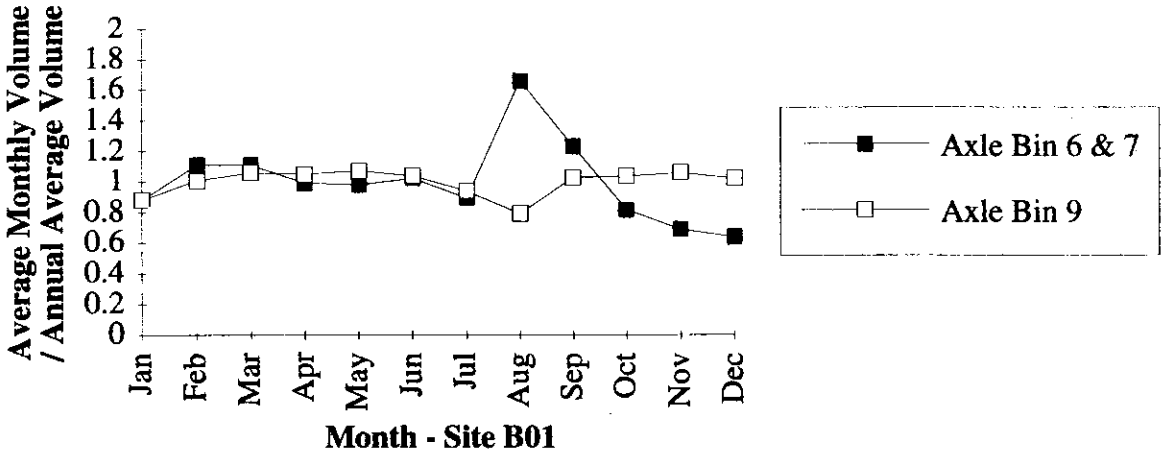

Figure 5. Illustration of Mean Absolute Difference (MAD = 0.20)

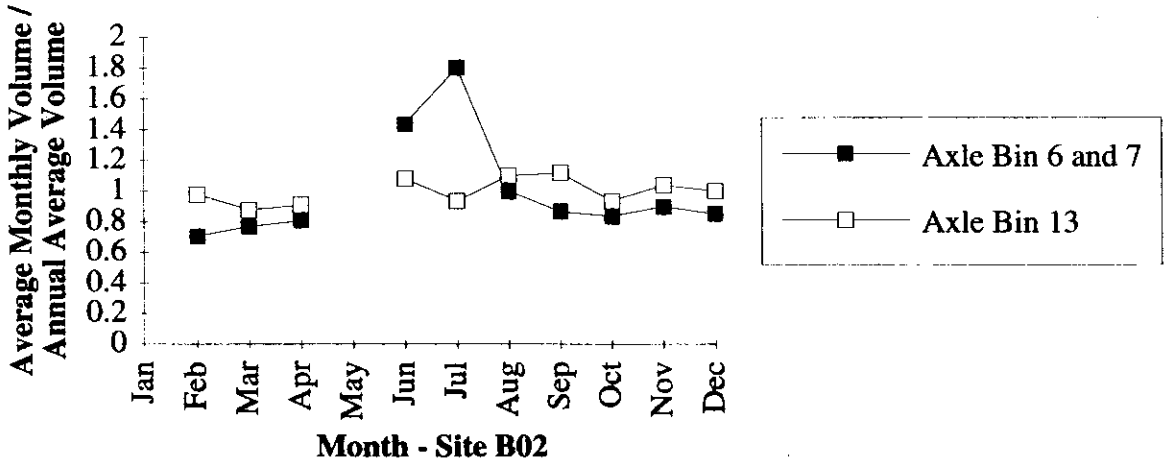

Figure 6. Illustration of Mean Absolute Difference (MAD = 0.25)

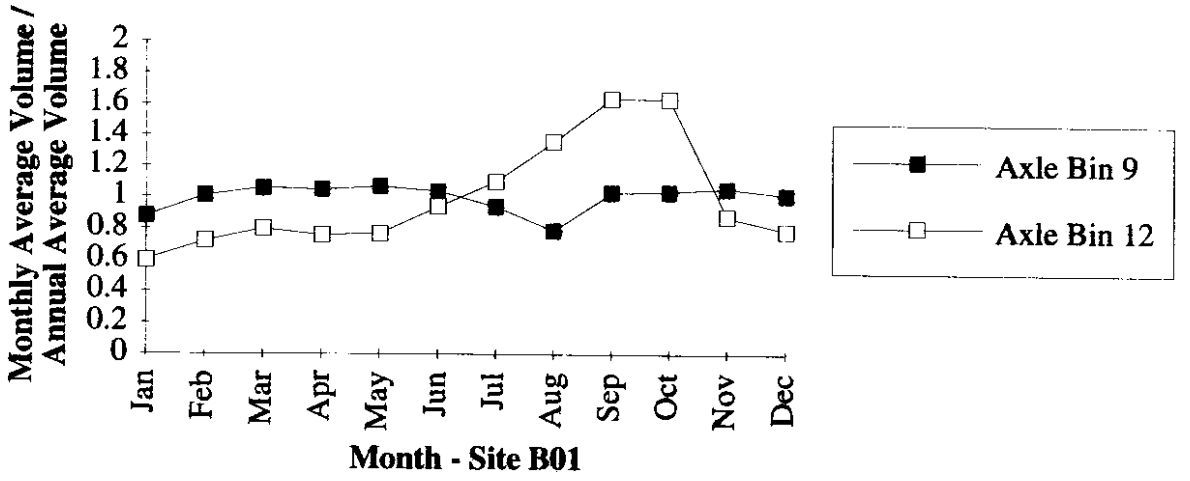

Figure 7. Illustration of Mean Absolute Difference (MAD = 0.32)

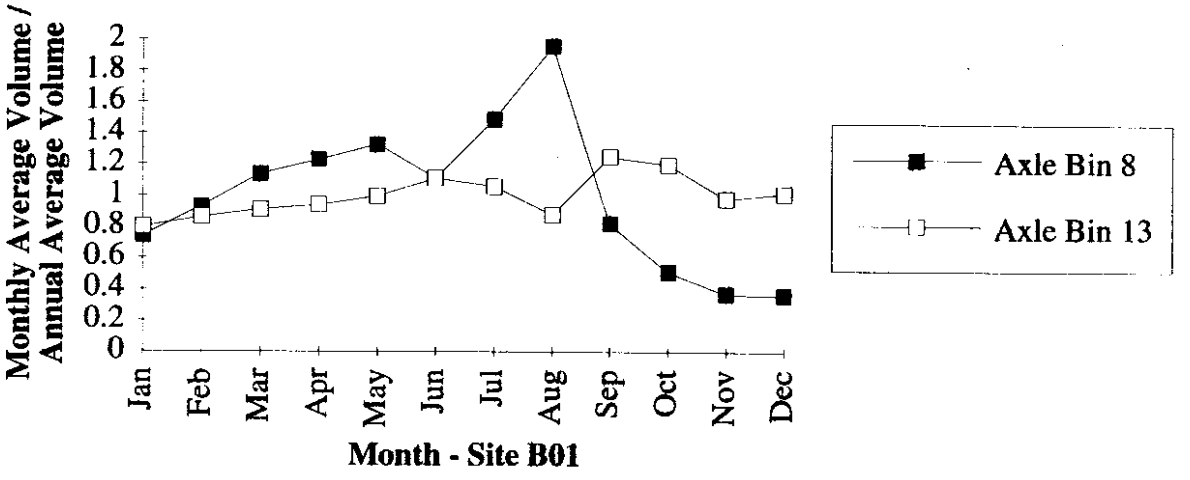

Figure 8. Illustration of Mean Absoulte Difference (MAD = 0.41)

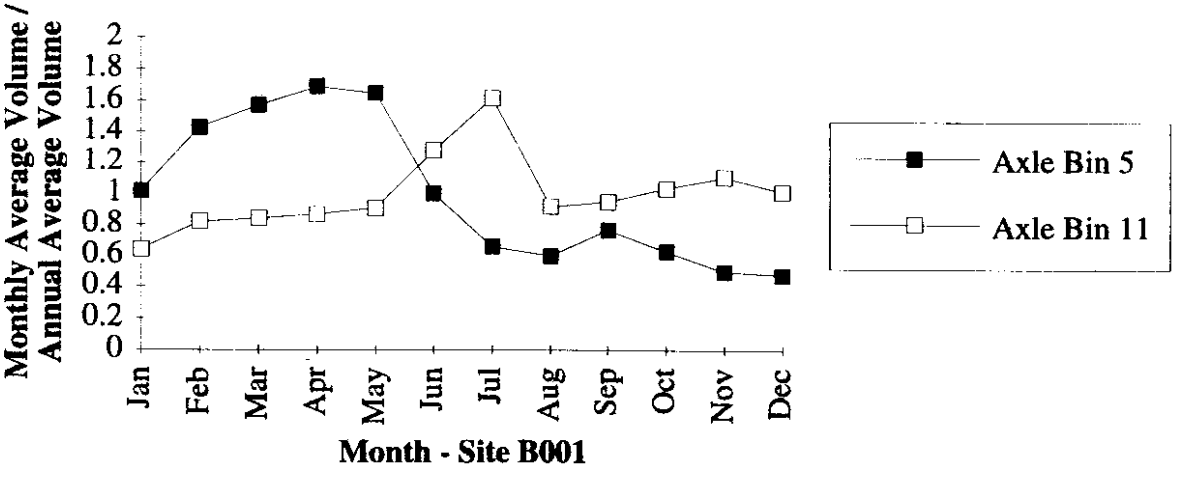

Figure 9. Illustration of Mean Absolute Difference (MAD = 0.55)

The values for MAD of 0.15 and 0.3 were somewhat arbitrary, but they were relatively easy to measure and apply. A possible enhancement to these criteria would be to make the acceptable value of MAD used in grouping analyses (i.e., the value of MAD used to indicate whether a new site should be included in the group) relative to the absolute value of the seasonal factors themselves. For example, a MAD value of 0.3 (essentially, an average error of 30 percent) would be considered very poor for an urban group where the seasonal factors only range from 0.9 to 1.1 (the error in applying the factor is 3 times the factor being applied); whereas that same variation may be considered quite good in a highly recreational, rural area, where the adjustment factors may range from 0.5 to 4.0. (In this case, the error may be less than 10 percent of the factor being applied.)

As will be discussed in the following chapter, this enhancement becomes necessary if acceptable factor groups will be developed for truck classes with high levels of seasonal variation and relatively small traffic volumes.

IMPACTS AND ACCURACY OF DIFFERENT COUNT PROGRAMS

In this task, the project team examined the effects of different counting programs on the accuracy of annual traffic volume estimates. The different counting programs included alternative

- count durations,
- numbers of independent counts performed per year,
- factoring techniques, and
- grouping techniques.

Because of the difficulty in calculating statistically valid measures of variability for the seasonal factors being applied, the researchers compared the accuracy of alternative techniques by computing AADT for the permanent counter locations and then comparing those AADT values with AADT estimates based on samples of data drawn from those stations and factored according to the technique being tested. To fully test a technique, multiple samples drawn for each site were compared, as were samples from

different sites. The mean, standard deviation, and range of errors were then computed for each site and for all sites. This process provided several answers for the expected error associated with any one technique. While having several different measures of "error" was complicated, it did reflect the uncertainty of using a relatively limited number of count locations to estimate traffic conditions over a wide geographic area.

The final portion of this task was to investigate the cost associated with each of the counting programs and the impact that each of these programs would have on resource requirements at the state level. After discussing counting programs with several states, the researchers realized that no one cost estimate could accurately describe the cost impacts of the different counting programs. Therefore, this material is presented in a more relative form that allows each state to account for the degree of automation that already exists within its agency, its specific staffing utilization, the availability of additional staff and equipment resources, and the sophistication of the agency in general.

COUNTS NEEDED FOR A STATEWIDE PMS

The final set of analyses performed for this project examined the impact of improved truck volume estimates on pavement management systems (PMS) in operation (or planned for operation) around the country. The researchers obtained information from the literature describing how truck volume and load information were used within the PMS process for nine PMSs. The primary sources of PMS description were two papers, "Pavement Management—Rehabilitation Programming: Eight States' Experience," produced by the USDOT in August 1983 and a draft report titled "Minnesota DOT Pavement Management System" dated December 8, 1986, and provided to the project team by FHWA. These two reports were supplemented by brief interviews with FHWA personnel involved in promoting PMS at the state level, university researchers working on the refinement of these systems, and Washington State Department of Transportation Materials Office engineers involved in the refinement of the WSDOT PMS system. The primary contacts for this study were Mr. Phil Hazen of

FHWA, Dr. Joe Mahoney of the University of Washington, and Mr. Dennis Crimmons of WSDOT.

This information was used in conjunction with the accuracy and cost information developed earlier in the project to develop conclusions about the benefit to be gained from improved truck volume estimates. Final conclusions were then drawn by comparing these benefits with the cost of obtaining those benefits.

CHAPTER 3

DISCUSSION OF FINDINGS

This chapter presents the results of the analyses described in the preceding chapter. Important findings have been underlined.

ESTABLISH TRUCK VOLUME PATTERNS

Comparison Among Vehicle Classes

The project findings reveal that the four vehicle classes collected by the permanent length classifying equipment have very different seasonal patterns, regardless of the volume or functional classification of the roadway or the geographic location of the site. In general, the longer truck categories show less seasonal variation (i.e., month-to-month changes in daily traffic volumes) than the short truck and automobile classifications. In addition, traffic volumes of Bin 2 vehicles (mostly larger, single unit trucks and RVs) tend to vary the most by season. This variance appears to be attributable to the recreational vehicles in this category.

Figures 10 and 11 illustrate the differences in seasonal truck volume patterns among vehicle classes (graphics illustrating additional sites have been included in the Appendix of this report). The monthly volume patterns on these charts, shown as the ratio of monthly average weekday volumes (MAWDT) to average annual daily volumes (AADT), are "typical" of the patterns found at many sites. The exact locations and sizes of seasonal peaks and valleys often shift from site to site, but the basic shape of the four curves is reasonably similar.

The characteristics and the magnitude of the differences in seasonal volume patterns for the various vehicle classes are discussed below.

Geographic and Functional Roadway Distributions

One of the findings expected from this study was that the functional classification of the road and the location of each data collection site would significantly influence the

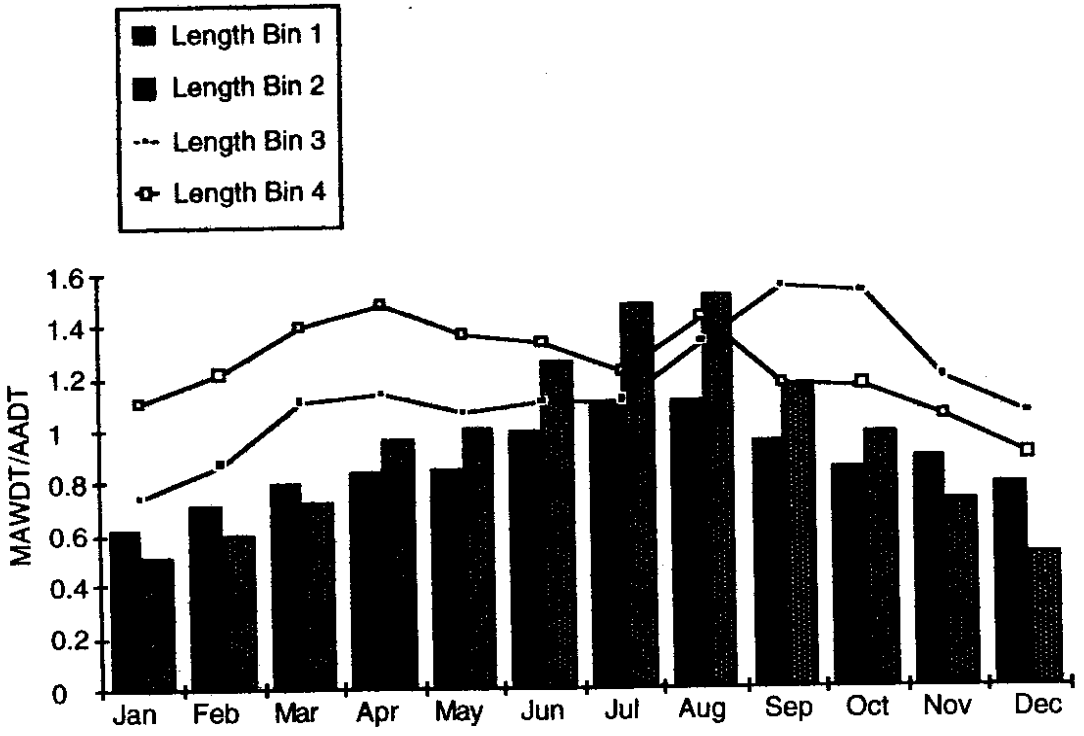

Figure 10. MAWDT/AADT Ratio for Site 61 in 1991

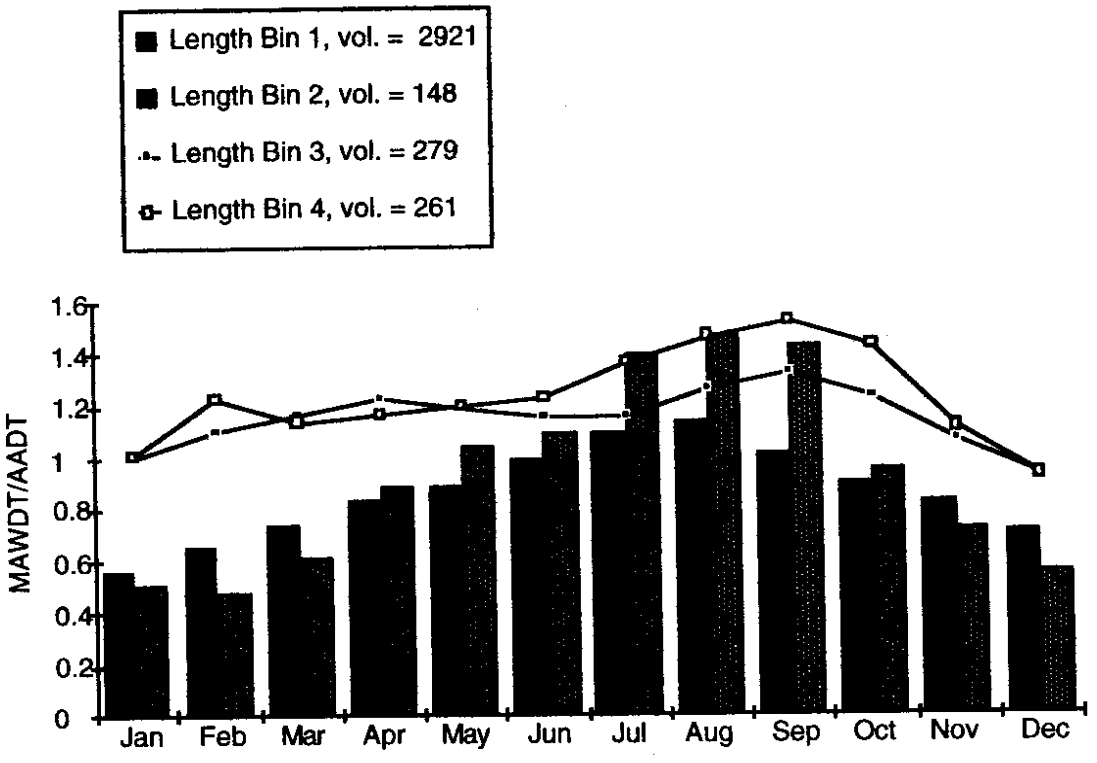

Figure 11. Average Monthly Weekday Volume / AADT, Site 41 - 1991

traffic patterns observed at that site. This is indeed the case. Unfortunately, as a result, the findings are biased toward the geographic and functional distribution of the sites available for analysis.

Because 14 of the 26 sites (53.4 percent) are on the interstate system, the project database is heavily weighted toward the interstate. The remaining sites are ten principal arterials, one collector, and one minor arterial. Ten of the sites are within urban area boundaries; however, because of the relatively small size of some of these urban areas, some of these urban counters display traffic volume patterns that are more characteristic of rural recreational routes.

Because of the distribution of counter locations, the findings of this study are weighted towards the higher volume rural roads in the state. While a number of urban interstate sites exist in the analysis dataset, few urban arterial sections are instrumented with permanent vehicle classifiers. This lack of classifiers reflects the fact that the Washington State Department of Transportation (WSDOT) operates few roads other than freeways in urban areas. (Most urban arterials are operated and maintained by local jurisdictions.) The over-representation of higher volume rural roads (particularly interstates) in the analysis database reflects WSDOT's concern for these roads. However, this distribution of equipped sites does limit the usefulness of the conclusions concerning traffic trends on lower volume rural highways and urban arterials.

In general, the higher is the functional classification of the road, the higher are the traffic volumes in all vehicle classes. The higher are the traffic volumes, the more stable are the traffic volumes from month to month and from year to year. Conversely, the lower is the road's functional classification, the lower is the traffic volume (particularly in the longer truck categories), and the more unstable is the traffic volume pattern, both from month to month and from year to year. While some low volume roads show reasonable stability in their traffic volume patterns, higher variation is present on these facilities.

The impact of geographic location can also be seen in the traffic volume patterns observed in the data. For example, data from counters located in areas subject to heavy recreational traffic show extreme seasonal patterns in Bin 2 vehicle volumes. Data from non-recreational sites may show minor volume increases in Bin 2 vehicles during peak recreational periods, but not to the degree found at recreational sites. In agricultural areas, the longer truck categories show traffic volume peaks that are not present (or at least not as noticeable) in other portions of the state.

The geographic influences change from one vehicle class to the next. For example, the recreational routes show increased automobile volumes (i.e., Bin 1) in the peak recreational periods; however, these increases are not as dramatic (in percentage terms) as those experienced by vehicles in Bin 2, which contains most of the recreational vehicles. Similarly, the two longer truck classes (Bins 3 and 4) are only minimally affected by the recreational peaks. Figures 10 and 11 show examples of these differences at two sites with fairly extreme seasonal variability.

The counter site that provided the data for Figure 11 is on a rural, primary arterial near Washington's south central border with Oregon. The counter site displays the fairly high seasonality of the rural area. In addition, it shows that the seasonal variation of longer truck classes (Bins 3 and 4) is much flatter than the seasonal variation of either automobiles or small trucks and recreational vehicles (Bins 1 and 2). The longer trucks counted at this site show a fairly high degree of variation in comparison to those counted at other locations because of an agricultural harvest haul that occurs in the late summer and early fall.

Figure 12 illustrates the volume patterns at a high volume, urban interstate location. As expected, although the seasonal volume patterns for all four vehicle classes at this site show less month-to-month variation than those in the rural site in Figure 11, recreational vehicle traffic still increases significantly during the summer months. At this urban site, the ratio of MAWDT volume to AADT for the two longer truck classes never

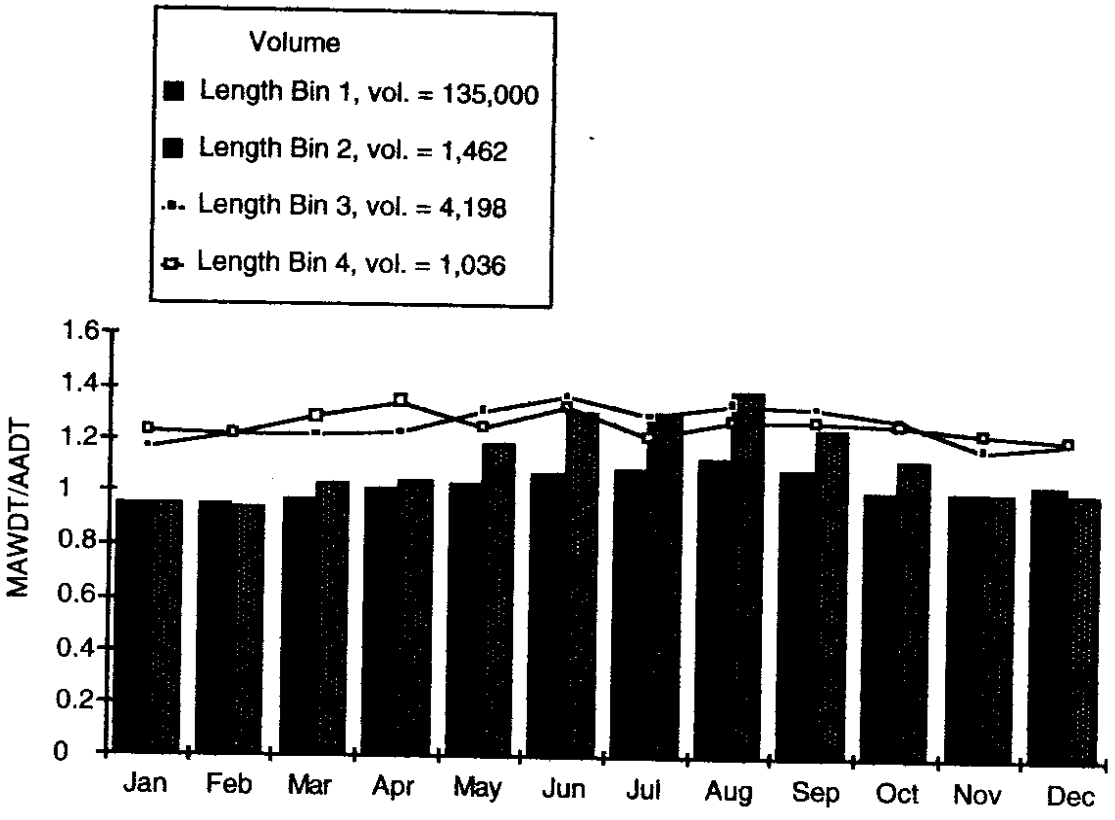

Figure 12. Average Monthly Weekday Volume / AADT, Site 809 - 1989

falls below 1.0. This ratio shows both that the weekday traffic volumes tend to be fairly constant throughout the year, and that the weekday volumes tend to be consistently higher than the weekend volumes. Both of these facts are important to consider when average annual conditions are estimated from either weekday or weekend traffic counts.

Figure 13 illustrates some of the problems that occur when seasonal factors are calculated for lower volume roads. In this case, the volumes of longer trucks are so small that relatively small changes in daily truck volumes cause the seasonal factor ratio (MAWDT/AADT) to reach fairly large values. In the case of Figure 13, this ratio reaches 2.5.

When a site has a low traffic volume level like the site in Figure 13 (AADT for Bin 4 is 14 vehicles per day), relatively small changes in volume significantly affect the computed seasonal factors. Consequently, low volume sites often have highly variable seasonal factors even though the absolute volume changes from year to year are small. This high variability complicates the search for groups of roadway sections that have similar traffic volume patterns and reduces the accuracy of AADT estimates produced with short-duration counts and seasonal adjustment factors. This problem is accentuated by more disaggregated classification schemes. That is, the FHWA 13-category classification scheme will produce a greater number of highly variable vehicle class seasonal factors than the four-length bin categories shown in Figure 13. This increase occurs because the more disaggregated vehicle classification scheme causes more vehicle categories to have low volumes, which are, in turn, more unstable than the more aggregated vehicle categories.

13-Bin Versus 4-Bin Classification Schemes

Figures 14 and 15 illustrate the volume patterns for the truck categories (Bins 4 through 13) of the 13-bin FHWA classification scheme. It is apparent from looking at Figures 14 and 15 that the 13 categories have very different seasonal patterns. This is particularly true if the categories containing recreational vehicle traffic are compared to

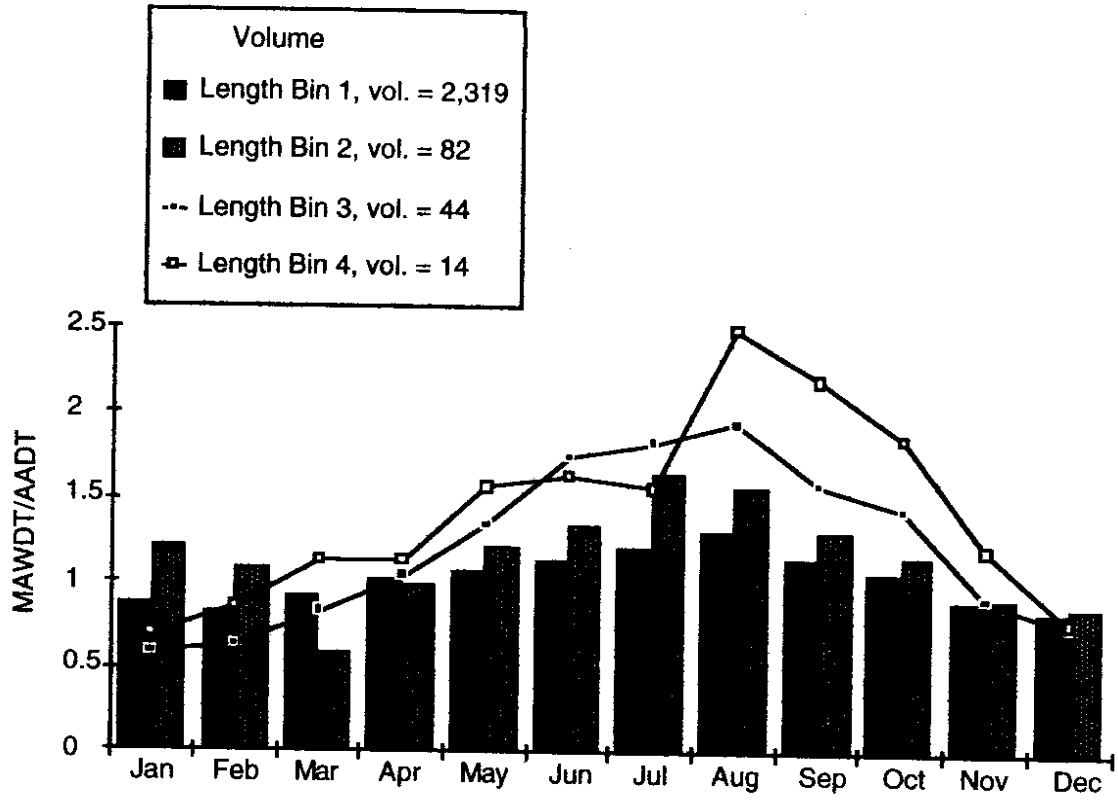

Figure 13. Average Monthly Weekday Volume / AADT, Site 820 - 1990

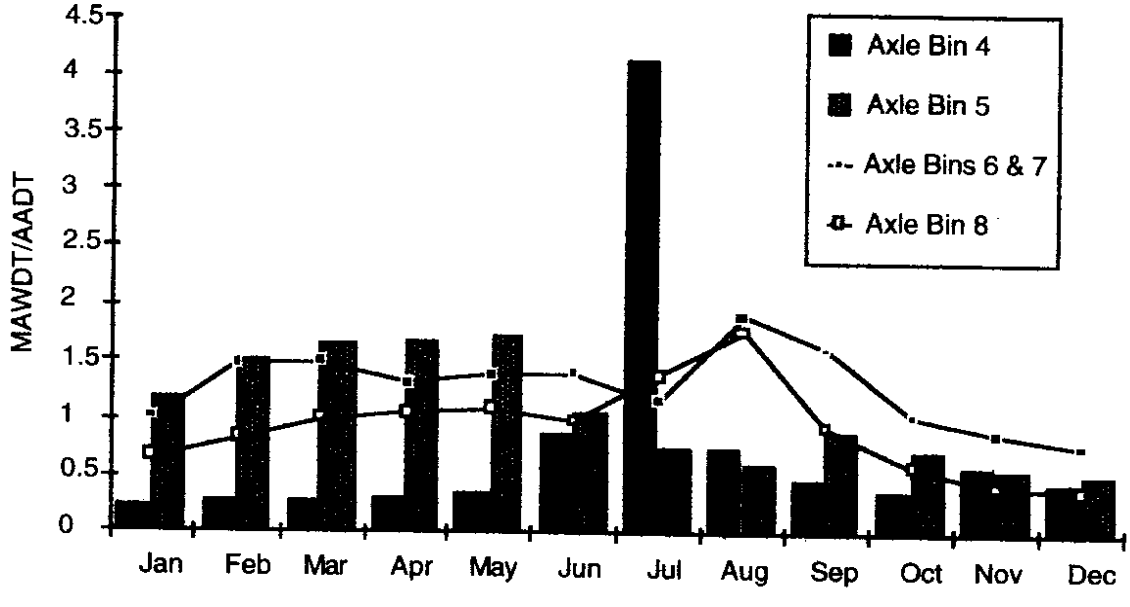

Figure 14. Seasonal Traffic Patterns of FHWA Vehicle Classifications for a Rural Interstate in Western Washington (Smaller Truck Categories)

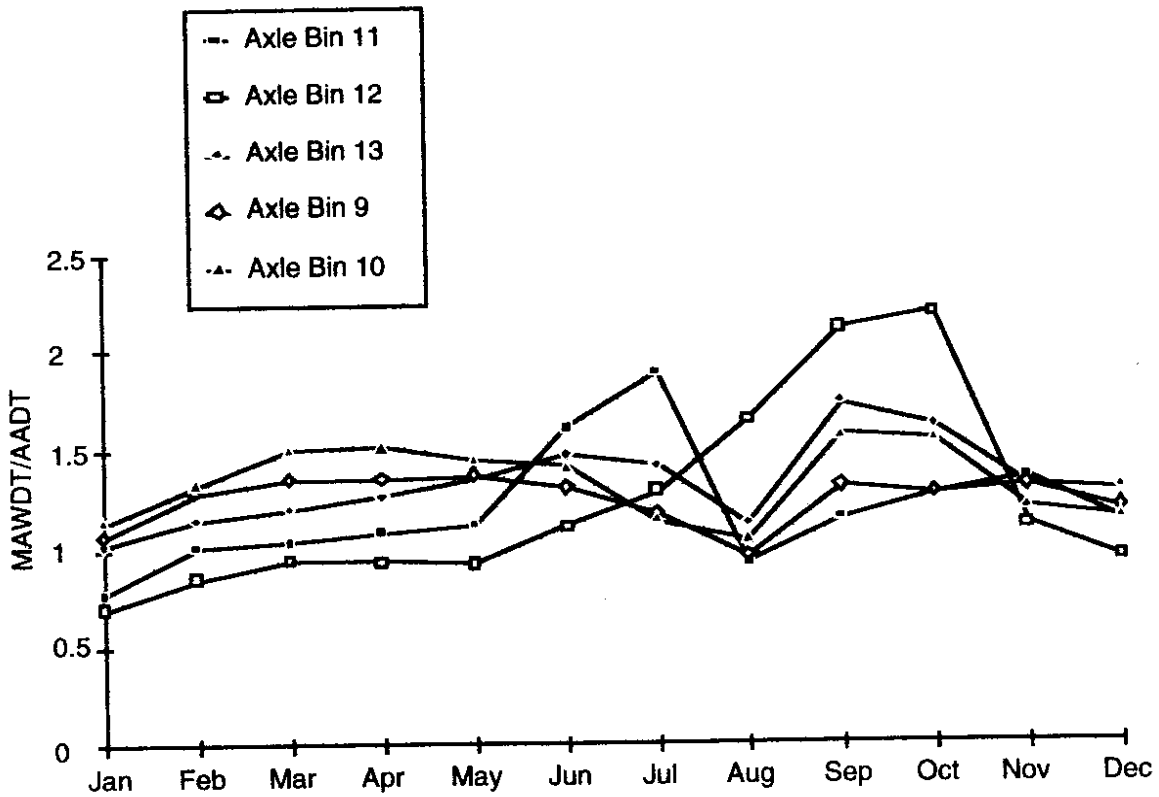

Figure 15. Seasonal Traffic Patterns of FHWA Vehicle Classifications for a Rural Interstate in Western Washington (Larger Truck Categories)

the categories that contain primarily commercial trucks. (In Washington, single unit RVs tend to be classified as Axle Bin 4 "Buses," and vehicles pulling RV trailers tend to be classified as Axle Bin 8 "Four or Less Axle Combinations." This is a result of the specific algorithm used by Washington classification equipment.) Recreational traffic has very high peaking characteristics, while commercial vehicle traffic has more consistent traffic volume patterns. Not surprisingly, the distribution of traffic between weekdays and weekends is also very different for these two types of travel.

For large commercial trucks (axle bins 9, 10, and 11, in particular), the seasonal factor (MAWDT/AADT) rarely falls below 1.0. This ratio reflects the fact that more commercial vehicle traffic occurs on the weekdays than on the weekends. Thus, even when some decrease in volume occurs in the winter months, the average weekday for the month is often higher than the average annual condition, which includes the lower weekend traffic volumes.

This same phenomenon is not true for recreational vehicle traffic. Much of the recreational traffic takes place on weekends. Therefore, with the exception of the summer months, the ratio of average monthly weekday to average annual condition tends to be less than 1.0. This pattern is illustrated best by Axle Bin 4 in Figure 14. This axle bin also shows an extremely high seasonal factor in July. This significant increase (the factor is greater than 4.0) was caused by both the large increase in RV traffic in the summer and by the fact that the 4th of July holiday was on a Thursday during the year illustrated. Thus, the "average" July weekday included a very high volume of RVs. (This large increase also illustrates a possible need to remove holidays from the datasets used to calculate "average" days of the week for factoring purposes.)[1]

The very large seasonal pattern in this group is also attributable to the low volume of RVs on the "average annual day." That is, while many RVs are on the road during the

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[1] There is also a distinct possibility that equipment problems contribute to the size of the variation shown in this graphic. Equipment errors can produce especially large seasonal factors for lower volume classifications where small changes in volume can result in very large seasonal factors.

summer, few RVs are present during the remainder of the year. Thus, the annual average volume is quite small. This makes the denominator in the ratio of MAWDT/AADT small, and consequently, a relatively modest increase in traffic volumes can result in fairly large seasonal factors.

When these disparate vehicle class patterns are combined into fewer categories (for example, the four length classes), the individual peak traffic movements shown in Figures 14 and 15 are "dampened." That is, the monthly volume patterns change less from month to month. The large increase in RVs still produces a travel peak in July and August, but the actual seasonal factor (MAWDT/AADT) is much lower. This "dampening" occurs for two reasons. The first reason is that the patterns for different vehicle types have different peaks. Therefore, volumes for some vehicle types within a composite vehicle class increase, while others decrease or stay constant. Thus, in some cases, the absolute increase in traffic volumes for a combined class is not as large as the increase for some individual vehicle types. The second reason is that even if the total volume increase is the same as or greater than that for any vehicle category, the combined vehicle group has a much higher total volume (the denominator in the ratio) than the individual vehicle category. Thus, for the same actual increase in volume, the computed adjustment factor is lower.

An example of this "dampening" effect can be seen in Axle Bin 8 in Figure 14. This axle bin contains relatively large numbers of commercial vehicles (small tractor semi-trailer combinations) and some RVs (primarily large vans and pickups pulling large trailers). The effect is that the lack of RVs in the winter months lowers the seasonal factor below 1.0, however, the presence of commercial vehicles prevents the seasonal factor from being very far below 1.0. In the summer, when large numbers of RVs are on the road, the seasonal factor increases well beyond 1.0, but because the volume of background commercial traffic is fairly large, the ratio of MAWDT/AADT (over 1.5) is considerably smaller than the ratio in Axle Bin 4, the other vehicle class containing RVs.

This dampening effect can be significant if a vehicle class that is "different" than the other classes in its length bin makes up only a small proportion of the total volume for that combined classification. In this case, even an extremely large percentage increase in the vehicle category with smaller volumes is insignificant in comparison to the larger background traffic volumes. The result is a seasonal factor that reflects the total class, not the smaller vehicle category.

The primary drawback to this dampening effect is that it masks the actual vehicle patterns that are occurring on the road. However, the dampening effect can prove advantageous. One of its advantages is that the seasonal factors for the larger vehicle categories tend to be more stable. Thus seasonal factors for more aggregated vehicle categories are more capable of predicting total traffic volume. These factors simply do not reflect the changes occurring in the vehicle mix within that volume with a high level of precision.

Stability Of Factors Over Time

The relationship between the stability of factors and the volume of the vehicle classification described above holds true for the analysis of factors over time at a single site. The analysis of monthly to average annual traffic ratios over time showed that, in general, the greater the traffic volume is on a road (or within a classification), the more stable is the monthly ratio of weekday traffic to annual average condition. That is, on interstate and heavily traveled, principal arterials, the monthly traffic volume patterns are reasonably stable over time (from year to year). Traffic patterns on lower volume roads are often (but not always) unstable from one year to the next. While some low volume sites have stable monthly factors, others have factors that vary considerably from year to year.

While the actual monthly factors computed for low volume roads may change significantly from one year to another, the general volume patterns remain reasonably constant even for low-volume roads. For example, there is a consistent peaking pattern

for each counting location that can be associated with summer or harvest period travel, but the timing and size of those peaks and valleys tend to vary from year to year. The data also revealed that different roadways within the same geographic area or functional classification often have very different monthly factors, even though the shape of their seasonal traffic volume patterns are similar.

Figures 16 and 17 show examples of changes in monthly to annual ratios from one year to another at a high volume site. Figures 18 and 19 show these ratios at a lower volume site.[2]

Stability Of Factors Over Distance on A Route

This analysis examined the variability in seasonal factors at geographically separated sites on the same facility. The stability of factors was examined for both Interstate 90 and Interstate 5. Both interstates carry long haul truck traffic. Interstate 90 carries goods from the interior of the U.S. to Western Washington and the ports of Seattle and Tacoma. It serves a significant agricultural haul from Eastern Washington and Idaho to the urban centers in the western portion of the state. Interstate 5 serves the long haul movement on the Pacific Coast, from Vancouver, British Columbia, to San Diego, California, and also serves as the primary highway corridor between Seattle, Portland, San Francisco, and Los Angeles.

In general, the data reviewed in this analysis show that each of these roads could be classified as a "factor group" for all four vehicle length classes, although some of these classes are on the boundaries of what is acceptable for within-group factor variation.

For the three sites on I-90, the seasonal patterns of the four traffic bins are similarly shaped, despite the differences in weather, land use, and industrial activity at the three counter locations. Figure 20 illustrates these similar shapes. If the three sites on

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2 Note that for Figure 18, a limited number of weekdays were available in April 1991. On several these days, the Washington State Patrol operated an enforcement action that may have diverted large vehicles over the classifier on SR 411. This may explain some of the abnormally high traffic volume during this month at this site.

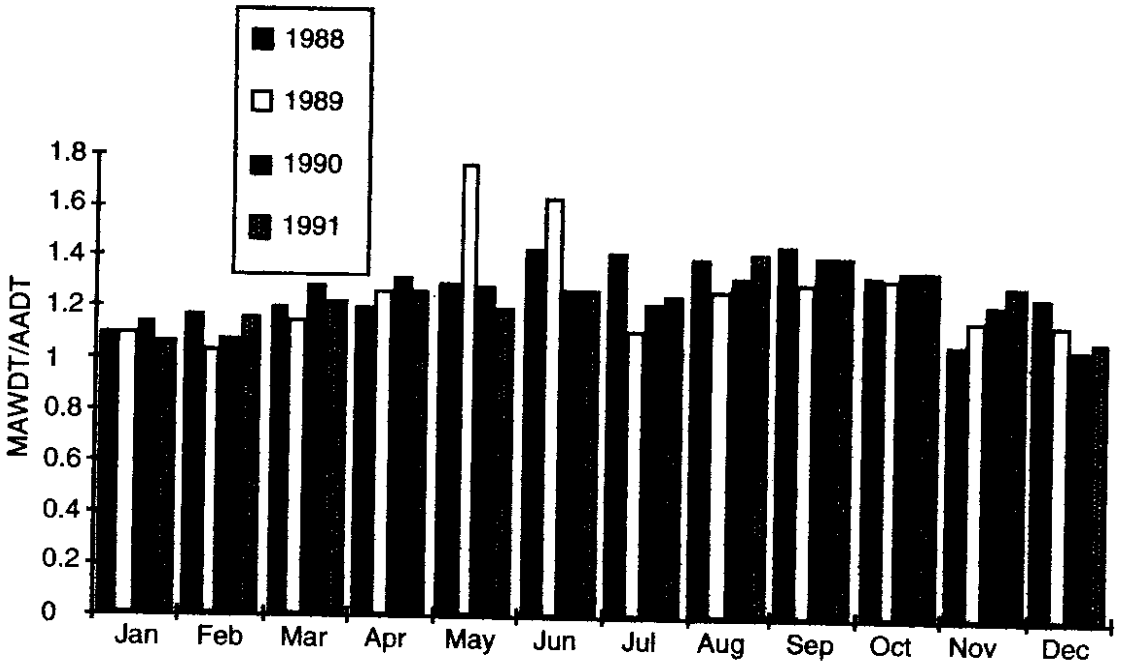


Figure 16. Average Monthly Weekday Volume / Average Annual Volume, Bin 4 at Site #1 on Interstate 5

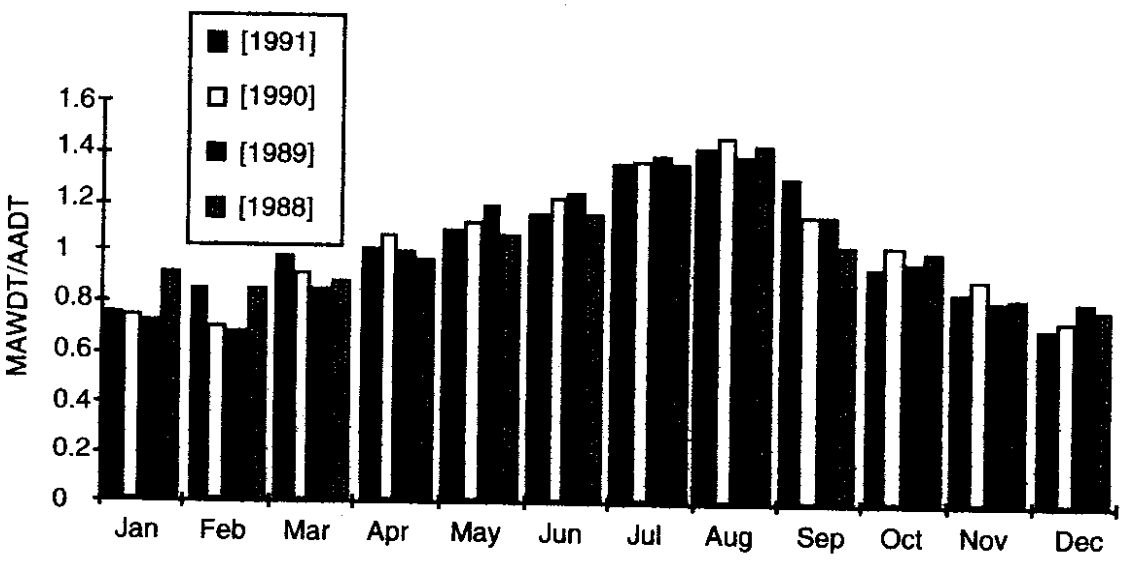


Figure 17. Average Monthly Weekday Volume / Average Annual Volume, Bin 2 at Site #1 on Interstate 5

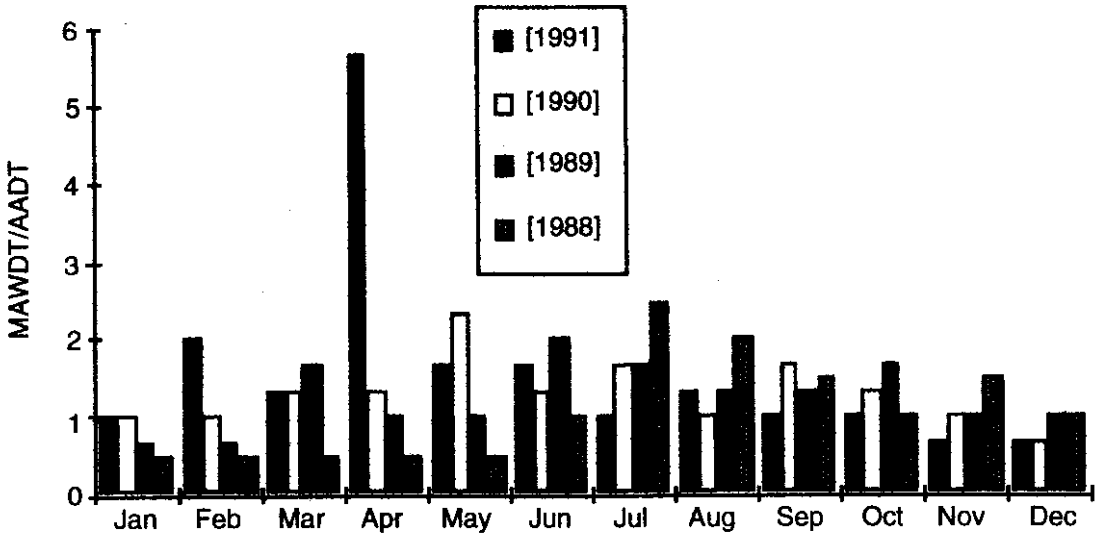


Figure 18. MAWDT/AADT for Length Bin 4 for State Route 410, Approximate Bin 4 AADT = 5

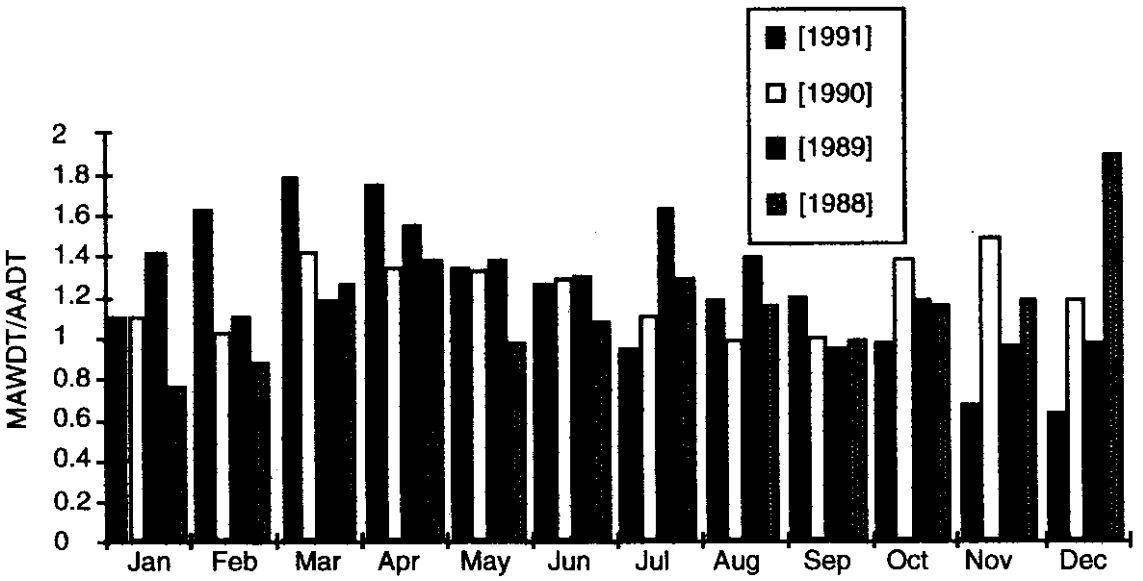


Figure 19. MAWDT/AADT for Length Bin 2 for State Route 410, Approximate Bin 2 AADT = 80

I-90 are treated as one "factor group" the mean standard deviation (MSD) within each group is roughly 0.09. The MSD for the 12 months ranges from 0.06 for Length Bin 2 to 0.11 for Length Bin 4.

Examination of the seasonal travel patterns for the four vehicle classes at the three sites shows the limitations of MSD's use for measuring the "goodness of fit" associated with group factors. The MSD provides a reasonable composite value for each group of 12 seasonal factors, but it does not reflect the variation in the quality of the factor group from month to month. For example, a comparison of Figure 20 (above) with Figure 21 reveals that Length Bin 3 traffic volumes show more variation among sites than Length Bin 2. Furthermore, within each length bin, the monthly factors are more closely related in some months than in others.

In general, the composite factors for the three sites have much less variation during summer (June through August) than during other months. For Length Bin 3, the worst time of the year for factoring is October. During this time period, the range between the seasonal factor at the site with the highest value and that with the lowest is 0.31. This range translates into an error of roughly 15 percent if the composite factor is applied to a count from either of the sites with more extreme seasonal patterns. (In this case, the composite factor applied to a count at Site 826 is too low; a composite factor applied to a count at Site 14 is too high.) This error is entirely attributable to the computation of a "group factor" and does not account for the error associated with daily variation in traffic levels.

While a 15 percent error may seem high, this error is much smaller than the error produced by factoring trucks on the basis of the seasonal pattern associated with total volume, or by applying the seasonal factors for one vehicle classification bin to the volumes in another bin. The variation in seasonal patterns among length bins is shown in Figure 22. If the Cle Elem site is used as an example, and if each of the four classification bins is treated as a "different site," the MSD for that "factor group" is 0.27.

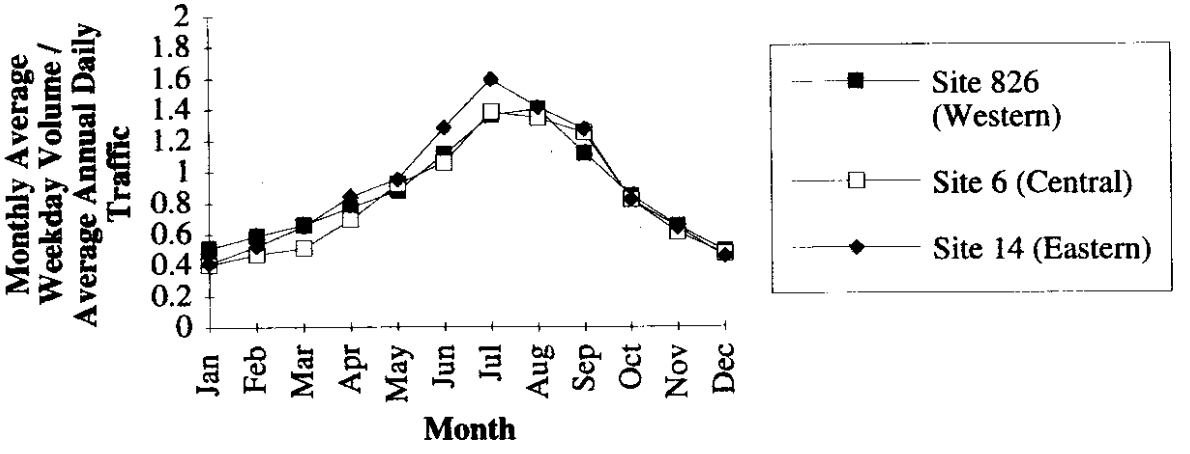


Figure 20. Comparison of Length Bin 2 Travel Patterns At Three I-90 Sites

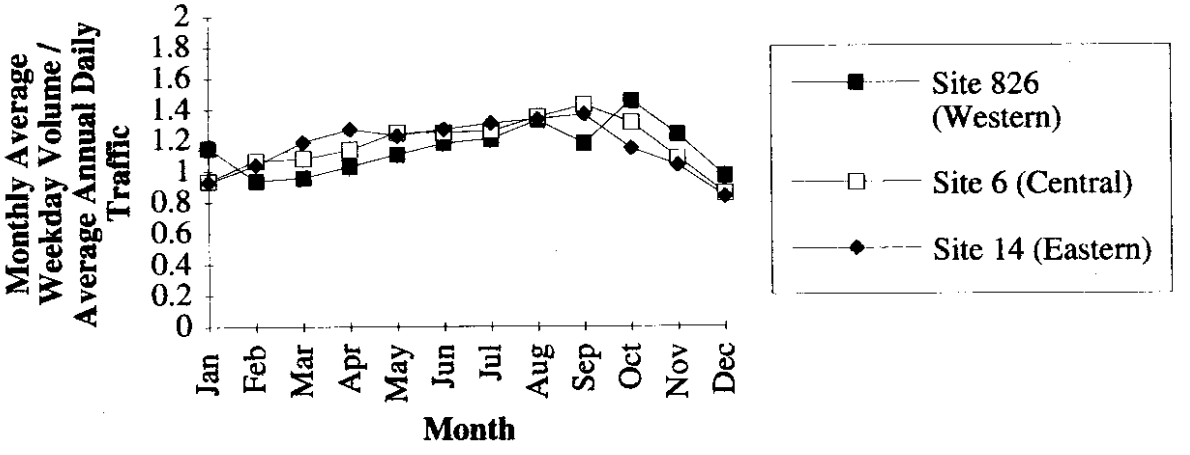


Figure 21. Comparison of Length Bin 3 Travel Patterns At Three I-90 Sites

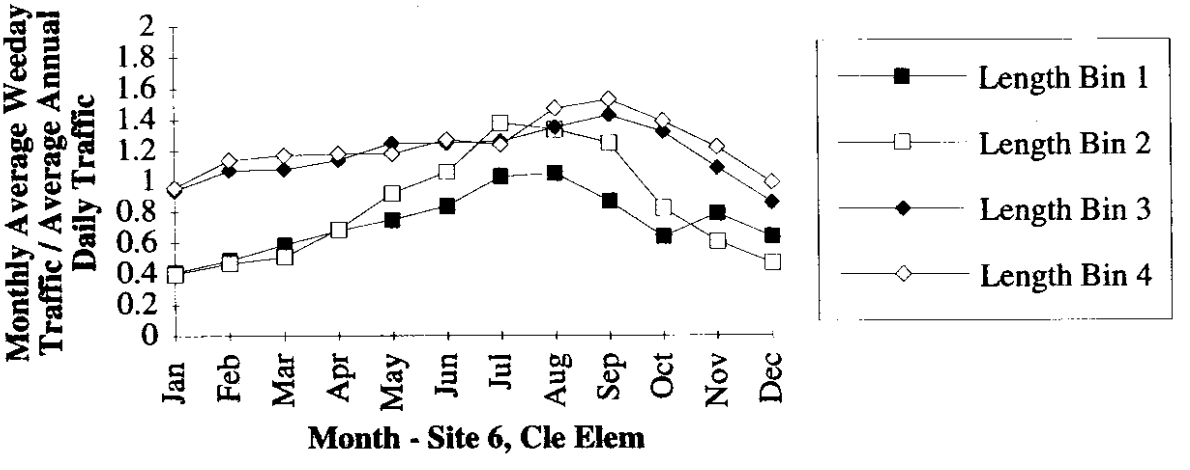


Figure 22. Comparison of Travel Patterns For Different Vehicle Classifications

This is more than twice the MSD for the "group" that consists of all three I-90 sites but contains only Length Bin 4. (That is, the error from using a factor that averages the four classification patterns at one site is more than twice the error caused by using multiple sites but only one vehicle class.)

If the volume factor (essentially Bin 1) is used to adjust all of the other vehicle classification counts, the average error ranges from 17 percent for Length Bin 2 to 49 percent for Length Bin 4.

On Interstate 5 all five sites could also be combined as one factor group. On I-5, the urban sites tend to have flatter weekday patterns than the rural sites, but the differences between the rural and urban locations are relatively minor.

All five sites have a minor seasonal fluctuation in the summer. Length Bin 2, which contains RVs, has the greatest seasonal fluctuation, even at the Midway site (located in the Seattle-Tacoma urban area) where the transit bus traffic should flatten out the factor.

The MSD among the sites ranges from 0.07 to 0.10 for the four length classifications. This is lower than the MSD of seasonal factors among vehicle classes within one site, which is 0.17. The MSD for the I-5 sites is lower than for I-90, primarily as a result of the lower seasonal fluctuation in traffic among cars. This is illustrated by comparing the Length Bin 1 volume patterns for the Marysville site on I-5 (see Figure 23) to those for Cle Elem on I-90 (see Figure 22, previously presented). One can see that the I-90 sites have significant reductions in traffic volume in the winter that do not occur on I-5.

The between-site variation on I-5 would be even smaller if not for several abnormal traffic volume months at some sites. For example, the Marysville site had a significant increase in Length Bin 4 traffic in May and June of 1989, followed by a significant drop in July. Because this volume pattern did not occur in other years, a

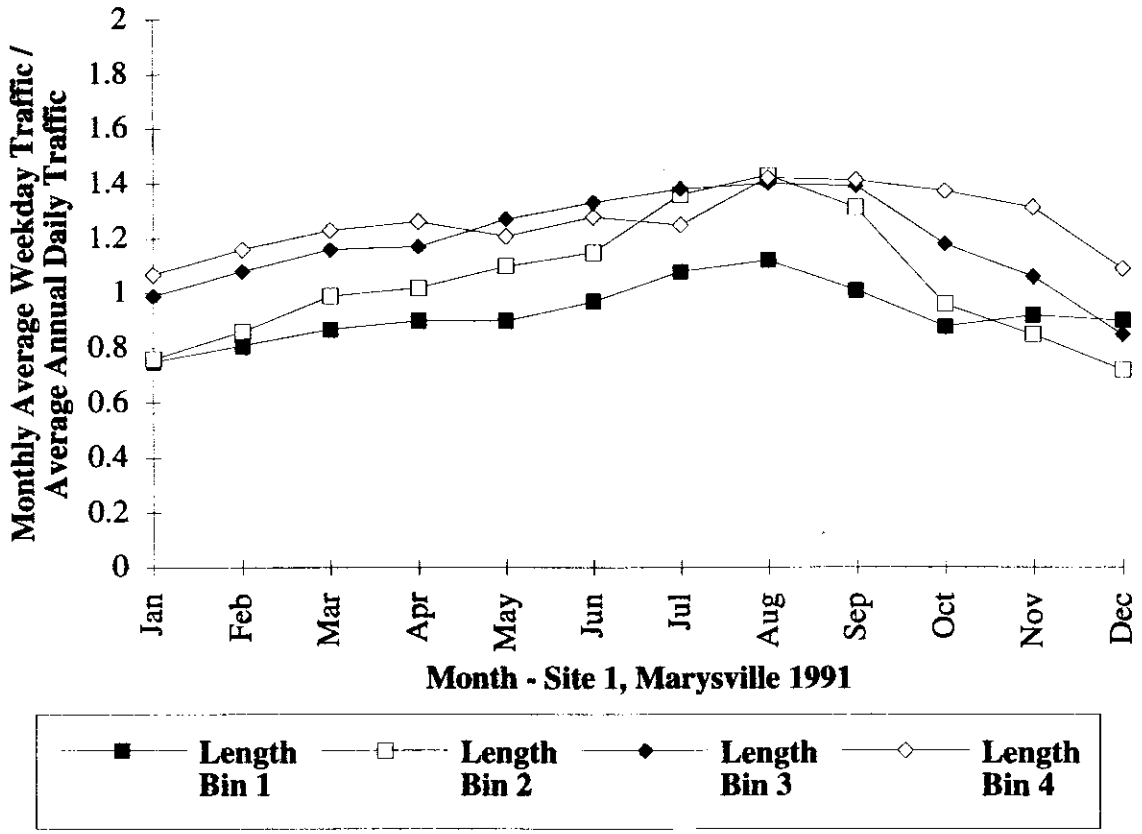


Figure 23. Comparison of Travel Patterns For Different Vehicle Classifications, Interstate 5

special effort was made to confirm that the counters were operating correctly during this period.

After examining the site, the researchers determined that the counters were operating correctly. The unusual traffic patterns were caused by heavy construction activity in the area. (Fill dirt was hauled by double-bottom dump trucks which fall into Length Bin 4.) However, this unusual activity increased the "normal" seasonal factor from roughly 1.4 to 1.8 in June of 1991. The increase in the monthly factor of 0.4 resulted in an MSD increase for the five I-5 sites of 0.16 (0.24 instead of 0.08).

While the interstate sites appear to provide factor groups that are (for the most part) reasonably consistent across the state, it is doubtful that this consistency would be true for smaller roads or for roads that carried less through traffic. However, it is possible that interstate traffic in other states could exhibit similar patterns within the confines of their borders.

Weekday Versus Weekend Traffic

The results of our analyses showed that in most cases Saturday and Sunday traffic volumes differ significantly from weekday traffic volumes. In the majority of cases, weekday traffic volumes are higher than weekend volumes. This is especially true for the longer truck classes, in which large, commercial vehicles dominate. However, for classes with a high percentage of recreational vehicles, weekend volumes are consistently higher than weekday volumes.

As part of this analysis the project team also tried to determine the elements that constitute a "weekday." The researchers computed the "average weekday" in three ways, depending on the definition of the weekend/weekday split. (That is, they computed and compared Monday through Friday weeks, Monday through Thursday weeks, and Tuesday through Thursday weeks.)

The conclusion the project team drew from these analyses is that in some locations and/or in some months, the incorporation of either Monday or Friday in the

weekday estimate is appropriate. In other locations and/or months, traffic volumes on these days are statistically different from those of Tuesday through Thursday. For the sake of consistency, researchers who performed analyses for this paper assumed that weekdays are only Tuesday through Thursday. While this may be a conservative assumption, the decision greatly simplified the performance of the analyses.

AXLE CORRECTION FACTOR ANALYSIS

This analysis looked at the variation in axle correction factors at the WIM sites. Not surprisingly, the axle correction factors are highly variable from site to site, as well as from month to month. Weekday and weekend axle correction factors also differ significantly.

In general, at all sites, the axle correction factor measured for weekdays is higher than that measured on weekends. In addition, the difference in axle correction factors among sites is more significant than the difference between axle correction factors from one month to the next. However, the difference in axle correction factors between weekdays and weekends is often as large the difference among sites.

For example, the axle correction factor near Pasco (SR-395) ranges from 2.8 to 3.0 during the weekdays (Monday-Thursday) and from 2.4 to 2.6 on the weekends (Saturday-Sunday). The Friday value falls between these two values, within a range of roughly 6 to 8 percent (See Figure 24). The axle correction factors for the Kelso (I-5) and Brady (SR-12) sites range from 2.4 to 2.6 on weekdays, but fall below 2.2 on weekends. Again, the axle correction factor for Friday falls between these extremes.

When the seasonal (month-to-month) variation is compared, the range between monthly factors is roughly 0.2—about half the range between weekday and weekend factors (See Figure 25).

Axle correction factors differ by weekday/weekend and by site. As a result, if an agency uses permanent counters to compute axle correction factors, it must take care to calculate and apply the appropriate factor to the appropriate count. As with conventional

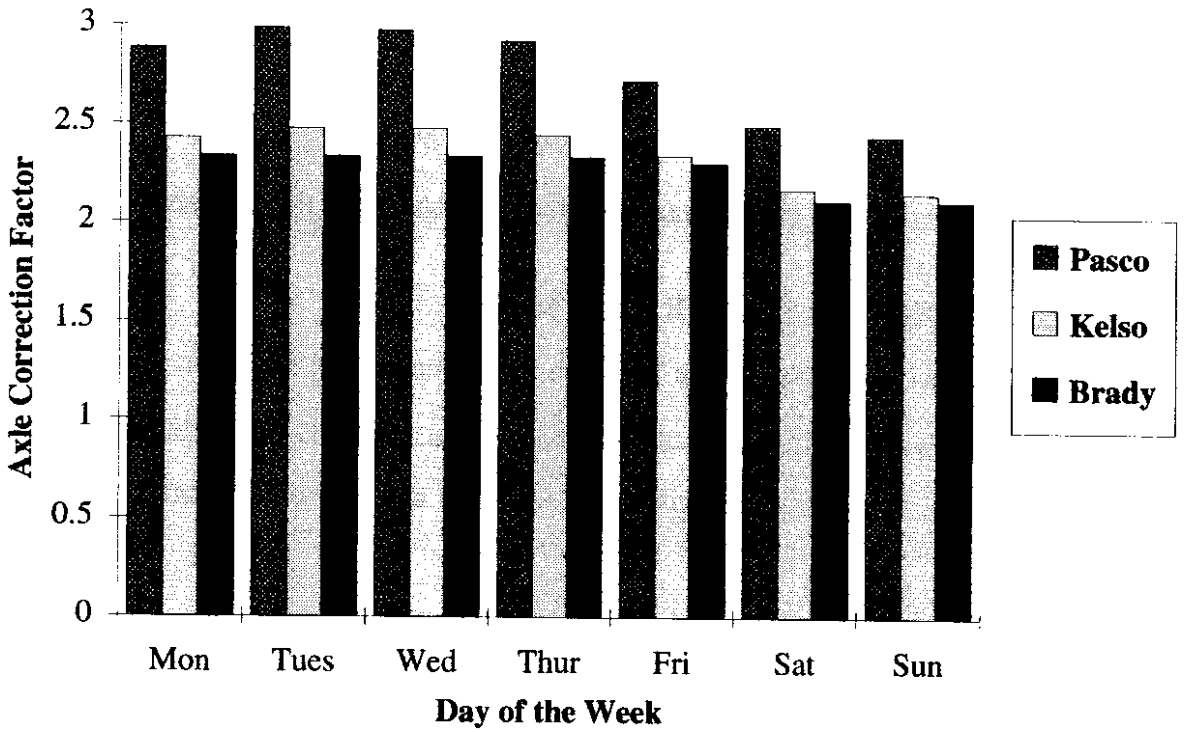


Figure 24. Axle Correction Factors By Day of Week

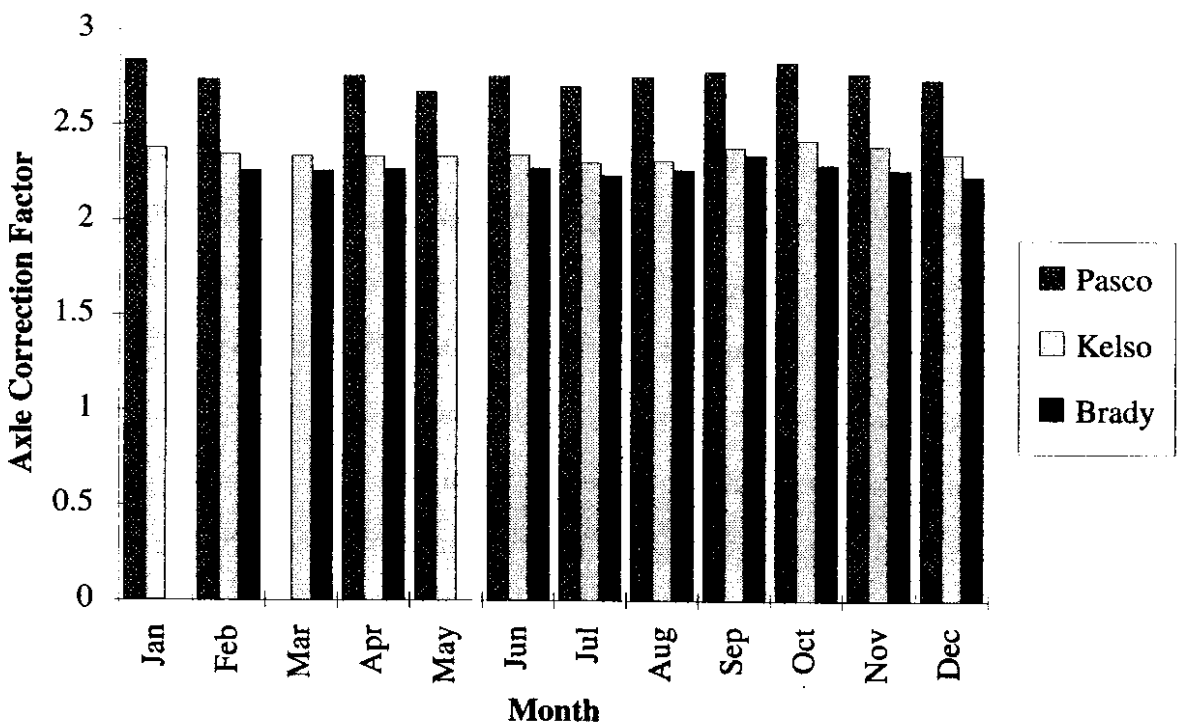


Figure 25. Axle Correction Factors By Month

seasonal adjustment factors, any adjustment factors applied to a short-duration count must apply to the appropriate day of the week, site, and facility. If this adjustment is not applied correctly, it will bias the estimate being produced.

For example, use of a weekday axle correction factor for a weekend road tube count will result in an underestimation of the number of vehicles using the facility. If that same volume count is used to estimate total truck traffic with the following formula:

# of trucks = # of axles counted / axle correction factor * percent trucks

the resulting number of trucks will also be underestimated. Applying an axle correction factor based on all seven days of the week will also result in the underestimation of total traffic on weekends.

Similarly, if an axle correction factor for the year (average of all seven days of the week) is used to adjust a weekday axle count to estimate daily traffic volume, the resulting traffic volume (and by extension, the number of trucks) estimate will be too high.

Essentially, the analysis indicates that the proportion of trucks to cars operating on the weekends is lower than that during weekdays. Both car and truck volumes tend to decrease on weekends, but truck volumes drop more significantly than car volumes. Thus, a single-axle correction factor for all seven days predicts too many trucks operating during the weekends and not enough during the weekdays. This prediction results in the underestimation of vehicles on the weekend and the overestimation of vehicles on the weekdays.

To avoid these problems, the states should use axle correction factors that are consistent with the axle counts being factored. For example, only data from weekdays from a permanent vehicle classification counter should be used to compute axle correction factors that will be applied to weekday counts.

As noted above, the seasonal differences in axle correction factors appear to be fairly small. For those sites at which sufficient data were available, the average axle correction factor collected in any of the months except July, September, and October did a reasonable job of replicating annual conditions (so long as weekday/weekend differences were accounted for). For the most part, the axle correction factors are relatively flat from January through June. A dip occurs in the factor in July, followed by a steady rise until October and then a decline back to the "norm."

It is not clear whether these patterns are true for all Washington sites. The limited number of sites available for analysis limits this project's ability to extend this analysis throughout the state.

DEVELOPING ALTERNATIVE FACTOR GROUPS

While a number of grouping techniques were tried, none of them worked as well as desired. The research team believes that this was not a limitation in any of the grouping techniques but, rather, a result of the high degree of variability associated with truck volumes. The variation in the truck volumes prevented the groupings from being as "tight" as those traditionally expected from total traffic volume factoring.

Three techniques were used to compute composite factor groups. These techniques included the following:

- a visual analysis,
- a modified cluster analysis, and
- a regression technique.

Each of these methods and its results are discussed below.

Visual Analysis

The first method employed a subjective, pictorial approach. This methodology included graphing the daily and average monthly traffic volumes and trying to visually match graphic volume patterns from different sites. Means, standard deviations, and expected errors were then calculated for each of the factor groups. Finally, the groups of sites were examined to determine the characteristics they had in common. These

characteristics would then be used to assign sites for which year-round data were not available to those groups.

The results of this analysis were unacceptable. The complexity of the traffic volume patterns for four vehicle classes made the determination of factor groups extremely difficult. Often, the volume patterns for separate vehicle classes were sufficiently different that the same sites would group differently for each of the four vehicle classes. For example, two sites would group together for Length Bin 2, but not for Length Bin 3. Thus, if the sites were grouped four times (once per vehicle class), a different factor grouping would result than if the sites had been grouped once with all vehicle classes contributing to the selection of that composite grouping.

A second problem was the high degree of variability present in the truck volumes, both from year to year and from month to month. This variability resulted in several sites being assigned to different groups, depending on the year of data examined. It also resulted in attempts to group sites together because of their similar travel patterns (i.e., volumes increased and decreased at the same time), only to find that the numerical variations in the factors for those sites were sufficiently different that they did not produce "tight" factors.

Finally, the visual grouping process did not yield a usable methodology for identifying how specific sites should be assigned to factor groups. Traffic counter locations with similar functional classifications and/or geographic locations were often not grouped together by the visual pattern matching process. In several cases, sites included in a visual pattern group had few characteristics in common that could be used to differentiate the roads belonging in that group from other roads belonging to other groups.

Modified Cluster Analysis

The second method employed a subjective cluster methodology that used a combination of objective and subjective criteria as inputs. For this procedure, objective

criteria obtained for each count location (functional class of roadway, traffic volume) and subjective criteria (whether the road was subject to recreational travel or agricultural harvest movements) were used to classify roads into factor groups. For example, one factor group consisted of interstate and principal arterials in rural areas that were subject to harvest hauls, but not subject to substantial recreational travel. This "subjective clustering" approach provided a methodology that allowed the creation of factor groups that were more intuitively attractive to the users of the traffic data.

A variety of subjective criteria were used to create alternative factor groups. The "fit" of these groups was then computed with the MSD and MAD values described above. In some cases, the subjective criteria assigned to specific sites were changed after the initial analysis has been performed (i.e., a site may originally have been classified as having little or no recreational movement, but after initial analyses had been performed, that site was reclassified as having a recreational trend).

By changing the subjective variables assigned to the respective permanent counter sites, the research team was able to produce "tighter" factor groups. However, the need to adjust these subjective values indicated how easily the variables could be incorrectly assigned in the first place. This need for adjustment limits the accuracy of assigning a short duration count to a factor group on the basis of subjective criteria, because the criteria assigned to that short count location may be incorrect.

To reduce the impact of subjective decisions on the accuracy of the factoring process, the project team developed several "rules of thumb" that were used along with counter data to determine the different subjective criteria that should be assigned to different roads. These criteria were mostly determined by examining a week of data from 3 or 4 months to reveal the basic travel trends associated with each road. This same methodology could be used to assign criteria to all roads, although it would require considerable expansion of a state's traffic counting process to complete this inventory of

counts. Once assigned, the factor criteria would likely remain unchanged, unless available data indicated that a change was necessary.

The results of this effort were better than the visual analysis for the following three reasons:

- Because the visual review of all traffic volume patterns was eliminated, the "noise level" associated with the mass of traffic data involved decreased. That is, the technician who performed the analysis did not lose sight of the basic task as a result of abnormalities in the data. These abnormalities (for example, an unusually high month of traffic volume for a vehicle class) tended to limit the confidence a reviewer had in a factor group, when mathematically, these abnormalities had only a moderate impact on the "tightness" of the factor group.
- Because readily obtainable criteria for identifying factor groups was used, the assignment of randomly collected short duration counts to factor groups was much simpler and more accurate than for the visually assigned grouping process.
- The intuitive nature of the factor groups lent credibility to the process for end users of the data.

While this modified cluster approach to factor group creation proved to be far superior to the simple visual classification methodology, the factor groups created still tended to have unacceptably high levels of within-group variability. Factor groups that had little within-group variability for a vehicle class in one year often had a much higher degree of variability in other years.

Thus, the modified cluster based factor groups, while reasonable, did not provide a methodology that the project team is comfortable recommending as a model to the nation.

Regression Analysis

The third approach to developing factor groups started with the modified cluster analysis described above to which the project team made two major modifications. The first modification was that instead of using monthly factors for each year to compute the factor groups, the project team developed monthly factors based on long-term trends, and used these factors to compute factor groups. A simple, time series-based approach called decomposition was used to calculate a single set of monthly adjustment factors at each permanent counter site on the basis of the monthly adjustment factors for multiple years of data at that site. The decomposition method is explained in Appendix A. The primary benefits to using the decomposition method are that the method:

- automatically accounts for missing values,
- discounts the presence of extreme data points, and
- reduces the impact of moderate to large year-to-year and site-to-site variability, which is a problem for the lower volume vehicle classes.

The drawback to this technique is that it is computationally and intellectually more complex than computing simple group averages. This complexity may cause problems for the DOT staff responsible for implementing and maintaining the factoring process.

The second modification the project team made to the cluster approach was to switch from employing a simple cluster approach (i.e., computing a simple average factor for sites that had similar patterns) to using multiple linear regression. The multiple linear regression approach used the same input criteria developed for the modified cluster analysis. However, it computed a different seasonal factor for each site, rather than a single factor for each site within a factor group.

The regression model chosen used a dummy variable that had a value of one (positive) or zero (negative) for each input variable except volume. The input value for volume was the monthly average weekday traffic for a particular vehicle classification, expressed in units of 1000s for Bins 2, 3, and 4, and in units of 10,000 vehicles for Bin 1. (Figure 26 shows the input variables used.)

Urban/Rural/Intermediate Designation

Urban = 1 if the route is in an urban area
Inter = 1 if the route is not really in a rural or urban location

Functional Class

inter = 1 if the route is an interstate highway
part = 1 if the route is a principal arterial
mart = 1 if the route is a minor arterial
collec = 1 if the route is a collector

Location

east = 1 if the route is located in eastern Washington
central = 1 if the route is located in central Washington
ec = 1 if borderline between eastern and central Washington

Recreational

rec = 1 if the route served recreational movements

Agricultural

agr = 1 if the route served agricultural harvest movements

Interaction Variables

recart = 1 if recreational and principal arterial
reccent = 1 if recreational and central
receast = 1 if recreational and eastern
recec = 1 if recreational and east/central

Other

volume = MAWDT in 10,000 vehicles for Bin 1
= MAWDT in 1,000 vehicles for Bins 2, 3, and 4
hrv = 1 if high proportion of RVs
I5 = 1 if the site was on interstate 5
I90 = 1 if the site was on interstate 90.

Figure 26. Input Variables For Washington Regression Factoring Approach To Factor Groups

One advantage of the regression approach was that it provided a direct computation of whether specific input variables had an effect on the seasonal factor "grouping" for a highway. (If an input variable was useful, it improved the predictive capability of the regression equation. If an input variable did not improve the predictive nature of the equation, it was discarded.) Thus, the final regression equation indicated those criteria that were important for defining a "factor group," although no specific "group" was identified as such. This result made the assignment of specific short duration traffic counts to "factor groups" easy and reduced the error associated with assigning specific locations to specific "factor groups."

On the other hand, there were too few permanent vehicle classification counter sites to determine the true input variables needed to compute seasonal factors, and thus, the end results were biased by the data available.

The results of this technique, while somewhat better than those for the modified cluster analysis approach were still not impressive. The R-squared coefficients for the groupings of stations were not high. Twelve different R-squared values were computed for each vehicle bin (one R-squared value per month). Table 1 shows these values.

Table 1. R-Squared Coefficients For Regression-Based Factor Calculation in Washington

Mean R-squared	0.900	0.826	0.810	0.735
Standard Deviation	0.066	0.205	0.137	0.158
High R-squared	0.975	0.981	0.956	0.955
Low R-squared	0.787	0.287	0.457	0.476

This table shows that R-squared values were highest for Bin 1, with an average of 0.9 and individual R-squared values ranging from 0.975 to 0.787, and lowest for Bin 4, with an average of 0.735 and individual R-squared values ranging from 0.955 to 0.476.

Because the automobile travel was the most stable both among sites and from year to year, it was not surprising that Bin 1 provided the most accurate regression results.

The results of the analysis of seasonal factors for the three truck classes were reasonably similar. Each truck classification showed reasonably good R-squared values for most months; however, each classification had at least one month for which the variability in the monthly factors was simply too large for the factoring process to account for accurately.

Washington Site Group Characteristics

Despite its inability to consistently develop accurate factors from these three grouping techniques, the project team was able to develop a useful description of the general trucking patterns monitored at the 23, 4-bin counter locations in the state. (There may have been other trucking patterns in the state that were not apparent in the data because of the limited number of counter locations.)

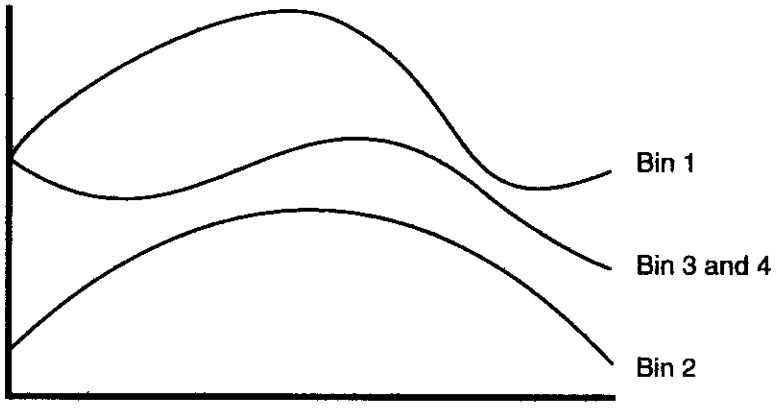
While the relative size (height) and timing of these patterns changed from site to site, which is reflected in the project team's inability to develop "tight" factor patterns, the basic shape of these patterns was fairly consistent. These patterns were best illustrated by showing graphs of traffic *as a proportion of total traffic*. The basic patterns found in Washington were

- recreational,
- agricultural, and
- urban/rural.

The recreational pattern for Bin 1 was convex with a peak in the summer and a smaller peak at the end of the year (see Figure 27). For Bin 2, the recreational pattern was bell shaped, with a large peak in the summer. Bins 3 and 4, the larger truck classifications, had concave volume patterns, with lower percentages during both the summer and the year's end.

The agricultural pattern of vehicle proportions showed relatively flat seasonality except for a significant increase in Bin 3 and Bin 4 traffic as a proportion of total traffic during the late summer and early fall. This increase in the proportion of traffic in Bins 3 and 4 was offset by decreases in Bin 1 traffic. However, Bin 2, which includes many of

RECREATIONAL PATTERNS



AGRICULTURAL PATTERNS

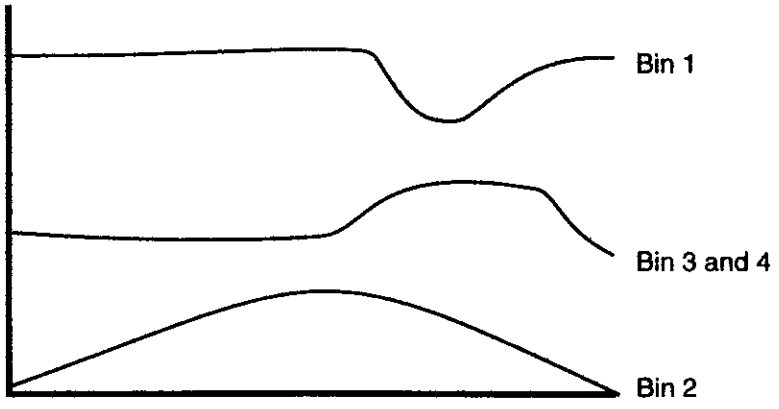


Figure 27. Shape of Washington Travel Patterns

the RVs, did not share the flat Bin 1 pattern. Instead, it followed a steady, convex shape throughout the year, with high summer traffic and low winter traffic volumes.

The final traffic pattern apparent in the Washington data related to the urban/rural location of the site. These classifications, like the recreational pattern were commonly used in conventional traffic volume factors. The urban pattern reflected the "flat" traffic pattern found in most urban centers, where traffic volumes change only marginally throughout the year. The rural pattern showed a higher level of traffic variation during the year.

The 4-bin analysis actually found three urban/rural style travel patterns in Washington. The urban and rural patterns were similar to those normally used. However, the third pattern (an intermediate pattern) indicated that traffic patterns at sites on the fringe of urban areas or in smaller urban areas, where "urban" traffic movements are overshadowed by "non-urban" movements, could fall somewhere between the flat urban and more convex rural patterns. The finding of this intermediate pattern was intuitively obvious, but it has not always been incorporated into traditional factoring procedures.

In general, the three patterns were differentiated as follows. The urban pattern was flat and had a high proportion of vehicles in Bin 1 (more than 90 percent). The rural traffic pattern had volumes that varied during the year and generally had less than 90 percent of its traffic in Bin 1. The intermediate pattern was relatively flat and had a moderately high proportion of vehicles in Bin 1 (near 90 percent).

Idaho Site Group Characteristics

As a check of the findings of this project, data from Idaho 4-bin classifiers were analyzed to determine whether the findings of the project were consistent across states. In general, the findings from the Idaho data were similar to the findings of the Washington data. That is, truck volumes were more variable than automobile volumes,

and the lower the volumes were at a site, the more likely that site was to have highly variable traffic patterns.

The same, basic day-of-week pattern existed in Idaho, with a significant drop in trucks proportionally to automobiles during the weekends. Only two Idaho sites (0036 and 0060) did not show the proportionate increase in cars relative to trucks on the weekends. However, in Idaho, Friday appears to be more closely related to the weekend than the weekdays, whereas in many Washington sites, Fridays are often weekdays.

While most of the basic travel patterns and research conclusions were the same for Idaho and Washington, the analysis of Idaho data did produce additional insight into the vehicle classification factoring process. The most obvious difference between Washington and Idaho travel patterns was that Idaho travel data displayed two annual volume patterns that were not present in the Washington data.

The project team called the first of these patterns the "ski pattern" because of its direct relationship to an increase in traffic associated with ski resorts in Idaho. (Curiously, Washington also has a large winter ski industry, but the affect of that industry on traffic volumes was not as pronounced in the Washington data. It was not clear whether this observation was a function of counter location, or whether a higher level of background traffic in Washington hid the effect of ski traffic.)

For Idaho, the project team also had to define two recreational patterns (Rec and Rec2) in addition to the ski pattern. One pattern was called the "striking," or extreme recreational, pattern. The project team also had to change the geographic variables included in the regression model. For Washington, the state was divided into eastern, western, and central geographic areas. For Idaho, a geographic location index consisting of north, southwest, southeast, and south central was used.

The other variables used in the regression analysis were functional class and urban/rural designation. As with Washington, an intermediate category was also used in the urban/rural variable.

The results of the regression analysis for Idaho, as in Washington, were mediocre at best (see Table 2). In general, the regression technique for Idaho produced a less accurate measure of the seasonality than it did for Washington. The project team believes that this result was less a function of the regression technique than it was a function of the higher degree of variation in the Idaho traffic volumes, as well as the generally lower traffic volumes (for all classes of vehicles) present in Idaho than in Washington.

Table 2. R-squared Coefficients For Regression Based Factor Calculation in Idaho

Mean R-squared	0.711	0.669	0.753	0.636
Standard Deviation	0.126	0.126	0.100	0.139
High R-squared	0.857	0.855	0.886	0.853
Low R-squared	0.438	0.476	0.516	0.406

Summary of Grouping Analysis Results

One of the important findings of this effort was that the groups that were detected in Washington did not necessarily exist in the Idaho dataset examined. Therefore, it is likely that the truck travel patterns apparent in other states will also differ substantially from those presented in this paper. This was not a surprising finding, given the nature of truck traffic (i.e., truck traffic varies considerably from site to site and is influenced both by the characteristics of the land use around each site and by the nature of the through travel).

For example, data collection in Florida has indicated that Florida's agricultural movement is consistent throughout the year. That is, many Florida roads experience little seasonal fluctuation in truck volumes. The increase in one seasonal commodity is balanced by the decrease in some other seasonal commodity. This pattern was not found in many parts of Washington, where significant volume fluctuations were apparent during harvest periods.

Similarly differences in recreational vehicle travel will be apparent among states. The Idaho ski traffic pattern may easily be found in states such as Utah, Wyoming, and Colorado. On the other hand, other traffic patterns in these states may limit the importance and visibility of these patterns, as apparently happens in Washington.

Even roads that carry significant levels of through traffic (such as the interstate system) may not have travel patterns in one state that are similar to those, on that same road, in neighboring states. In Washington, travel patterns on the interstates remain fairly constant in shape from one side of the state to another. However, significant changes in the actual monthly adjustment factors occur as the urban/rural character of the highways changes, and as the interstates intersect with other highways, cities, or freight generating land uses.

The differences in the Idaho travel patterns highlighted the concern expressed at the beginning of this report, namely, that the results presented in this report were based on a limited geographic sample of data points. Although the travel patterns found are representative of the sites included in the study; they may not be representative of all of Washington's traffic. Additional, important truck travel patterns may exist in Washington (for example, a different agricultural haul) that were not measured simply because of the location of the permanent counter sites available for this project.

IMPACTS AND ACCURACY OF FACTORING COUNTS

The use of seasonal factors (MAWDT/AADT) to convert short counts to AADT estimates was tested for each site. In the "best" alternative, a monthly factor was computed for each site and then used to convert short counts *from that same site* to AADT estimates. Different count durations were tested, including individual weekdays (T, W, Th) and combinations of weekdays (T-Th, T-W, W-Th). The calculations produced reasonable AADT estimates, but they also showed the error inherent in factoring attributable to the day-to-day variations in traffic volumes.

By selecting count data from a variety of days and months, the project team was able to measure the average error, and the standard deviation of those errors, associated with factoring. By increasing the number of days included in each sample, the project team was also able to determine the impact of count duration on the expected error associated with an annual estimate.

Tables 3 through 6 show the expected error associated with factoring for all counter locations available for this study . For Length Bin 1, the average error in the estimate of annual volume ranged from 6 percent to 9 percent, depending on whether the count that was adjusted (factored) was 1 or 3 days long. 95 percent of all estimates were within 18 percent (the mean error plus 2 standard deviations around that error) of the actual annual volume.

Length Bins 3 and 4 had the highest level of volume variation, and consequently, the highest error in the estimates of annual volumes. Mean errors ranged from 9 percent to 23 percent, again depending on the length of the count. 95 percent of all the estimates were within 17 percent to 60 percent of the actual annual volume. (If only 2- and 3-day counts were used, the mean error ranged from 9 percent to 15 percent, with a 95 percent level of confidence of between 17 percent and 36 percent.)

The fact that a 3-day count provided the basis for a more accurate estimate of annual average volumes than a single day estimate was expected. This was true for all four vehicle classifications. However, an interesting finding was that Thursday traffic was more closely related to the MAWDT/AADT ratio than either Tuesdays or Wednesdays. This was true for all four vehicle classes. This finding was also evident in the fact that annual estimates based on counts performed on Wednesday and Thursday were more accurate than estimates based on made on Tuesday and Wednesday.

Another surprising finding was that the annual estimate based on the 3-day count (Tuesday through Thursday) was only marginally better than the estimates based on the 2-day, Wednesday through Thursday, value. If travel was entirely random, the third day

of traffic data should have provided an improvement in the AADT estimate. (This held true when the Tuesday - Thursday estimates were compared to the Tuesday - Wednesday estimates.) This result was caused by the "goodness of fit" of the Thursday data (see the previous paragraph). After thoroughly analyzing the data, the project team was not able to explain why Thursday provided better estimates of annual travel than the other weekdays.

Table 3. Error Due To Factoring
Bin 1—No Site Association Error

Day	Mean Error	Std. Dev. of Error (among sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.059	0.037	0.019
Tues-Wed	0.067	0.041	0.019
Wed-Thurs	0.061	0.041	0.017
Tues	0.091	0.044	0.040
Wed	0.074	0.050	0.022
Thurs	0.060	0.035	0.022

Table 4. Error Due To Factoring
Bin 2—No Site Association Error

Day	Mean Error	Std. Dev. of Error (among sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.90	0.031	0.024
Tues-Wed	0.107	0.038	0.030
Wed-Thurs	0.091	0.030	0.019
Tues	0.146	0.053	0.051
Wed	0.120	0.044	0.037
Thurs	0.112	0.044	0.039

Table 5. Error Due To Factoring
Bin 3 - No Site Association Error

Day	Mean Error	Std. Dev. of Error (among sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.088	0.039	0.027
Tues-Wed	0.108	0.045	0.034
Wed-Thurs	0.087	0.046	0.021
Tues	0.159	0.083	0.064
Wed	0.120	0.067	0.046
Thurs	0.110	0.069	0.047

Table 6. Error Due To Factoring
Bin 4 - No Site Association Error

Day	Mean Error	Std. Dev. of Error (among sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.116	0.086	0.025
Tues-Wed	0.145	0.106	0.035
Wed-Thurs	0.116	0.105	0.027
Tues	0.231	0.173	0.083
Wed	0.182	0.211	0.055
Thurs	0.162	0.184	0.071

While the errors associated with these annual estimates may seem large, especially for the larger truck classifications, the errors were much lower than if the factoring had not been performed. The following tables indicate the size of the errors that could be expected in annual average volume estimates that were based on unfactored, short-duration counts used directly as a measure of annual average conditions.

Table 7. Error If No Seasonal Factors Were Applied
Bin 1

Day	Mean Error	Std. Dev. of Error (among sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.149	0.091	0.022
Tues-Wed	0.156	0.10	0.025
Wed-Thurs	0.145	0.079	0.023
Tues	0.149	0.102	0.035
Wed	0.138	0.088	0.021
Thurs	0.132	0.075	0.028

Table 8. Error If No Seasonal Factors Were Applied
Bin 2

Day	Mean Error	Std. Dev. of Error (among sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.271	0.089	0.063
Tues-Wed	0.287	0.099	0.062
Wed-Thurs	0.260	0.084	0.066
Tues	0.291	0.123	0.076
Wed	0.248	0.099	0.064
Thurs	0.241	0.097	0.065

Table 9. Error If No Seasonal Factors Were Applied
Bin 3

Day	Mean Error	Std. among . of Error (between sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.259	0.083	0.068
Tues-Wed	0.264	0.098	0.072
Wed-Thurs	0.273	0.062	0.062
Tues	0.274	0.129	0.076
Wed	0.265	0.112	0.067
Thurs	0.271	0.093	0.059

Table 10. Error If No Seasonal Factors Were Applied
Bin 4

Day	Mean Error	Std. Dev. of Error (among sites)	Std. Dev. of Error (Mean w/in years)
Tues-Thurs	0.323	0.159	0.064
Tues-Wed	0.321	0.179	0.075
Wed-Thurs	0.369	0.167	0.073
Tues	0.332	0.219	0.076
Wed	0.260	0.221	0.068
Thurs	0.401	0.302	0.119

A comparison of Tables 3-6 and Tables 7-10, shows that the errors present if the short counts were not factored would be considerably larger than the errors if factors are applied. For Length Bin 1 the errors after factoring would be roughly half those if factors were not used. This relationship holds true (with some minor variation in the size of the error differential) for all vehicle classes and count durations.

Another important fact the project team discovered was that increased count duration had no effect on the predicted error if no factors were applied. (In the study sample, the error actually decreased with a shorter count duration in several instances, although this decrease was not statistically significant.) That is, using 3 consecutive days of counting to estimate annual conditions would be only marginally better than using one day of counting, if seasonal adjustment factors were not applied. This finding was not surprising, as the majority of the error associated with unfactored counts was seasonal bias, rather than random variation. Counting for multiple consecutive days did not reduce the bias portion of the error.

To provide a measure of the effect "grouping" had on the accuracy of factors being applied to specific sites, the project team used the output from the regression approach to factoring and computed multiple AADT estimates by class for the tests sites. These AADT estimates were then compared to the actual AADT value by class, and the differences were determined.

Table 11 shows the results of this analysis.

Table 11. Error Due To Factoring With The Regression Technique

	Bin 1	Bin 2	Bin 3	Bin 4
Average Error (fraction of AADT)	0.078	0.126	0.113	0.177
Standard Deviation	0.034	0.058	0.073	0.079
Maximum Error	0.130	0.204	0.254	0.305
Minimum Error	0.045	0.043	0.042	0.063

A comparison of these errors to the errors in Tables 3 through 6, which describe the impact of factoring on annual estimates, shows that the regression process only added an additional 3 percent to 5 percent to the error in the annual estimate. However, the standard deviation of that error also increased by roughly 3 percent for vehicle Length Bins 2 and 3. This combination of moderately high average error and moderately high standard deviation resulted in the potential for relatively large errors associated with specific factoring estimates.

This potential was confirmed by the presence of several large errors in the tests performed for this analysis, as shown in Table 11. Still, while a 30 percent error is quite large, it is considerably smaller than many of the errors that would be present if unfactored truck counts were used as annual traffic estimates or if seasonal adjustments were made on the basis of seasonal patterns for total volume.

AN ALTERNATIVE TO FACTORING

The difficulties experienced by the project team in developing and applying traditional factoring approaches to truck volumes led to the exploration of other rational methods for estimating annual traffic volumes based on short-duration counts. The most basic method for estimating traffic volumes is counting vehicles at multiple times during the year at the same location and then averaging the counts.

The advantage of this method is that counts from different times of the year reflect the various volume patterns that occur during the year and result in a balanced estimate of high and low volume periods. Secondary benefits include the removal of the need to

- determine factor groups;
- allocate individual roadway segments to specific factor groups; and
- develop, maintain, and apply seasonal factors by truck category.

The initial test of the multiple count technique was to collect data four times during the year for 1 week during each counting session. Approximately 3 months were left between counts. Traffic counts were not collected during weeks that contained holidays. Annual average volumes by class were developed by computing simple averages from the 28 days of data present in each sample site.

A summary of the results of these tests is shown below.

Table 12. Average Error of Annual Traffic Estimates Based on Four, Week Long, Vehicle Class Counts

	Bin 1	Bin 2	Bin 3	Bin 4
Mean Error	0.029	0.038	0.045	0.042
Standard Deviation	0.023	0.026	0.038	0.035
Maximum Error	0.077	0.084	0.157	0.118

These results were better than the results obtained by computing annual volumes using seasonal factors developed from a specific site and applied only to that site (see Tables 3 through 6). More importantly, the above table shows that this system provided estimates

of annual traffic for each of the four length bins within 10 percent almost 90 percent of the time. (The mean plus two standard deviations was 7.4 percent for Bin 1, 9.0 percent for Bin 2, 12.1 percent for Bin 3, and 11.1 percent for Bin 4. The mean would drop to 6 percent for Bin 1, 8 percent for Bin 2, 7 percent for Bin 3, and 9 percent for Bin 4 if the sites with the largest variations were dropped from the calculations.)

The errors associated with the multiple count approach were roughly 1.4 to 2 times better than the errors associated with the calculation and application of site-specific seasonal factors. Furthermore, the error associated with factoring short counts was underestimated because no error associated with computing group factors, or assigning a site to a group was included.

Limitations To This Alternative

There were three primary drawbacks to this methodology for calculating annual average truck volumes based on multiple counts. The first was the difficulty in obtaining the staffing resources necessary for collecting 7 consecutive days of vehicle classification data four times per year per roadway section of interest. The second drawback is the need to collect classification data for all 7 days of the week. The problem was that the potential for the portable axle sensors, used by the classifiers, to come loose before the end of the scheduled count increased dramatically as the duration of the count increased. The final drawback was the cost of collecting the required number of counts.

All of these drawbacks were valid concerns. To address these concerns, the effects of shortening the duration of traffic counts and reducing the number of counts required were examined.

Potential Refinements To The Alternative

Reducing the Number of Counts

One way to reduce the cost of the proposed traffic counting program, as well as reduce the chance for axle sensor failure would be to reduce the number of counts taken. One method of reducing the number of counts required for calculating annual estimates

would be to count fewer times during the year. While this would not reduce the probability that axle sensors for portable classifiers might fail, it would significantly reduce the staffing and equipment requirements needed to count a specific location.

The drawback to this methodology would be that a reduction in the number of counts performed over the course of a year would increase the possibility that a seasonal bias would be present in the data collected. The truck volume graphs presented earlier in this paper showed that, at least in Washington and Idaho, truck volume patterns were not uniformly distributed across the year. Collecting four samples throughout the year might limit the problems associated with sampling this non-uniform distribution. Reductions in the number of counts taken might decrease the chance that the collected traffic counts would accurately balance the high and low volume time periods present at different sites.

A test to reduce the count program to two week-long counts per year, spaced 6 months apart, produced mixed results. Roughly three quarters of the sites tested experienced a decrease in the accuracy of the annual estimates when the number of counts included in the annual estimate calculation was reduced from four to two. However, a quarter of the estimates actually provided better annual estimates when based on 2 weeks of data than on 4 weeks of data. This heightened accuracy occurred when the 2-week periods were more representative of the full year's traffic patterns than the 4-week periods.

Two-week periods provided more accurate representations of the full year's traffic patterns than the 4-week periods in the following two cases:

- when the two counts balance a high volume period with a low volume period, and
- when both count periods reflected "average" travel conditions.

If the travel patterns for a site or road were well known, the counts could be scheduled so that either one of these conditions would occur. (If a specific time period was known to be "average," even one weeks worth of truck volume data would be able to accurately estimate annual conditions.) However, if the travel patterns were different from what

they were assumed to be, the reduced number of counts would bias the data that were collected. That is, the current under/over estimation process would be repeated.

A test with a cycle of 3 counts per year was also conducted. For this test, 3-week long counts were conducted 4 months apart. The results mirrored those of the two-count period experiment, described above. On average, the four-count program produced better count estimates than the three-count program, but this improvement was not uniform. As with the comparison of the two-count program, in general, the four-count program did a better job of estimating the annual conditions for locations with more variable traffic (i.e., those with non-uniform peak periods).

Note that in each of these cases, a full week of data still had to be collected to account for the differences in traffic between weekdays and weekends. Particularly for the larger truck classifications, there appeared to be very few times during the year when weekday truck volumes were equivalent to average annual conditions.

Reducing the Duration of counts

Another alternative counting approach would be to reduce the duration of the traffic counts used. This counting approach would reduce the likelihood that axle sensors would fail during the count and lowers the cost of data collection.. Traffic counts would be shortened if counts were taken during the weekdays only (as most traffic counts currently are). The axle sensors would then only be on the ground for 3 to 4 days, greatly reducing the chance that a sensor would be dislodged.

The problem with this approach would be the need to account for the differences in traffic that occur on the weekdays versus the weekend. As noted earlier, weekend traffic is not homogeneous (i.e., Saturday traffic is different from Sunday traffic, which is different from Friday traffic). Furthermore, the relationship among the different days of the week varies from site to site, from vehicle class to vehicle class, and from season to season. Thus, if only weekdays or weekends were counted, some adjustment factor would still have to be applied to estimate average annual conditions.

This approach was tested by counting 3 consecutive weekdays, four times each year. Each of the weekday estimates was then factored to represent the average annual condition; the 12 counts were then averaged. The tests for this technique were performed with factors developed from the same data from which the sample days were taken (i.e., no group factors were used). Thus, these test results were "best case" results and included no error associated with either the computation of group factors or the assignment of individual sites to specific factor groups.

The results of this test were quite respectable. In most cases, mean errors for the annual estimates ranged from 1 percent to 5 percent, with standard deviations near 5 percent. Thus, under this "best case" scenario, this counting approach provided annual estimates that were as accurate as those provided by using 4-week long counts. Whether this technique was actually accurate depends on how "tight" the factor group was, and how well a specific site was assigned to its factor group.

Table 13. Average Error of Annual Traffic Estimates Based on Four, 3-Day Long, Factored, Vehicle Class Counts

	Bin 1	Bin 2	Bin 3	Bin 4
Mean Error	0.013	0.037	0.021	0.049
Standard Deviation	0.035	0.055	0.047	0.047

However, note that much of the accuracy of this method was due to the averaging of the four counts, rather than to the accuracy of the adjustment factors. The error within the individual estimates of annual conditions (prior to their averaging) was often over 20 percent. However, these errors were normally distributed about an error of 0.00. Thus, when points were averaged (12 points were averaged to obtain a single annual estimate), the mean value for each site was often quite good, even though the individual data points used to make that estimate did not accurately replicate the annual conditions.

Another alternative method to account for differences in weekday/weekend travel without counting for 7 days at a time would be to count the weekend and only one weekday. That weekday could be either before or after the weekend. The 1 weekday counted (either Thursday or Tuesday) would then be used as a surrogate for the missing 2 weekdays. The project analysis showed that these 3 days were statistically similar in traffic volume and, thus, the 1 day's count would be representative of the missing 2 days. This counting method would reduce the count duration by 2 full days and increase the chance that the sensors would stay in place for the duration of the count.

Tests of this approach showed a reduction in the accuracy of the traffic estimate; however, this reduction did appear to be evenly distributed about the true AADT. Removing 2 weekdays from the count (i.e., counting Thursday through Monday, or Friday through Tuesday), decreased its accuracy. This decrease ranged from 1 percent or 2 percent at sites with stable vehicle classification volumes, and from 6 percent to 10 percent at sites with unstable vehicle classification volumes. In general, sites with stable vehicle classification volumes had higher traffic volumes and no especially severe traffic movements. Sites with unstable vehicle classification volumes often had very high peak recreational traffic movements or low volumes of traffic. Some sites had stable traffic conditions in some vehicle classifications, but not in others.

This methodology appeared to heighten the sensitivity of the annual estimate to the "representativeness" of specific days of data. That is, if the 1 weekday included in the volume estimate was actually representative of the "normal" traffic conditions, then the annual estimate was accurate. If the one weekday included in the count was "unusual" for some reason, the effects of this "unusual" count were magnified by a factor of three.

With lower volume vehicle classes, this magnification could lead to measurable increases in the error associated with annual volume estimates. However, this error might or might not be significant for the purposes of pavement design. The importance of the error in volume estimates for specific vehicle classes would be affected by the volume of

other truck classes on the road, the average load for that specific class of vehicle, and the pavement design itself. Unfortunately, the pavement depth designs for lower volume roads are usually the most sensitive to errors in the truck loading estimate, and the lower volume roads are most susceptible to having "unusual" traffic volumes on a given day. Conversely, high volume freeway sections with thick pavement designs are relatively insensitive to errors in the estimate of vehicle loading.

COUNTS NEEDED FOR A STATEWIDE PAVEMENT MANAGEMENT SYSTEM (PMS)

The project team examined written material describing nine states' pavement management systems. These states included

- Arizona,
- Arkansas,
- California,
- Florida,
- Idaho,
- Minnesota,
- Nevada,
- Ohio, and
- Washington.

In all of these states, some measure of traffic was used in the pavement management system. However, in none of these systems did truck volumes or an estimate of actual equivalent single axle loads (ESAL) play a leading role in the determination of expected pavement deterioration rates or pavement rehabilitation prioritization.

In almost all cases, the need for pavement maintenance or rehabilitation was determined by the current pavement condition and the expected remaining life of that pavement. The expected life was predicted in years, not ESALs, and was usually a predetermined function based on standard deterioration curves adjusted (in some cases) to reflect actual pavement performance. In none of the examined PMS were the deterioration rates based directly on ESAL estimates measured on individual road segments.

The literature review showed that traffic and/or truck volume estimates were used only peripherally in pavement management systems. Often, some measure of traffic (usually AADT, occasionally truck percentage) served as a variable that categorized the expected deterioration rate into one of several deterioration regimes (high, medium, or low rates of deterioration). In several states, traffic estimates were also used to help determine the expected cost of the maintenance/rehabilitation projects required to correct network or project deficiencies as part of the network optimization/budget preparation phase of the pavement management system. In no case reviewed was the pavement management system sensitive to expected ESAL loading changes based on monitoring of actually applied loads or traffic volumes. One state that used a site-specific, automated, pavement design module to estimate the cost of maintenance and rehabilitation needs did indicate a desire to upgrade its existing PMS-based design process to account for growth trends developed through a permanent vehicle classification system.

The use of cumulative years and current pavement condition to determine expected pavement life within the structure of PMSs, rather than the use of cumulative ESALs, was in part due to the lack of valid truck data available at the time these systems were designed and implemented. Deterioration rates were used to predict remaining pavement life, rather than actual loading rates. Deterioration rates were used partly because the PMSs lacked accurate loading data and partly because the use of actual deterioration rates allowed the PMS to account for a variety of causes of pavement deterioration (e.g., poor quality construction, unexpected environmentally caused distress, poor mix performance), in addition to differences between the expected and predicted loading rates.

Several states expressed a desire to use ESAL values directly within the equations incorporated in their PMS. The necessary revisions to PMS procedures would be performed as part of ongoing efforts to update and improve the pavement management systems. Specific revisions discussed would generally have the PMS perform more in-depth design work for pavement rehabilitation and maintenance.

CHAPTER 4

IMPLEMENTATION

This chapter addresses the implications of the findings presented in the previous chapter, and the impacts of the findings on the implementation of factoring procedures for improving the estimation of annual truck traffic volume estimates.

IMPLICATIONS OF THE FACTORING ANALYSES

None of the factoring approaches selected and tested within this effort consistently produced annual traffic estimates within the accuracy desired. The limitations in the techniques tested appear to be due primarily to the variable nature of truck traffic and the relatively low volume of truck traffic (within some vehicle classes) on many highways rather than to problems inherent with the techniques tested. Unless a new technique can be developed that can more accurately account for the variability inherent in truck traffic volumes, it is unlikely that a factored, short duration truck count on a moderate to lower volume road will be within 25 percent of the actual value, 95 percent of the time.

However, while the factoring procedures tested in this project do not provide annual truck volume estimates within tight error bounds at many locations, application of seasonal and weekday/weekend adjustment factors does provide significant improvements to estimates of annual truck volumes. These improvements exist both from a moderate reduction in variation present in the annual estimate and from a substantial reduction in the bias associated with that variation.

According to the analyses performed for this project, the best method of accounting for seasonal and day-of-week variation in truck traffic volumes is to count traffic at a site multiple times during a year, and then to average those counts. The preferred methodology is to collect data four times during the year. Each count should be 1 week long and the four counts should be spaced equally throughout the year (i.e., at

3-month intervals), this method of data collection and analysis provides estimates of annual truck volumes within 7.5 percent to 12.2 percent of the true value 95 percent of the time.

Because this data collection methodology is expensive, it is probably not a practical approach for producing all truck volume estimates. However, this method should be used whenever new pavement will be applied to a highway; because the potential benefits from accurate data are very large, given the cost of any pavement project (usually over $1 million in direct costs) and the relatively low cost of vehicle classification data collection activities using portable, automatic classifiers.

For most other truck volume data needs, the benefit obtained from the increased accuracy of multiple counts is not outweighed by the cost of collecting the data. In most states, two sources of traffic counting funding are available, funding for specific projects (charged to that project budget) and funding for general purpose traffic counts. Given the limited availability of these "general purpose" funds, the project team recommends the development of a short count factoring procedure for use in improving the annual truck volume estimates available to other data users who do not have access to additional data collection funding.

Because low volumes appear to cause a significant portion of the variation inherent in the truck traffic estimates, the project team recommends that this factoring procedure be based on an aggregated vehicle classification scheme, rather than FHWA's 13-category Scheme F. While this research did not attempt to identify the appropriate number of classification categories, a general rule of thumb the project team devised on the basis of its use of Washington data is that the number of vehicle classes should range between four and six. These vehicle classes should be aggregates of classes routinely collected by a state as part of its ongoing data collection effort. (That is, the vehicle classifications could be either length-based, or an aggregation of axle-based vehicle classes.)

Limiting the number of classifications reduces the chance that individual vehicle classes will include so few vehicles that the adjustment factors computed for those classes will not be statistically reliable. The development of these vehicle classes should be state specific and should entail a review of the travel patterns of different vehicle types, the availability of seasonal pattern information from permanent counting devices, and the types of vehicle classification equipment used by the state.

The "best" factoring technique investigated in this project was the regression approach using monthly seasonal factors aggregated over several years as dependent variables. This approach has several major advantages and disadvantages that are highlighted below.

Advantages of using the regression approach described in Chapter 3 include the following:

- The regression approach allows direct testing of specific, independent variables. The testing determines the factors that affect seasonal variation of truck travel.
- The final product of the regression approach is a simple, easy to apply methodology that eliminates much of the human error present in the application of traditional seasonal factors to individual, short duration counts.
- The use of multiple independent variables allows the creation of more "factor groups" than would normally be realistic with traditional factoring procedures, without making the application of those factors unnecessarily complex.
- The use of the decomposition method to aggregate multiple years of data for a permanent site reduces the impact unusual variation has on the computation of seasonal factors. (For example, the presence of a construction event near a permanent recorder site will not bias the seasonal factors computed for the year as much as it would if only one year of data were used.)

- Similarly, the decomposition approach moderates the effects of variability in year-to-year truck volumes at a site and provides a more stable seasonal factor applicable to a wider range of sites.

Disadvantages of the regression approach are as follows:

- The regression approach is considerably more complex than traditional factoring procedures and may be difficult for state DOT personnel to implement correctly.
- The limited data sets available for inclusion in the development of the regression equations may make some of the regression output unreliable or biased towards the available data.
- Where "unusual events" are geographically widespread (e.g., the Mt. St. Helens eruption), the decomposition method limits the impact of those unusual traffic patterns on AADT estimation by discounting the "unusual" traffic patterns. This biases the estimation of annual conditions at sites that actually were impacted by those unusual conditions by under estimating the impact of those conditions.

The modified cluster procedure is also an acceptable method for developing factor groups. Both of these methods could be improved upon, and additional research should be pursued to develop better techniques.

IMPLICATIONS FOR PAVEMENT MANAGEMENT SYSTEMS

The literature findings discussed in the previous chapter suggest that the improved accuracy of truck volume estimates possible through the factoring techniques discussed in this report will have a relatively limited, direct impact on existing pavement management systems. (By pavement management system, this discussion includes that part of the PMS that predicts the need for rehabilitation and/or maintenance work and estimates the anticipated design or cost of that work.)

This is not to say that significant advantages will not be obtained from improvements in the truck loading estimates used to design pavements. Improvements to pavement management will occur as a result of the design of new pavement sections and the selection and design of maintenance and rehabilitation treatments at sites identified by the PMS. These pavement designs will perform better than their predecessors because the load estimates used in the designs will be more accurate as a result of improved truck volume and load forecasts based on permanent counter site data.

Because traffic plays only a peripheral role in the estimation of deterioration rates, improved estimates of actual loadings will not change the expected deterioration rates associated with individual pavement sections. Instead, these deterioration rates will continue to be based on current pavement condition, historical performance, and expected pavement deterioration rates. In some cases, and for some states, improved loading estimates will change specific pavement sections from one "deterioration curve" to another (e.g., the section will move from a "low traffic" deterioration curve to a "high traffic" curve). These changes will result in better deterioration rate estimates; however, improvements related to the accuracy of pavement deterioration rate predictions should be relatively minor.

The real improvements in pavement performance will come from the design phase for projects identified as needing rehabilitation or maintenance. Once these projects have been identified by the basic PMS, states should arrange for site-specific vehicle classification counts at those sites, following the count duration and factoring guidelines described in this report. The result of these counts will be a very reliable estimate of baseline traffic loading for use in the design process. While error will still exist in the final loading estimate used for the pavement design (primarily as a result of the errors inherent in forecasting traffic conditions), the potential for a pavement design reaching its expected design life (in years) will be greatly enhanced. When safety factors are included in the pavement design, as recommended in the current AASHTO pavement design

procedures, to account for the variation inherent in input variables (traffic, soil condition, materials) the number of pavement sections meeting or exceeding their expected design life should increase.

Over time, as more pavement sections reach or exceed (thanks to the safety factors) their expected design lives, improved design and forecasting procedures should result in improved pavement performance for the system as a whole.

A second advantage of improved traffic load estimates is that they will allow forensic analysis of failed pavements. The Strategic Highway Research Program's Long Term Pavement Performance (LTPP) effort is a large-scale effort to review existing design assumptions and determine better pavement design procedures. However, most states undertake forensic reviews of pavements that fail prematurely to determine the cause of their failure. Lessons learned from these forensic studies are then applied to future pavement projects to prevent similar premature failures from occurring.

One common cause of "premature" pavement failure is the use of load estimates that significantly underestimate the actual level of traffic loading. The underestimated load results in a pavement that actually meets it design life in ESALs but fails prematurely in terms of the number of years it lasts. For example, if a pavement is designed to withstand 1 million ESALs per year for 7 years, but actually receives 2 million ESALs per year in loads, the pavement will fail in 3.5 years. The perception is that the pavement failed prematurely, when in actuality, the pavement met its design criteria (7 million ESALs).

By using a relatively small sample of vehicle classification counts and accurately factoring those counts to represent annual conditions, engineers will be able to reliably estimate actual loadings on a pavement section. This precision will allow an accurate forensic study of failed pavements and will, in turn, significantly improve subsequent pavement designs for those road sections. Eventually, statewide pavement design procedures will be markedly improved.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

CONCLUSIONS

The analyses described above indicate that in most cases, an unadjusted, 24-hour vehicle classification count is a poor estimate of average annual conditions. At most sites, an unadjusted, 24-hour weekday count will consistently overestimate the annual average number of larger trucks (tractor semi-trailer and larger combination vehicles) using that road.

Except during the peak recreational travel periods, unadjusted weekday counts will underestimate the average annual volume of RVs using the roadway. If counts are taken during peak recreational periods, weekday counts will overestimate the average annual RV volumes.

A comparison of the Length Bin 1 patterns (Length Bin 1 is primarily automobiles and pick-ups and contains the vast majority of total vehicle volumes) to the other three vehicle length classifications shows that in most cases, the use of traditional seasonal factors to adjust short-duration truck volumes is inappropriate for estimating average annual truck volumes. The analyses described in this report show that during most portions of the year, the seasonal adjustments for different vehicle classes are significantly different.

Where the monthly adjustments for both total volume and individual vehicle classes are all above or below 1.0, use of an adjustment factor based on total volume will usually improve the AADT estimate, although this improvement is rarely as good as that produced by a class specific factor. When one factor (either the factor for total volume, or the factor for the specific vehicle class) is above 1.0 and the other is below 1.0, the adjustment based on total volume will always provide an estimate of total truck traffic that is worse than the unfactored volume estimate.

Seasonal adjustment factors for truck volumes can be developed from data routinely collected by permanent vehicle classification counters. Use of these adjustment factors will improve the estimation of annual average truck volumes, but not with the accuracy associated with total volume adjustments currently performed using seasonal factors developed using conventional ATR equipment.

Where funding allows, a more accurate estimate of annual truck volumes (by class) can be obtained by counting several different times during a year at that site. These multiple counts should contain data from an equal number of the seven days of the week and be spread evenly throughout the year. Four, week-long counts are recommended to provide annual estimates within $\pm$ 10 percent, 90 percent of the time at specific sites.

Improvements made in the estimation of annual vehicle volumes by vehicle classification will have a positive impact on a state's pavement management system both as a result of improved pavement life due to better design information, and as a result of more accurate forensic analyses for those pavement sections that fail prematurely. While most PMS do not use truck volume estimates directly in their pavement deterioration prediction functions, improvements to the accuracy of truck volume estimates should produce long term improvements in pavement life as a result of improvements in pavement design information.

RECOMMENDATIONS

The project team recommends that wherever possible and financially appropriate, each state should collect multiple, site specific vehicle classification counts whenever pavement design projects are to be performed.

Where it is impractical to collect this much data at a specific site, seasonal adjustments should be applied to individual short duration vehicle classification counts. These adjustments should be based on permanent vehicle classification counters operating year round, not on seasonal factors based on total volume counts.

In most cases, aggregated vehicle classifications should be used for developing seasonal factors. The 13 FHWA vehicle classifications are too disaggregated to provide stable seasonal adjustment factors for the majority of moderate and low volume rural roads. For these roads, a more stable factor applied to all FHWA vehicle classifications within that aggregated group is preferable. The exception to this recommendation is for high volume interstate and principal arterial routes, where sufficient volume is present to calculate stable adjustment factors for all 13 FHWA classifications.

APPENDIX A

INTRODUCTION TO THE DECOMPOSITION METHOD

APPENDIX A

INTRODUCTION TO THE DECOMPOSITION METHOD

This analytical method was selected both because it is a relatively simple type of time series analysis, and because it could help reduce the impact of the year to year seasonal factor variation for the lower volume traffic counter locations.

INTRODUCTION

The decomposition method is a time series technique designed (in the context used for this study) to convert monthly factor values from multiple years into a single set of 12 month moving averages. Use of averages reduces the impact of unusual traffic patterns caused by "special" events that occur near traffic counting devices, but that may not be applicable to counts spread over a wide geographic area. (For example, construction may occur near the counter. The decomposition method balances the seasonal trend for this year (impacted by the construction activity) with the normal trend observed over the past few years.)

A number of variations exist within the basic analysis process labeled "decomposition." The "classic" decomposition method assumes that time series data (such as daily traffic volumes) are made up of some pattern plus an error component. The pattern itself consists of three parts, a trend line (up, down, or unchanging), a cyclic term, and a seasonal term. The error term accounts for the unexplained variability (i.e., randomness) within the pattern itself. The cyclic term was designed to account for the cyclic nature of business cycles (decomposition was developed in the 1920's by economists studying business trends), and is not directly applicable to vehicle volumes. For our project, the cyclic term was ignored.

MATHEMATICS

This appendix can is not appropriate for teaching the decomposition method. This report simply provides an outline of the steps involved in the process. The reader is referred to standard texts on statistics for more information on this technique. An initial reference is "Forecasting, Methods and Applications," by Spyros Makritakis, Steven Wheelwright, and Victor McGee, 1983.

The decomposition method selected (called Census II) consists of four basic steps. The first step is called "Trading Day Adjustments." It is used to adjust monthly values for differences in the number of days included in each month. Because our analysis uses average weekday values already (and incorporates the AASHTO mechanism for accounting for differences in the number of weekdays in each month), this step is not necessary for the factoring analysis.

The next step in the Census II technique is a preliminary estimation of seasonal factors and a preliminary adjustment for seasonality. The tasks involved in this second step are as follows.

- Monthly average weekday traffic volumes are computed for each month for each site using the process described in the main body of this report.
- A centered 12 month moving average of these values is calculated for use with every month of data. (This is illustrated in Figure A-1.)
- Average monthly seasonal estimates (SE) are then computed by dividing the average monthly weekday volumes by the corresponding 12-month moving average and multiplying by 100.
- A 3 X 3 moving average of the different SE values for each year is then computed for each month of estimates at each site. (See Figure A-2.)
- The standard deviation of the annual differences between the initial monthly estimate and the 3 X 3 MA factor is then computed. (See Figure A-3)

Year	Month	Data
1988	1	MAWDT1
	2	MAWDT2
	3	MAWDT3
	4	MAWDT4
	5	MAWDT5
	6	MAWDT6
	7	MAWDT7
	8	MAWDT8
	9	MAWDT9
	10	MAWDT10
	11	MAWDT11
	12	MAWDT12
1989	1	MAWDT13
	2	MAWDT14
•	•	•
•	•	•
•	•	•

To compute a centered 12 month average for the seventh month, compute two different averages, one centered on month 6 and one centered on month 7. Then average these two values.

12 Month Average 1 = MA1 = (MAWDT1 + MAWDT2 + ... + MAWDT12) / 12

12 Month Average 2 = MA2 = (MAWDT2 + MAWDT3 + ... + MAWDT13) / 12

Centered 12 Month Average = (MA1 + MA2) / 2

This process leaves six months at the beginning and end of the time series for which 12 month averages can not be computed. These values are estimated later in the analysis process as described in the text.

Figure A-1. Illustration of Computation of a Centered 12 Month Average (C12MA)

For Bin 4, May

Year	Initial Estimates (MAWDT / C12MA) or SE	Introduction of Extra Values[1]	3 Month Moving Average (3MA)	3 X 3 Moving Average (3X3MA)
		122.8		
1987		122.8	117.0	
1988	105.3	105.3	122.8	118.6
1989	140.3	140.3	116.1	117.5
1990	102.7	102.7	113.7	110.1
1991	98.2	98.2	100.5	104.4
		100.5	99.7	
		100.5		

Figure A-2. Computation of a 3 X 3 Moving Average

[1] 122.8 is computed as (105.4 + 140.3)/2. 100.5 is computed from (102.7+98.2)/2

Year	Initial Estimate	3X3MA Factor	Deviations Squared
1988	105.3	118.6	176.9
1989	140.0	117.5	506.3
1990	102.7	110.1	54.8
1991	98.2	104.4	38.4
		Σ =	776.4

The standard deviation is the square root of the sum of the squared deviations, divided by the number of cases. SD = Sqrt(776.4 / 4) = 13.9

The 1989 value of 140.0 is considered extreme because 140 > 117.5 * 1.5 = 138.4

The 1989 value is replaced with the average of the 1988 and 1990 values
repalcement = (105.3 + 102.7) / 2 = 104.0

Figure A-3. Calculation of Standard Deviation of the Difference Between Initial and 3X3 Factors and Replacement of Extreme Values

- The standard deviation computed above is then used to determine extreme values. Extreme values are determined as those initial monthly factors which lie more than a specified number of standard deviations away from the 3 X 3 MA. (For this project we determined that values that were greater than 1.5 times the standard deviation from the norm were extreme values and should be replaced.)
- Extreme SE values are then replaced by the average of the initial SE values of the years preceding and following the year in question. (See Figure A-3)
- Missing data are replaced in the same manner.
- The missing 6 months of 12-month centered moving averages at the beginning and end of the time series are then estimated as the moving 12-month average for the corresponding months in either the year after (for the first six months) or before (the last six months) the missing data.
- The 3X3 moving averages are then recomputed using the revised/edited data. (Call these 3X3SEA)
- Preliminary seasonal factors are then calculated by dividing the original monthly average weekday traffic volumes by the corresponding seasonal value from the 3X3SEA matrix.

This completes the second step of the Census II procedure. The third step refines these preliminary estimates of seasonality, and computes the effects of trends and randomness.

- Randomness in the preliminary estimates is removed by applying Spencer's 15-month weighted moving average (a 5X5X4X4 MA).
- To avoid loss of seven values at the beginning and end of this series, missing values are estimated as before (the average of the previous months).

- The final seasonal irregular values are calculated by dividing the values given by Spencer's 15-point formula into the original data.
- As applied in the previous steps, replace extreme values and adjust the ratios so they sum to 1200, and recalculate the 3X3 MA.
- To get the final seasonal factors in terms of AADT, multiply the seasonal factor obtained in the previous step by AAWDT and divide by AADT.
- These values are the "stable factors" or average seasonal adjustments for the vehicle volumes.

The final step in the Census II process is the computation of summary statistics. Rather than using the decomposition method's statistics, we directly applied the factor estimates to the actual daily vehicle classification counts, and compared those annual estimates with the known AADTs. These results are described in the main body of this report.

COMMENTS ON USE OF THE DECOMPOSITION METHOD

While this technique seems convoluted and complex, it can be computerized, so that little staff intervention is require. It remains to be seen whether improvements in the accuracy of AADT estimates from applying this technique in other states warrant the difficulty in explaining it and training staff in its use. Other issues that should be examined when considering the use of the decomposition method are discussed below.

One of the main advantages of the decomposition technique is that it allows the calculation of the impact of missing values on seasonal factor estimates (e.g., the loss of a month of data from a permanent recorder due to equipment failure.) This calculation is based on the impact of replacing extreme values with expected seasonal averages. Essentially, in the decomposition method, if a month of data is normally an extreme point (July is always high) the value used by the decomposition method to replace the missing point is also extreme, so any error introduced will be small. If the missing data point is actually abnormal (either abnormally high or low, for example, that July had extremely

low volumes), the decomposition method would have identified the month as an outlier and replaced it anyway.

Therefore the results of the analysis with or without the missing month's data would be fairly similar, and the "error" calculated by the procedure is still fairly small. Essentially, the "error" allowed by the decomposition method is determined by the extreme value replacement statistics used in the analysis (in the case of this project 1.5 standard deviations), and for our tests is limited to about 10 percent. This estimate is based on actual computations made by removing valid extreme data points from the test data sets, recomputing the seasonal factors, and measuring the changes in accuracy of AADT estimates produced by the new seasonal factors.

The problem with the replacement of extreme values by the decomposition approach is that it automatically removes "real" extreme values from the seasonal factor computations. If editing has been done before hand (so that there is confidence in the reliability of the monthly estimate that has just been discarded), this will bias the seasonal factor computation towards "normality" and away from the truth. That is, the decomposition process resists the incorporation of "unusual" data in the computed factors. This will create errors if the "true" factors are indeed "unusual." On the other hand, if the raw data editing process is weak, this approach prevents data of marginal quality from significantly biasing the computation of AADT estimates.

Another concern is the averaging of more than one year of data to estimate seasonal factors. Use of multiple years of data means that the factoring process no longer tracks individual yearly events. This produces a trade-off between understanding the "normal" (and thus expected) seasonal patterns versus knowing what actually happened during the year in question.

The argument for tracking yearly events is that those events did indeed take place and should be reflected in the AADT calculations. This is particularly true if the AADT calculations are "revised" at the end of each year so that "current year" factors are applied

to the estimates. (That is, when a count is taken in July of 1993, it is impossible to use a 1993 factor to estimate 1993 AADT until after December 31, 1993. The factor applied, at least initially, is usually based on 1992 seasonal information.) In most states, "preliminary" estimates are not revised to reflect differences in the annual seasonal factors. (That is, the 1993 AADT estimate computed with 1992 seasonal factors is not revised in 1994 to reflect 1993 seasonal patterns.)

Where this revision does not take place, use of multiple years of data to calculate seasonal factors is preferable to using a single year of data. Using multiple years of data will provide a better measure of "normal" conditions than the use of a single (but wrong) year of data. (This is primarily due to the impact of differing weather conditions on travel patterns.)

It is not clear whether seasonal factors developed from multiple years of data are "better" estimates than those based on revised "actual year" seasonal patterns (i.e., revised factors). (The AASHTO guidelines sidestep this issue. They recommend the use of same year factors, but acknowledge the use of multi-year factors.) The use of multiple year patterns (particularly with smoothing) will tend to reduce the impact of unusual events on the factor calculation. If the unusual events are point based (something caused traffic near a permanent counter to be unusual), then this smoothing will improve the accuracy of the factors, particularly as the factors are applied over a large geographic area. If the "unusual" trend affects a wide area, the smoothing will bias the AADT calculations away from this trend.

For example, in the case of the Mt. St. Helens eruption, the use of the multiple year technique is worse than using the factors for that year, because traffic volumes during the month immediately following the eruption were highly unusual for most roads in the state. If the "normal" seasonal factor is used (whether it be obtained from the previous year or from multiple years), the factoring process will assume that more vehicles are using the roads than actually are.

In the case of major construction activity on a road near a permanent counter, the effect of the smoothing caused by multiple years of seasonal data is good. Roads not experiencing the effects of that construction event are likely experiencing their "normal" seasonal fluctuations. Thus, using the multiple years of data will provide a more accurate estimate of seasonal fluctuations, especially when that method automatically excludes extreme values as does the decomposition method described above.

The unanswered questions are as follows. Where do the effects of major snow storms and other types of disruptions fit within the above continuum? What about the effect of abnormal winter conditions (e.g., the lack of snow for an entire winter in an area that normally experiences snowfall?) What about the impacts of general economic conditions on recreational traffic?

Because these questions can not be answered at this time, it is difficult to select between the proposed methods. In general, using factors from multiple years will be better where variation from year to year is low, and using a single (correct) year will be better, where variation is high, and the effects of unusual events need to be incorporated in the factor process.

APPENDIX B

REGRESSION METHOD FOR DEVELOPMENT OF SEASONAL FACTORS

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REGRESSION METHOD FOR DEVELOPMENT OF SEASONAL FACTORS

This appendix describes the criteria used for selecting independent variables as part of the multi-variable, regression approach to developing seasonal factors for estimating annual truck volumes from short term truck counts. As noted in the main body of this report, a series of potential independent variables were selected for analysis. These variables were used to indicate the existence of a particular characteristic for each site. If a site had that characteristic, it received a unit value of one (1) for that variable. If the site did not have that characteristic, the variable was given a value of zero.

As part of the analysis, it was determined that several of the important independent variables appeared to have synergistic reactions. (That is, the presence of two specific variables acting together had a different impact than the effect of those variables acting independently.) As a result, a series of "interaction" variables were defined. These variables were created specifically to test the interaction of some of the independent variables.

One exception to the dummy variable approach was the creation of a variable that represented the effects of total volume (by class) on seasonal fluctuation. That is, the higher the volume of trucks, the less dramatic was the fluctuation in traffic volumes throughout the year. The "dummy value" for the volume variable was set equal to the actual traffic volume count expressed in units of 1000 vehicles for Bins 2, 3, and 4 and units of 10,000 vehicles for Bin 1. For example, for a site with a short count volume of 1,325 vehicles per day, the independent variable used in the seasonal factor calculation would be 1.33.

The dummy variables used as input to the analysis are shown below.

Urban/Rural/Intermediate Designation
- Urban = 1 if the route is in an urban area
- Inter = 1 if the route is not really in a rural or urban location

Functional Class

inter = 1 if the route is an interstate highway
part = 1 if the route is a principal arterial
mart = 1 if the route is a minor arterial
collec = 1 if the route is a collector

Location

east = 1 if the route is located in eastern Washington
central = 1 if the route is located in central Washington
ec = 1 if borderline between eastern and central Washington

Recreational

rec = 1 if the route served recreational movements

Agricultural

agr = 1 if the route served agricultural harvest movements

Interaction Variables

recart = 1 if recreational and principal arterial
reccent = 1 if recreational and central
receast = 1 if recreational and eastern
recec = 1 if recreational and east/central

Other

volume = volume in 10,000 vehicles for Bin 1
= volume in 1,000 vehicles for Bins 2, 3, and 4
hrv = 1 if high proportion of RVs
I5 = 1 if the site was on interstate 5
I90 = 1 if the site was on interstate 90.

Once the dummy variables were created, the project team ran a step-wise regression analysis to determine which of the proposed independent variables caused a statistically significant improvement in the accuracy of the estimate of annual conditions. This analysis was performed using a common statistics package. (We used the "S" statistics package, but any commonly available package such as SAS, or SPSS can be used to perform these tests.)

Note that an independent variable did not have to be considered significant for all twelve seasonal factors. The analysis considered that each monthly seasonal factor was independent of the other monthly seasonal factors.

The project team used three separate statistical tests to determine which independent variables should be kept for each seasonal factor. These tests were the T-test (which was used to determine whether including that independent variable significantly

improved the prediction of the annual condition), the R-squared value (which was used to provide a measure of the overall quality of the prediction of annual conditions), and the F-test (which was used occasionally to confirm that a relationship between the selected variables existed.) Each of these tests is discussed below.

The T-test was the most commonly used statistic for evaluating the coefficients in the regression model. It was used to determine whether the calculated coefficient for each regression model variable was significantly different from zero. If this test was true, the coefficient was incorporated into the factoring process, provided it improved the accuracy of the factor being developed.

For the project tests, the value for the degrees of freedom was set to the number of cases in each dataset. When the level of significance (commonly called "alpha" in statistics) is set equal to 0.05, the standard T-test uses a rejection level of 2.0 (the "2-T rule of thumb"). We used a lower rejection level of 1.0 because of the high degree of variability in the data set. A T-test criteria of 1.0 corresponds to a level of significance of roughly 30 to 35 percent for a two-tailed test.

The R-squared statistic provides a measure of the variance explained by the regression equation being tested. Generally, the higher the R-squared value, the better the equation. However, the R-squared test is susceptible to scale problems that exist in traffic volume estimates, so that it is possible to have high R-squared values for poorly fitting equations and/or fairly low R-squared values for equations that provide reasonably good predictors. (Essentially, the R-squared test does not measure "fit" well when some sites have high volumes and others have low volumes. In these cases, the accuracy of low volume sites is heavily discounted by the accuracy of the high volume sites.)

R-squared is also impacted by the number of variables included in the multi-variate equation. As more variables are added, R-squared has a tendency to increase, even when the predictive quality of the equation does not improve. This problem can be

resolved by using a corrected R-squared value. This corrected R squared is the value reported in the main body of this report.

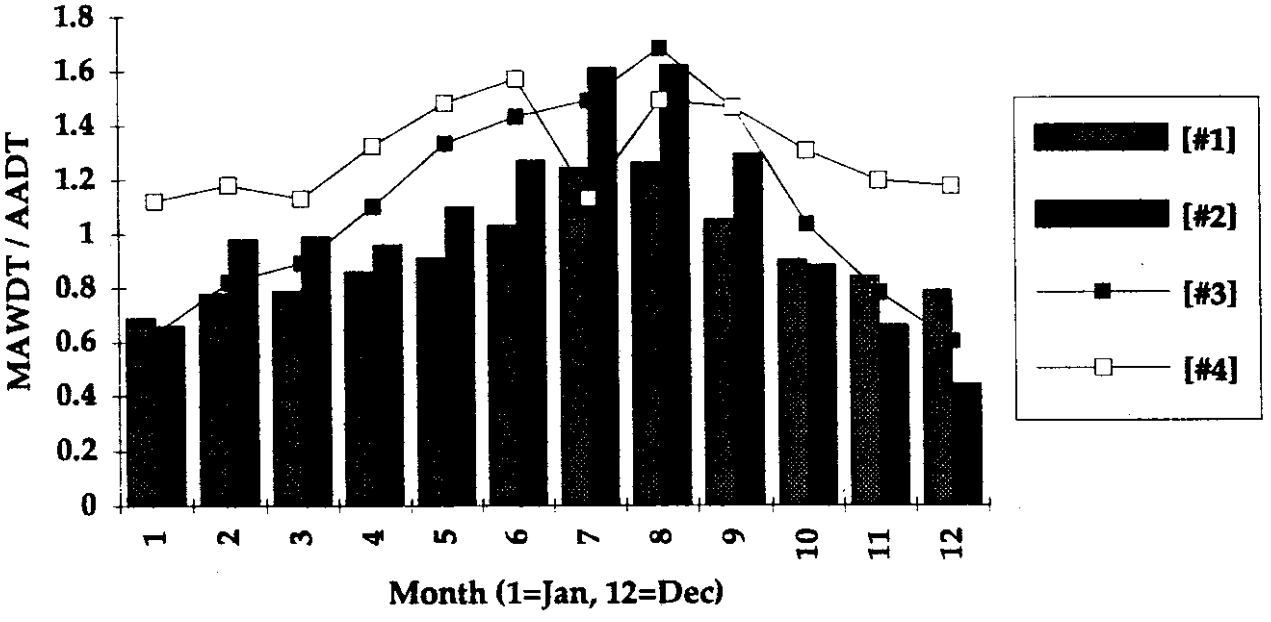
The R-squared statistic is a relative measure of "goodness of fit." Therefore, no specific "acceptance/rejection" criteria is associated with this test. For this project, the R-squared values were relatively low. This indicates that a large portion of the variability inherent when adjusting short term counts in order to estimate annual conditions could not be accounted for by the regression equation. This was not surprising. However, as noted in the main body of this report, the regression equations did contain a significant predictive capability, significantly improving the annual estimates, even though the R-squared values were often quite low.

The final test used was the F-statistic. This statistic was only used as a reasonability check, because when the T-test and R-squared values are reasonable, the F-test also tends to be acceptable.

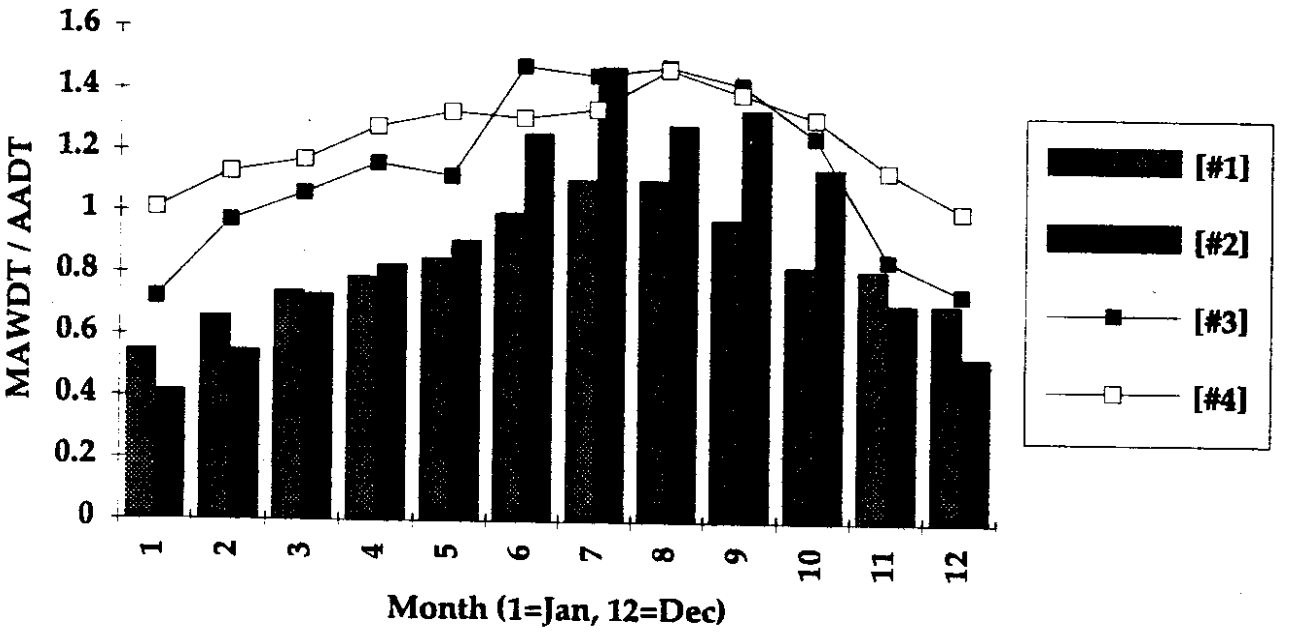
APPENDIX C

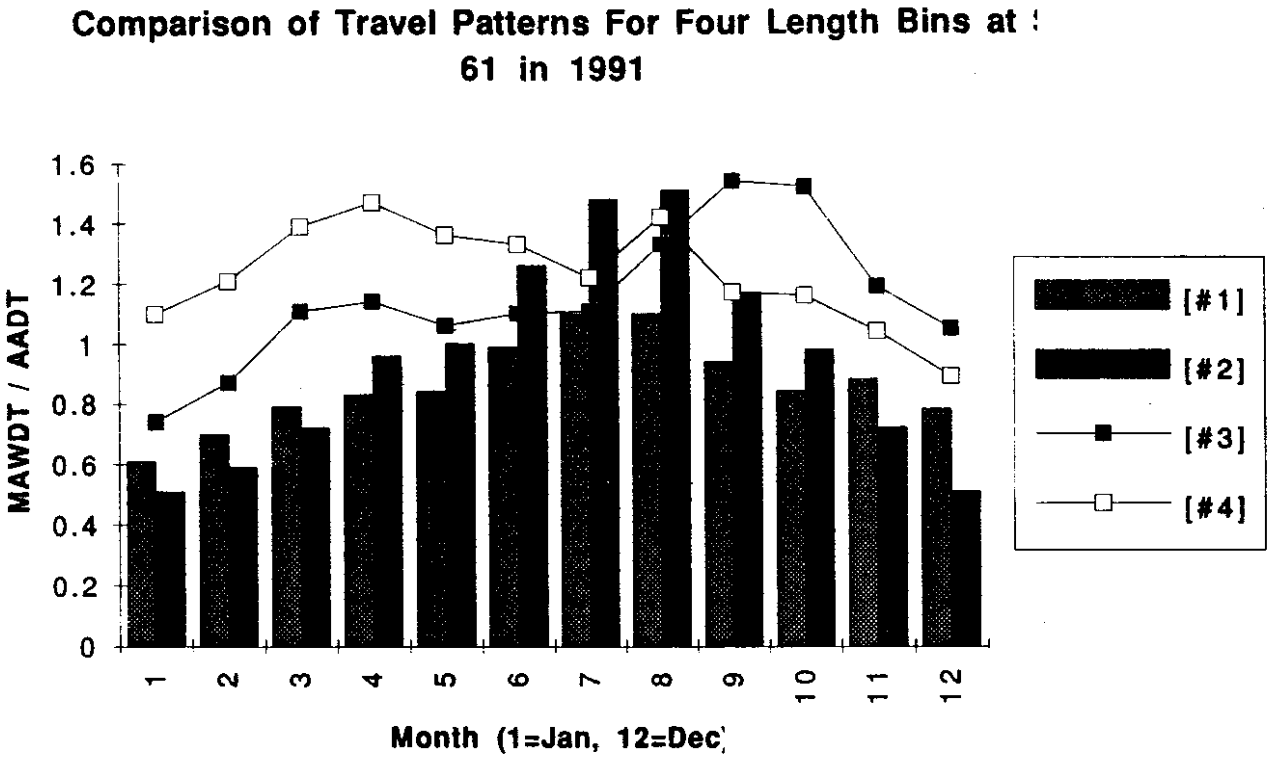
ADDITIONAL GRAPHICS ON TRUCK SEASONALITY

Comparison of Travel Patterns Between Four Length Bins at Site 85 in 1991

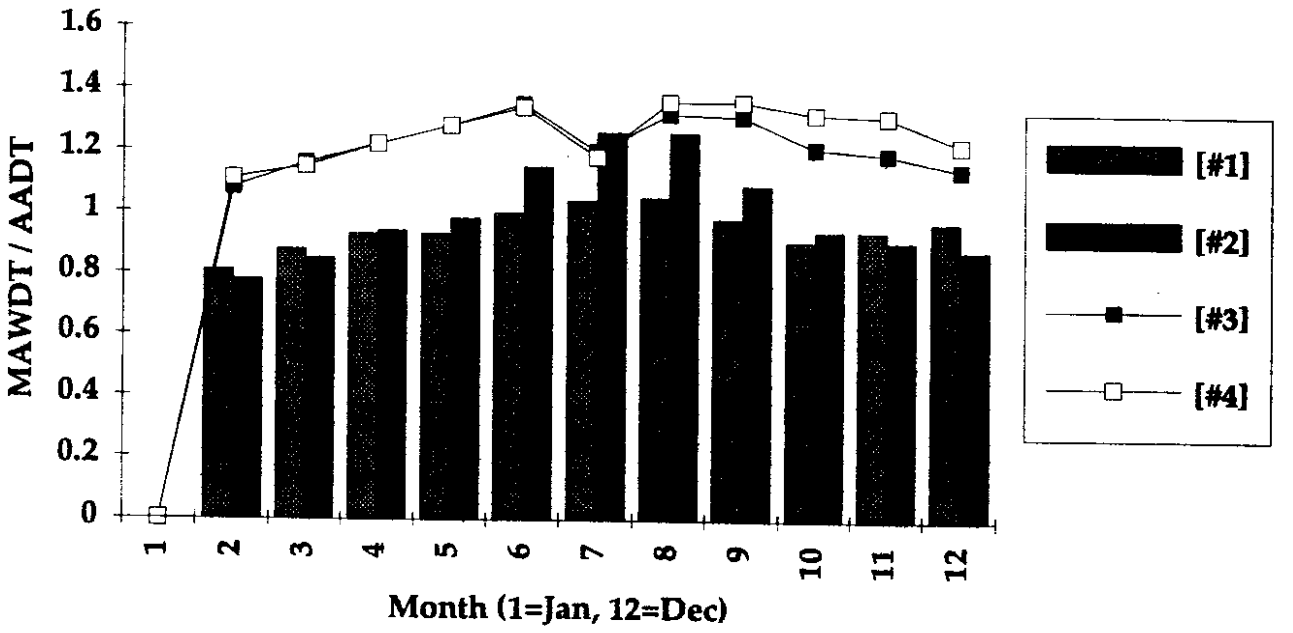


Comparison of Travel Patterns For Four Length Bins at Site 67 in 1991

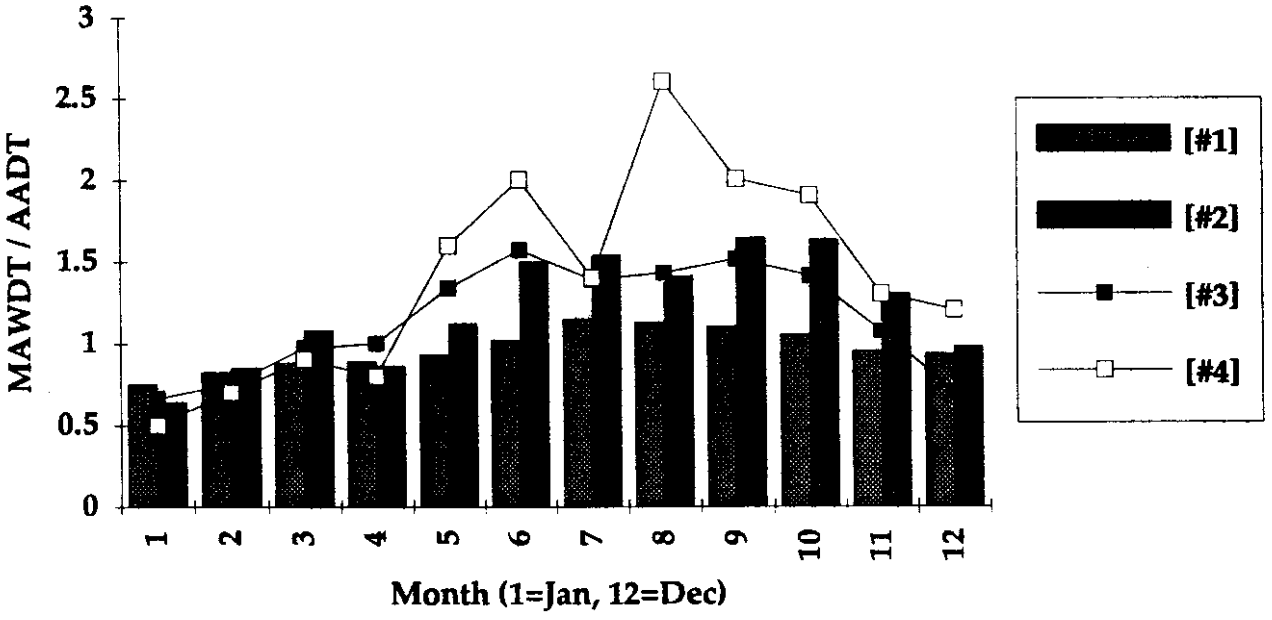



Comparison of Travel Patterns For Four Length Bins at
61 in 1991
MAWDT / AADT
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
2
3
4
5
6
7
8
9
10
11
12
Month (1=Jan, 12=Dec)
[#1]
[#2]
[#3]
[#4]

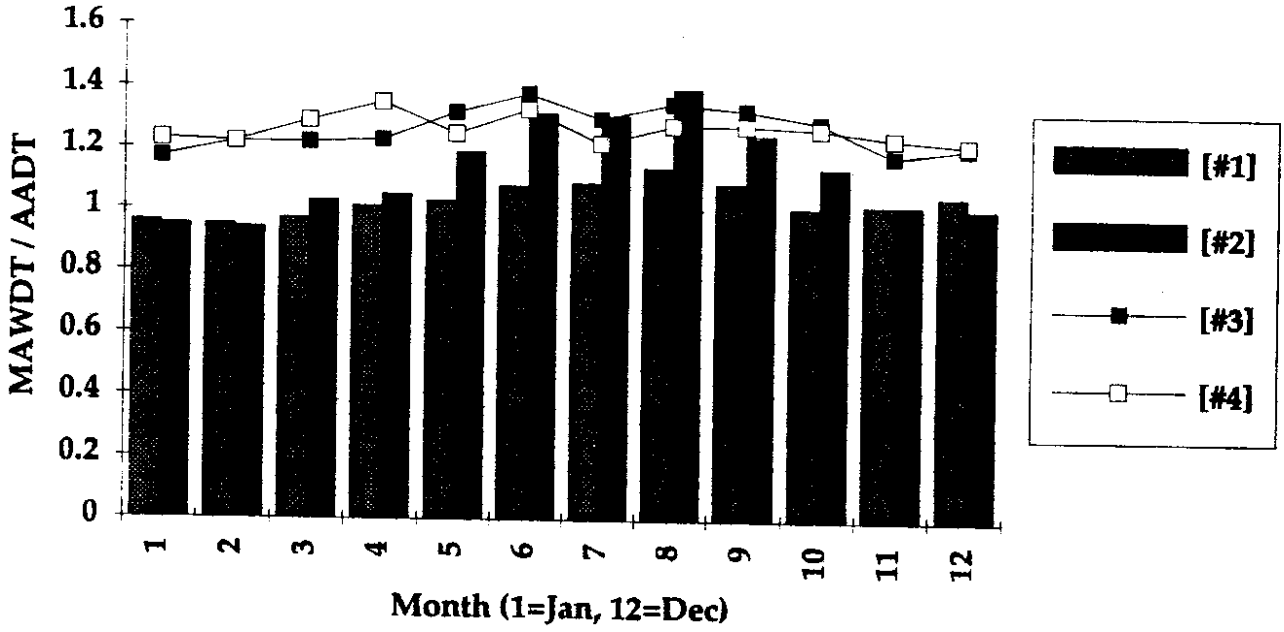
Comparison of Travel Patterns For Four Length Bins at Site 60 in 1989



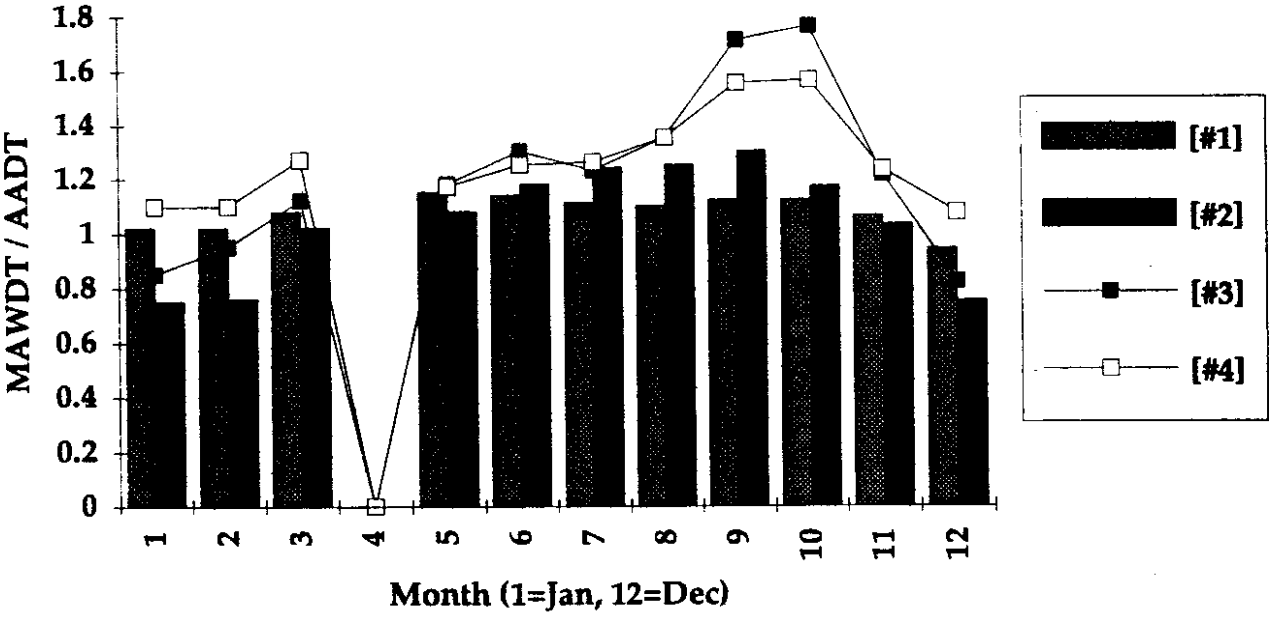
Comparison of Travel Patterns For Four Length Bins at Site 78 in 1991



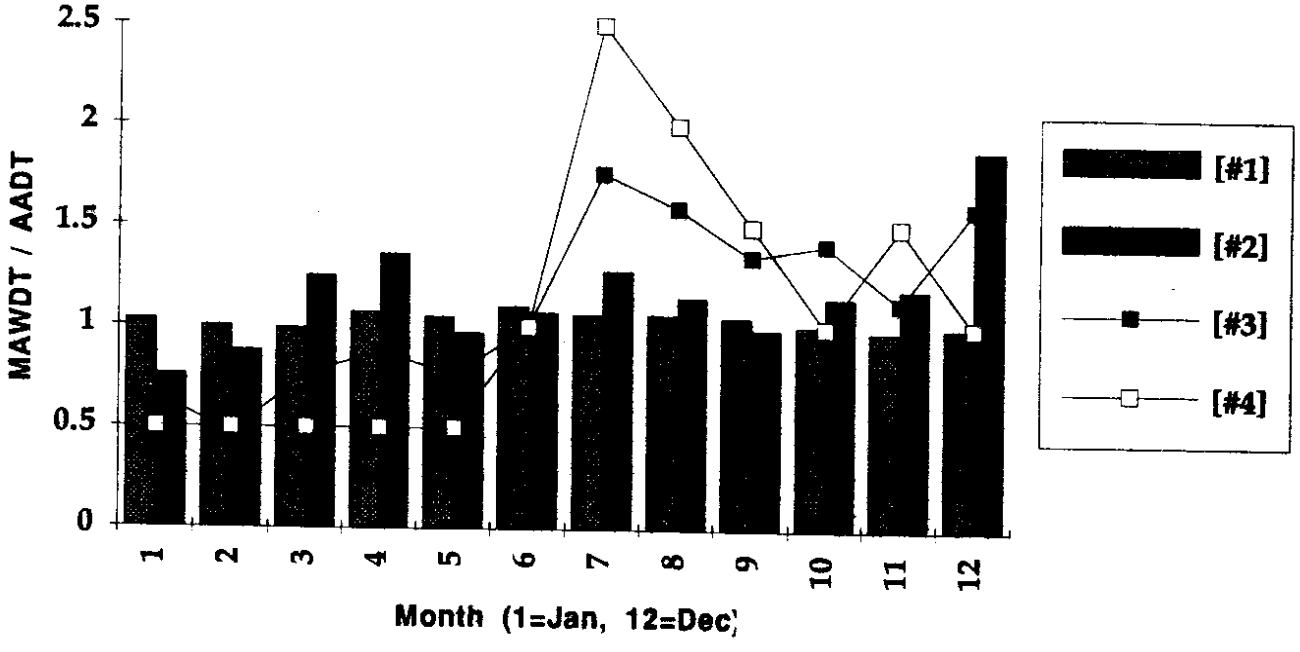
Comparison of Travel Patterns For Four Length Bins at Site 809 (I-5 Midway) in 1989



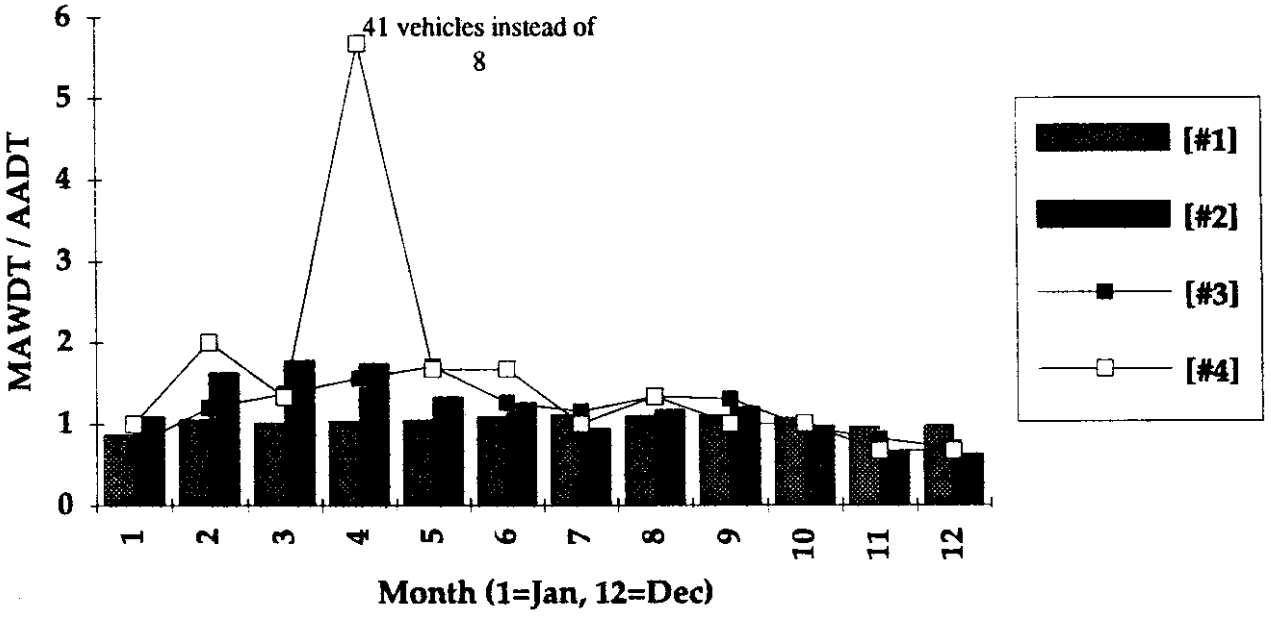
Comparison of Travel Patterns For Four Length Bins At Site 81 in 1990



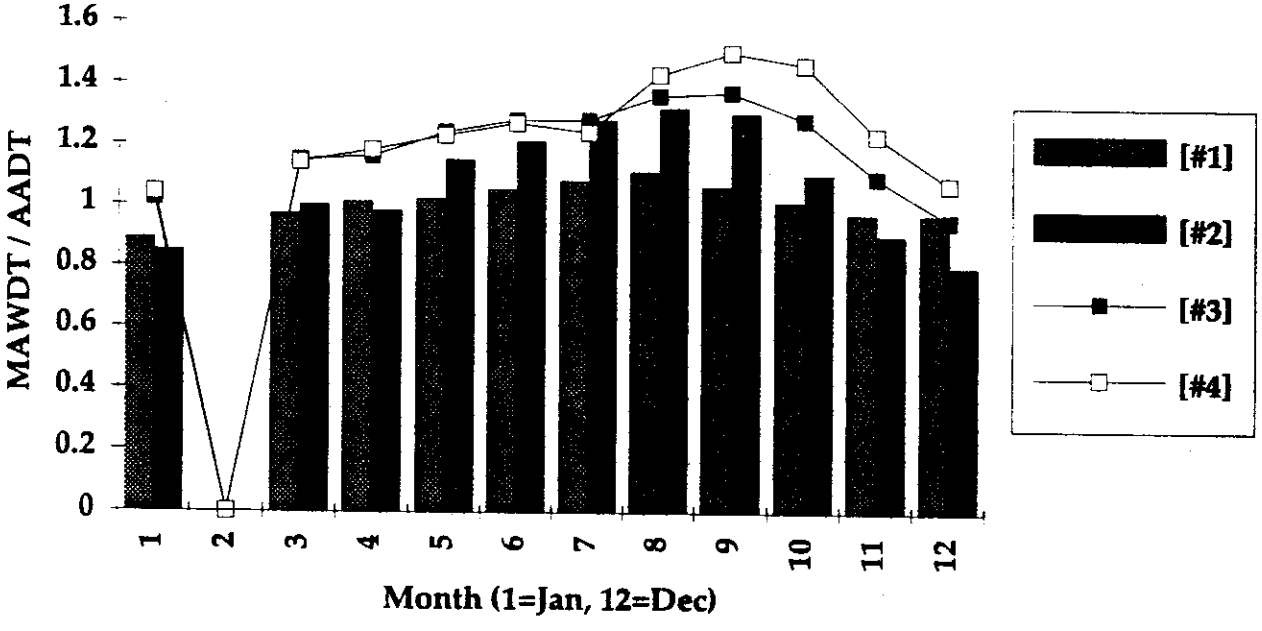
Comparison of Travel Patterns For Four Length Bins at Site 819 in 1988



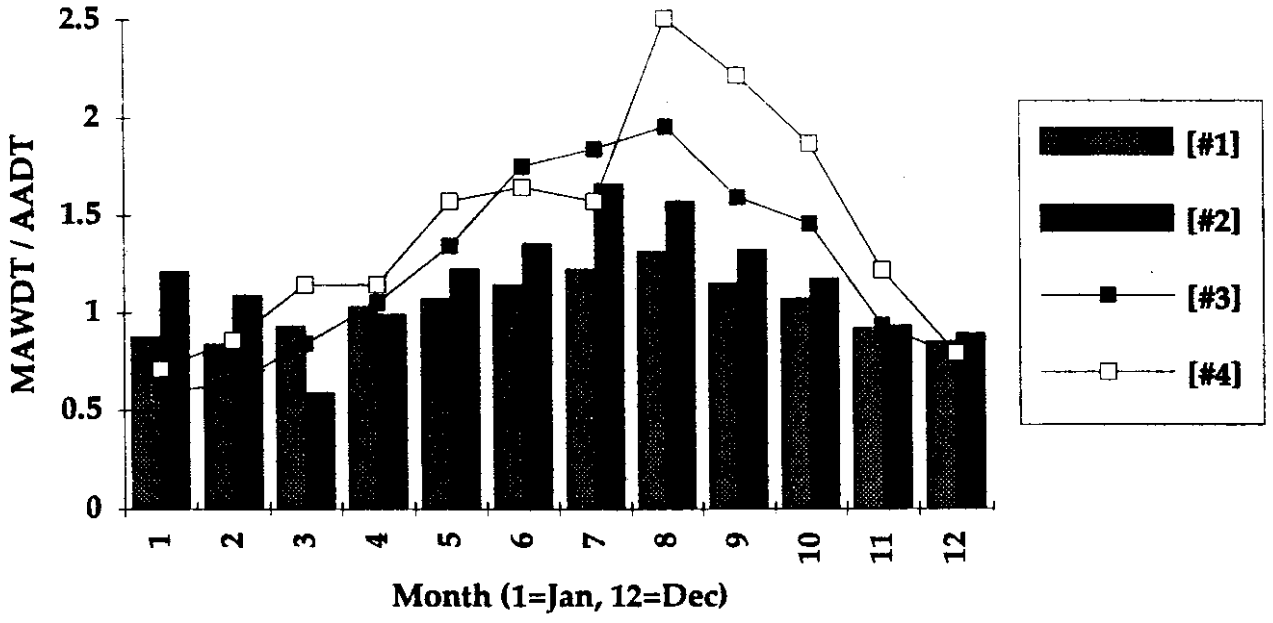
Comparison of Travel Patterns For Four Length Bins At Site 819 in 1991



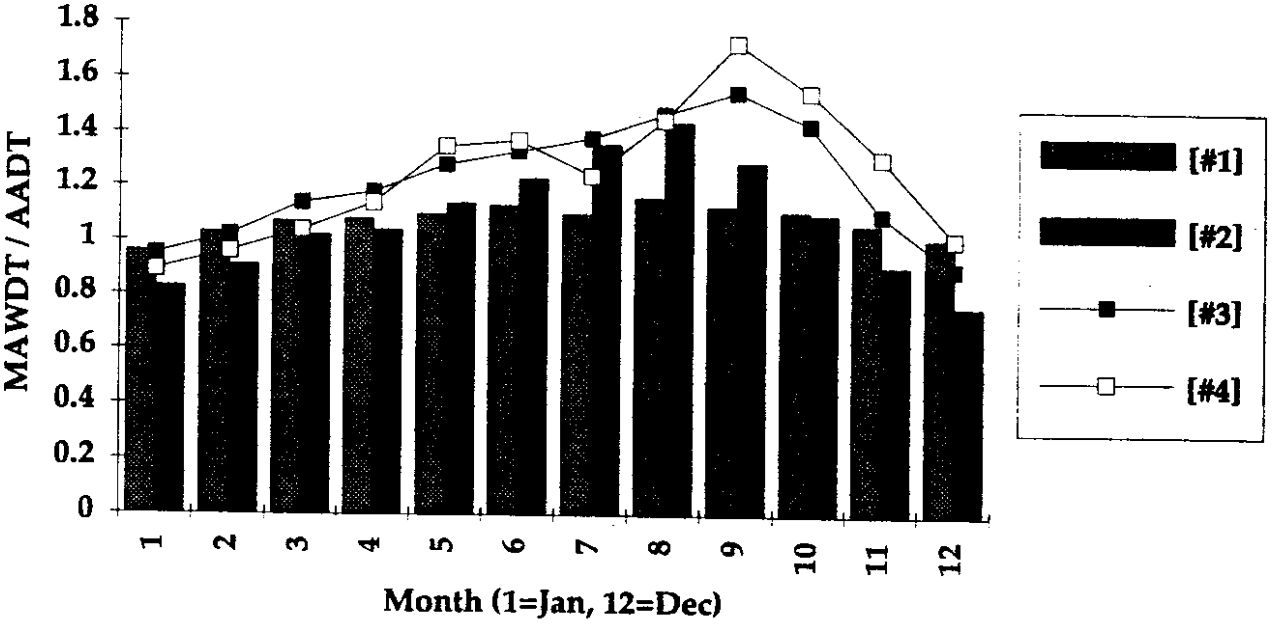
Comparison of Travel Patterns For Four Length Bins At Site 82 in 1991



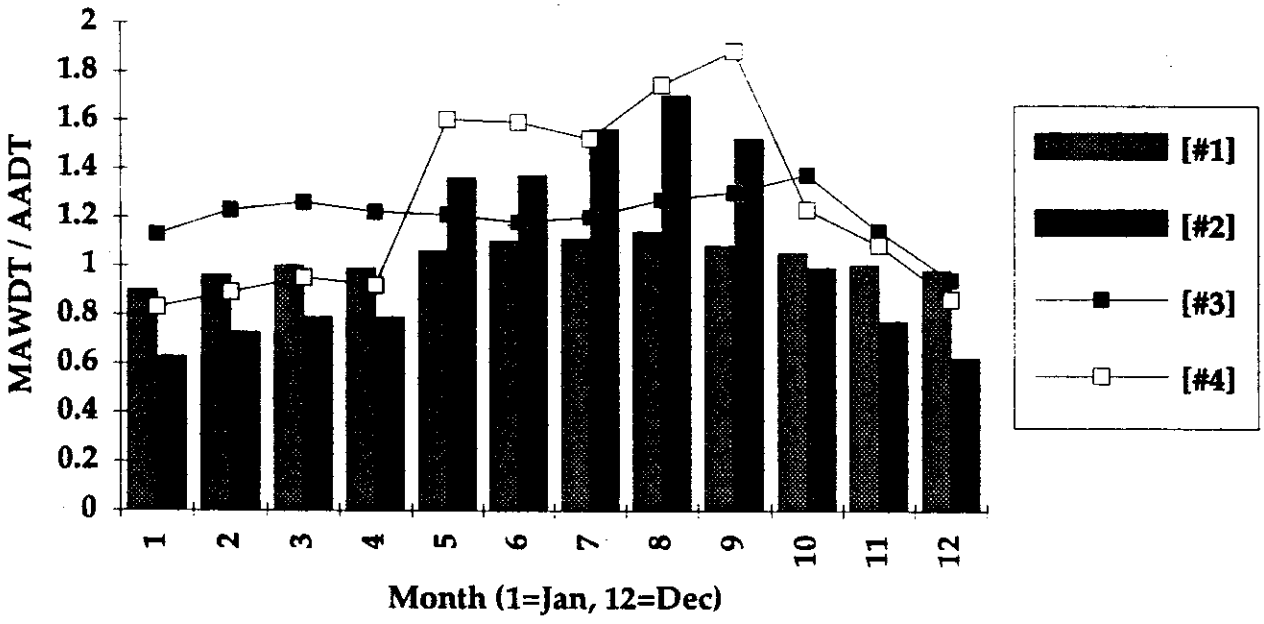
Comparison of Travel Patterns For Four Length Bins At Site 820 in 1990



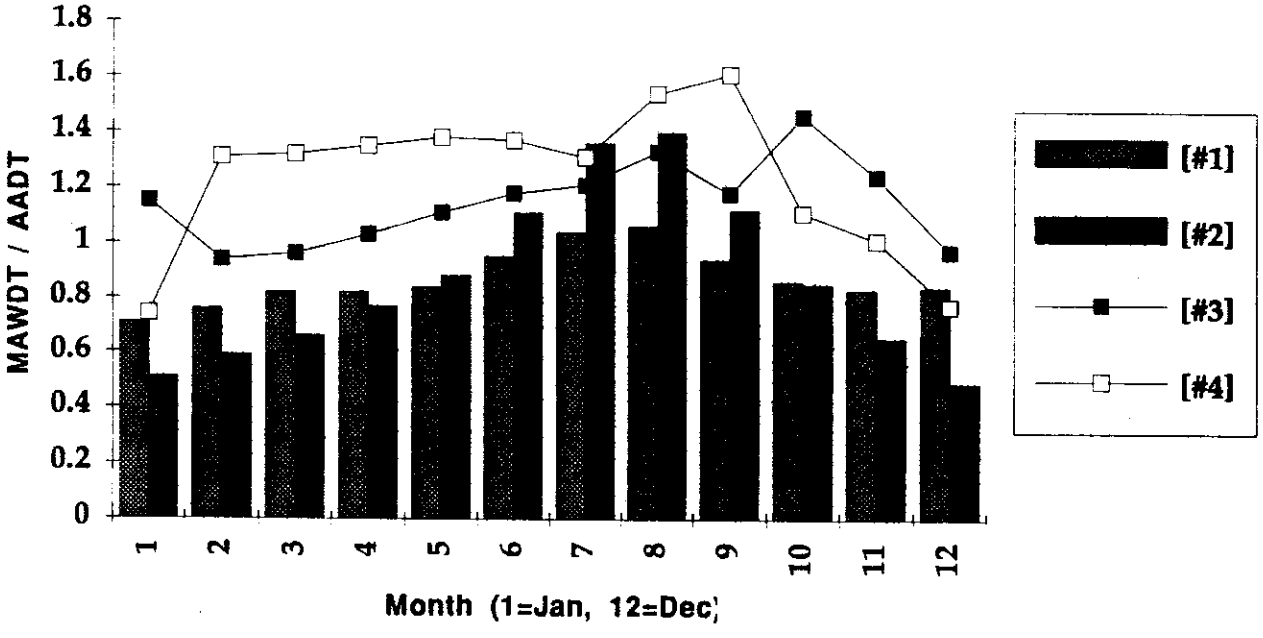
Comparison of Travel Patterns For Four Length Bins At Site 824 in 1991



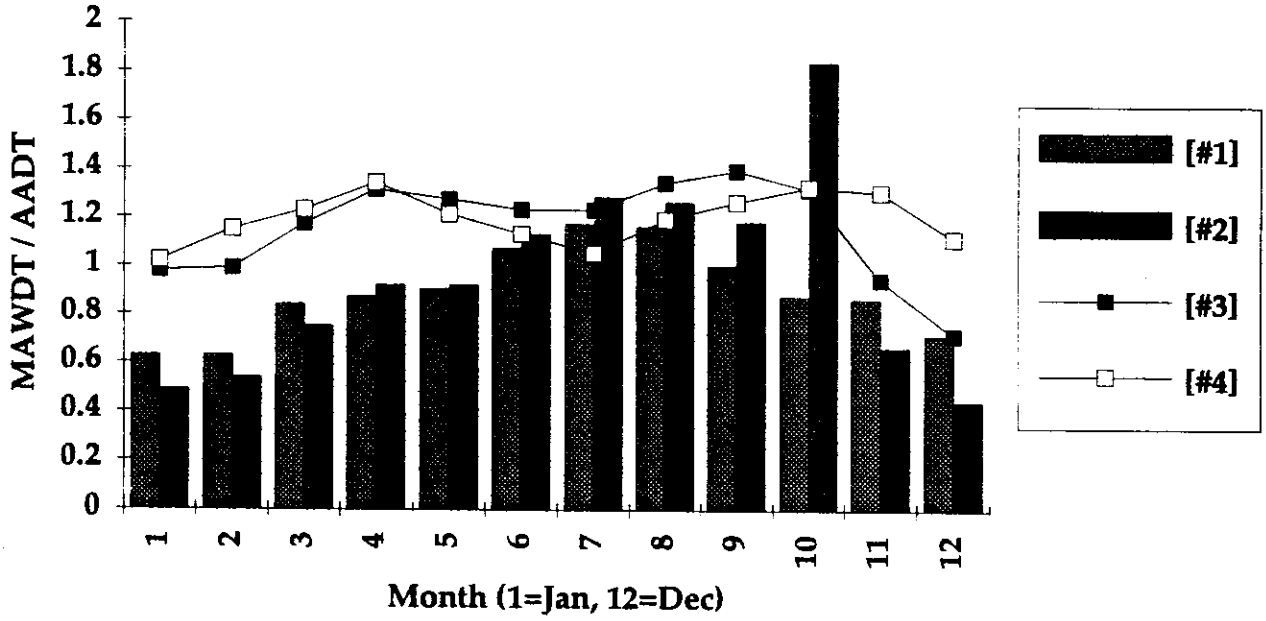
Comparison of Travel Patterns For Four Length Bins At Site 825 in 1991



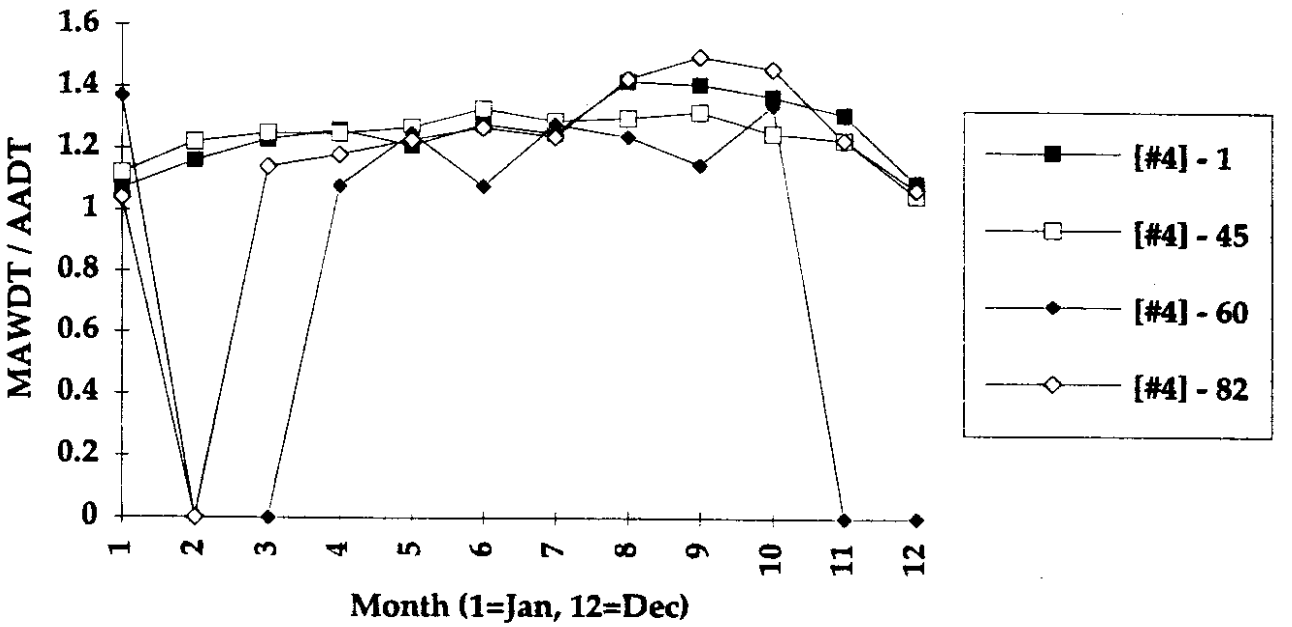
Comparison of Travel Patterns For Four Length Bins At Site 826 in 1991



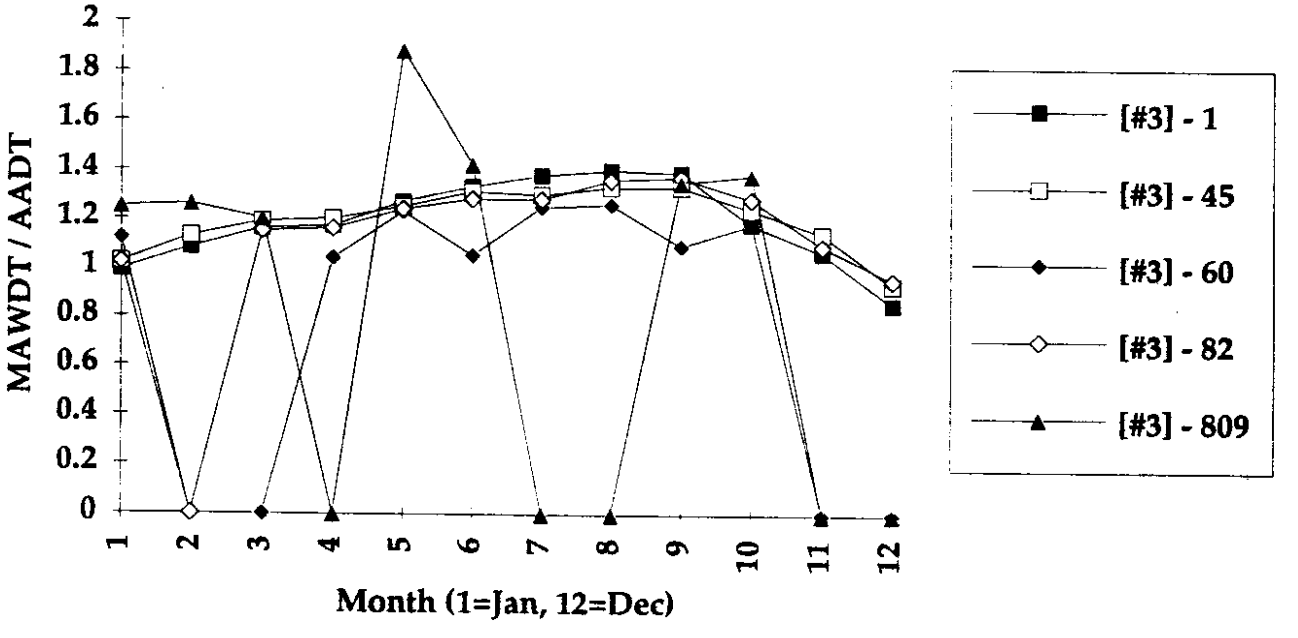
Comparison of Travel Patterns For Four Length Bins At Site 86 in 1990



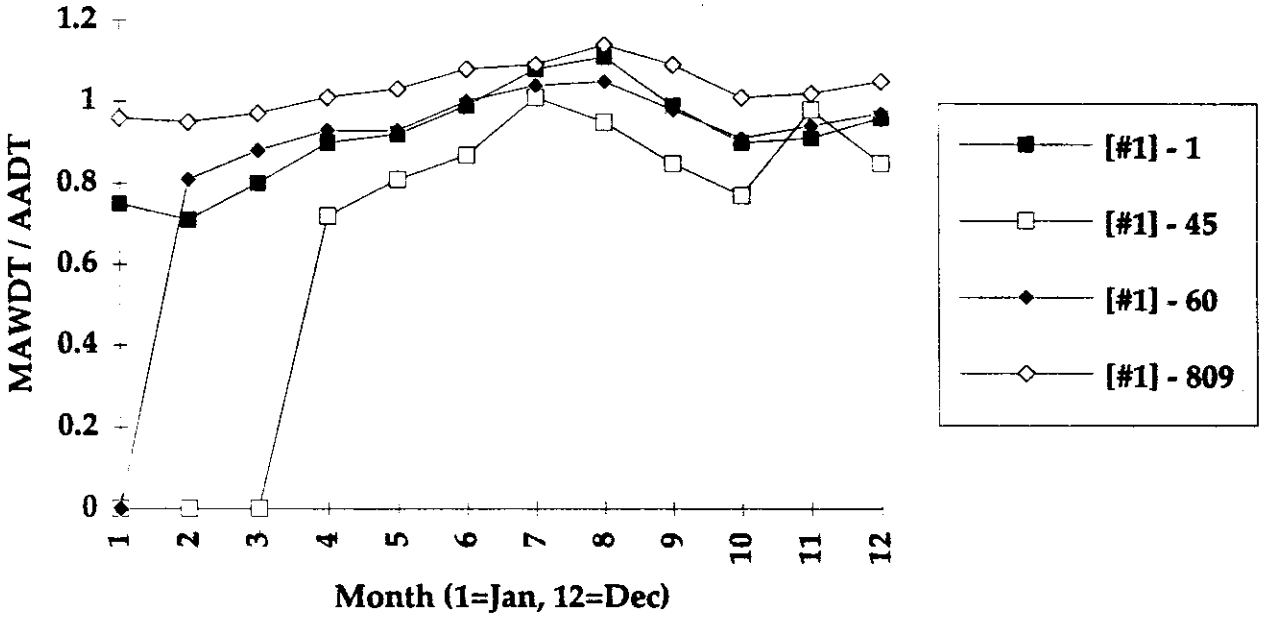
Comparison of Travel Patterns For Length Bin 4 At Four Sites on I-5 in 1991



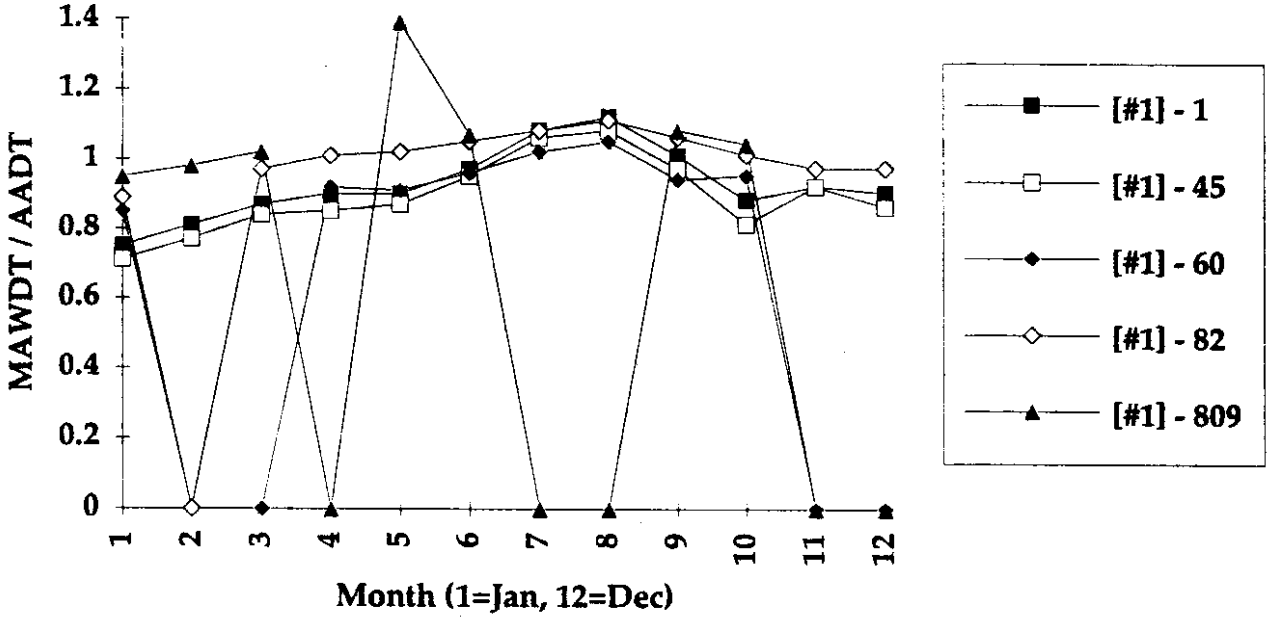
Comparison of Travel Patterns For Length Bin 3 At Five Sites On I-5 in 1991



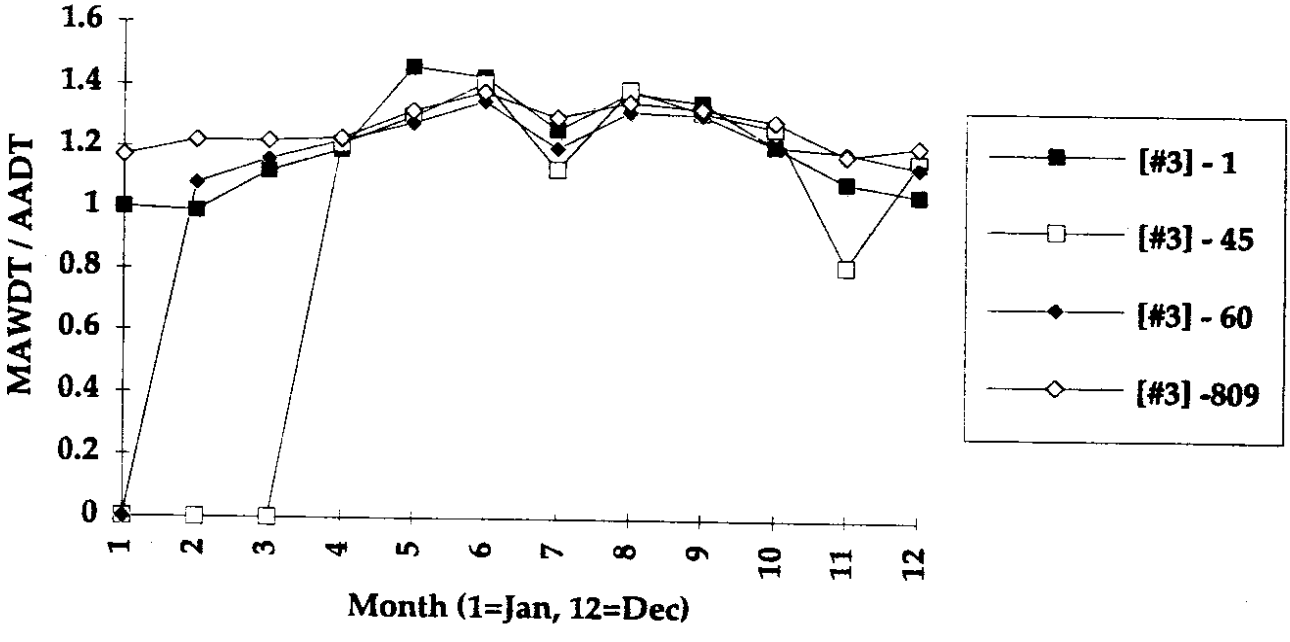
Comparison of Travel Patterns For Length Bin 1 On I-5 At Four Sites in 1989



Comparison of Travel Patterns For Length Bin 1 At Five Sites On Interstate 5 in 1991



Comparison of Travel Patterns For Length Bin 3 At Four Sites On Interstate 5, in 1989



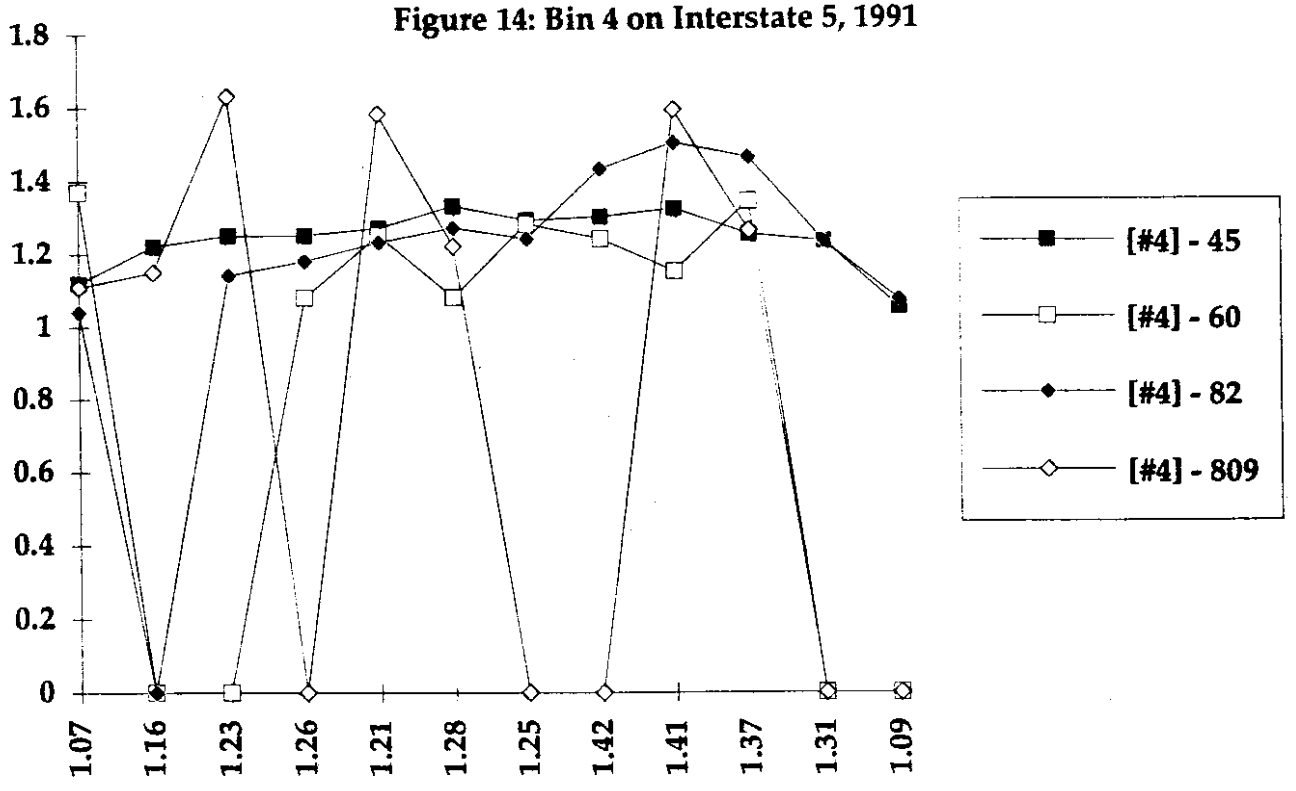
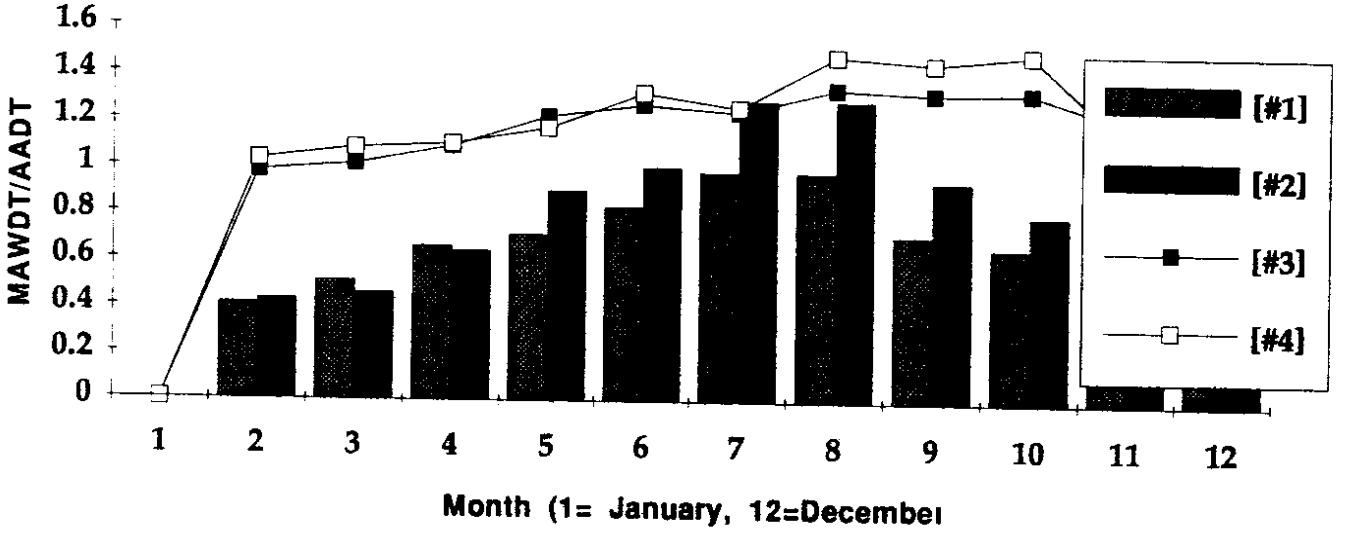
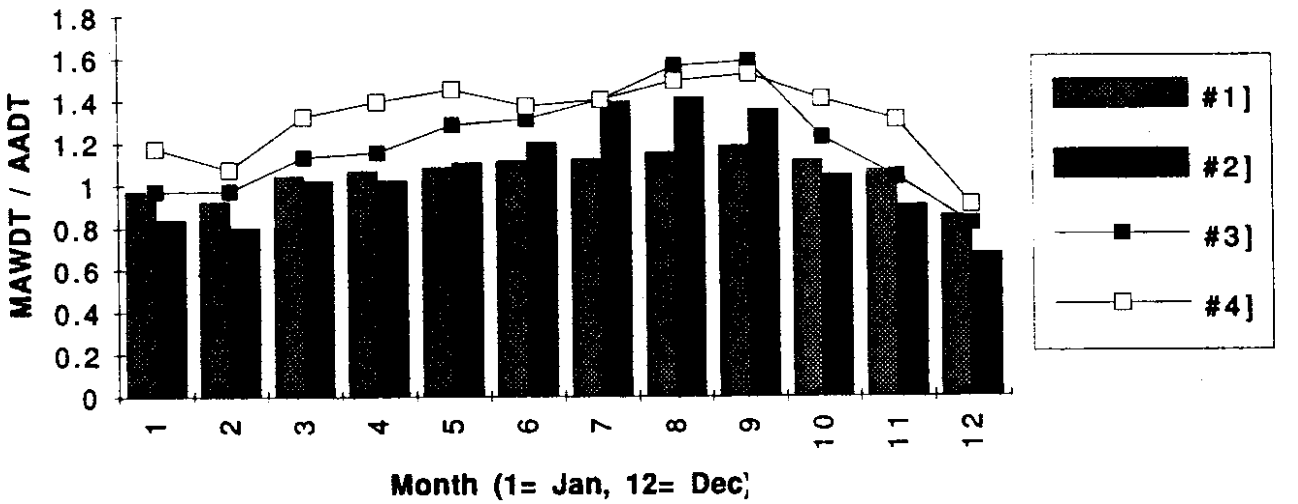


Figure 14: Bin 4 on Interstate 5, 1991
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1.07
1.16
1.23
1.26
1.21
1.28
1.25
1.42
1.41
1.37
1.31
1.09
[#4] - 45
[#4] - 60
[#4] - 82
[#4] - 809

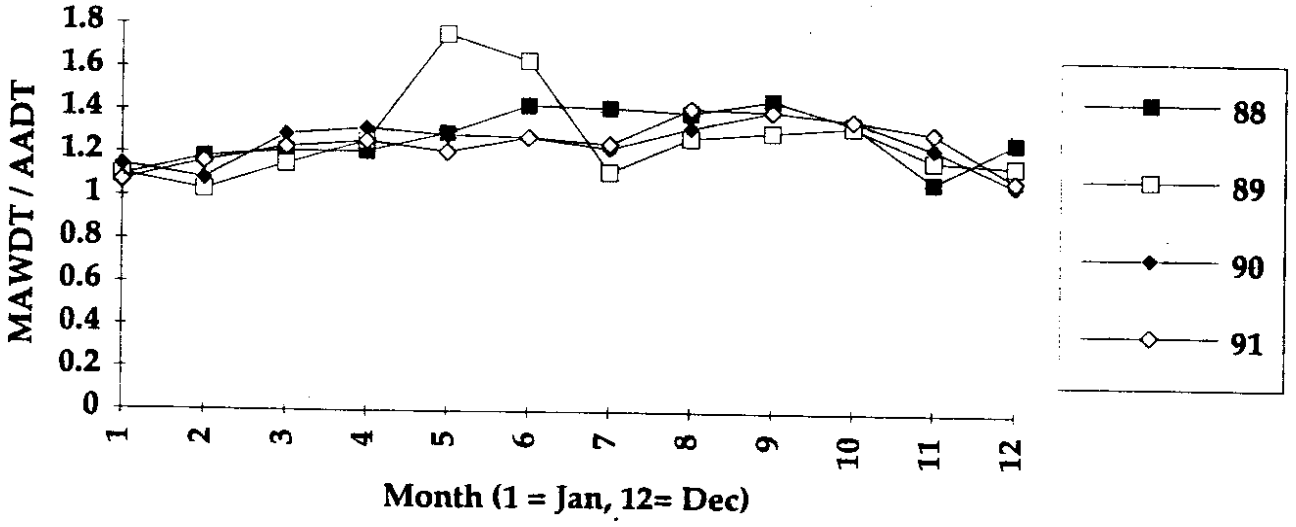
Comparison of Travel Patterns By Length Class, Site 6 - 1989
(Weekdays Only)



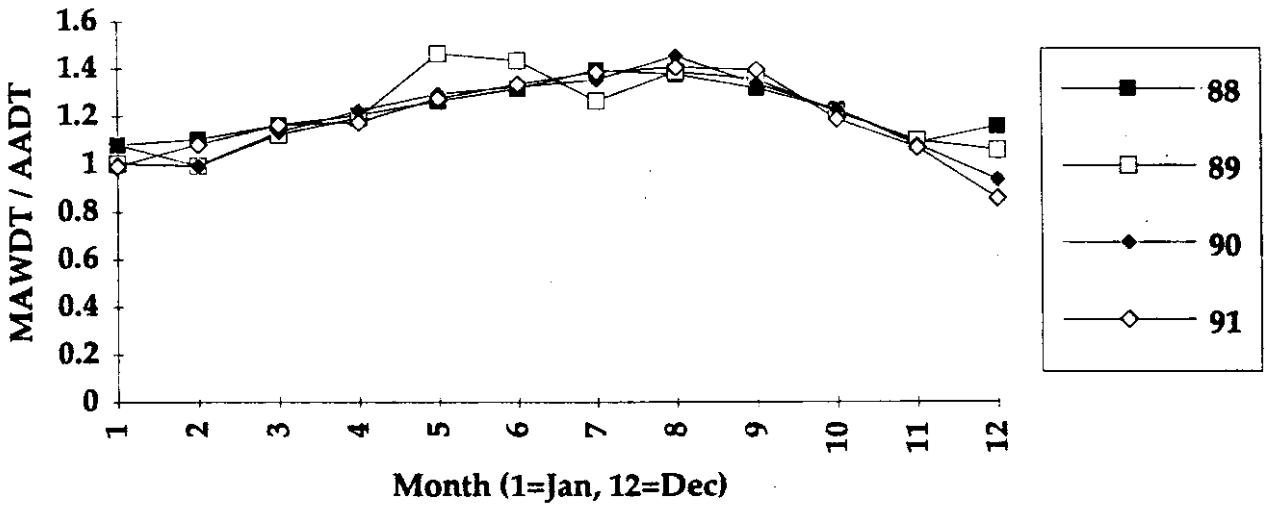
Comparison of Travel Patterns By Length Class, Site 50 - 1990 (Weekdays Only)



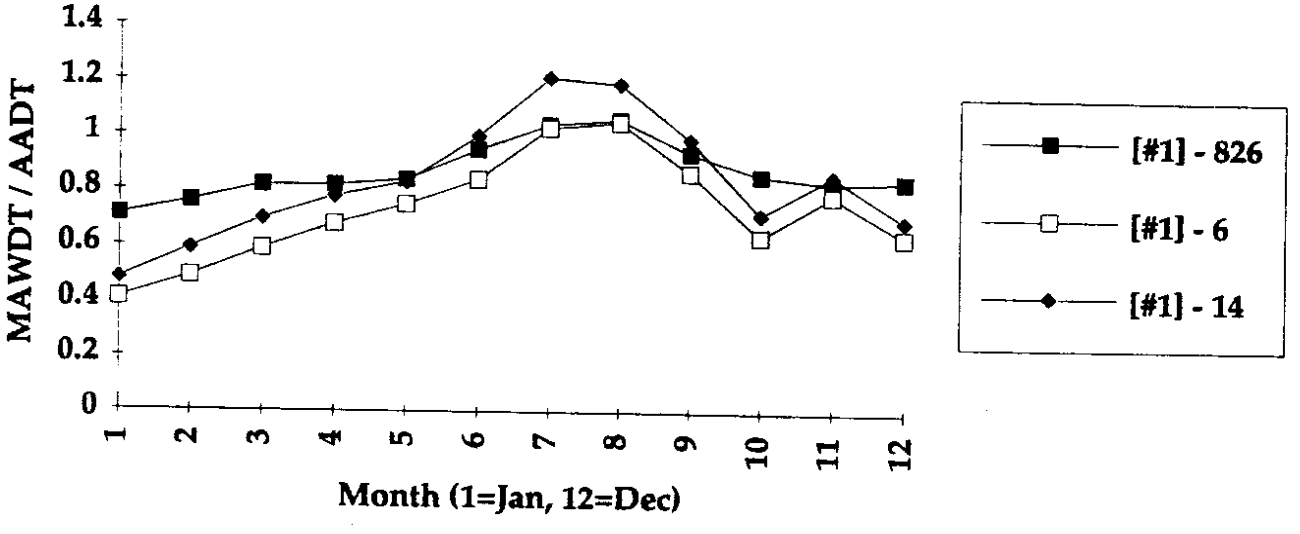
Difference in Weekday Length Bin 4 Seasonal Patterns Over Time
(I-5 at Marysville)



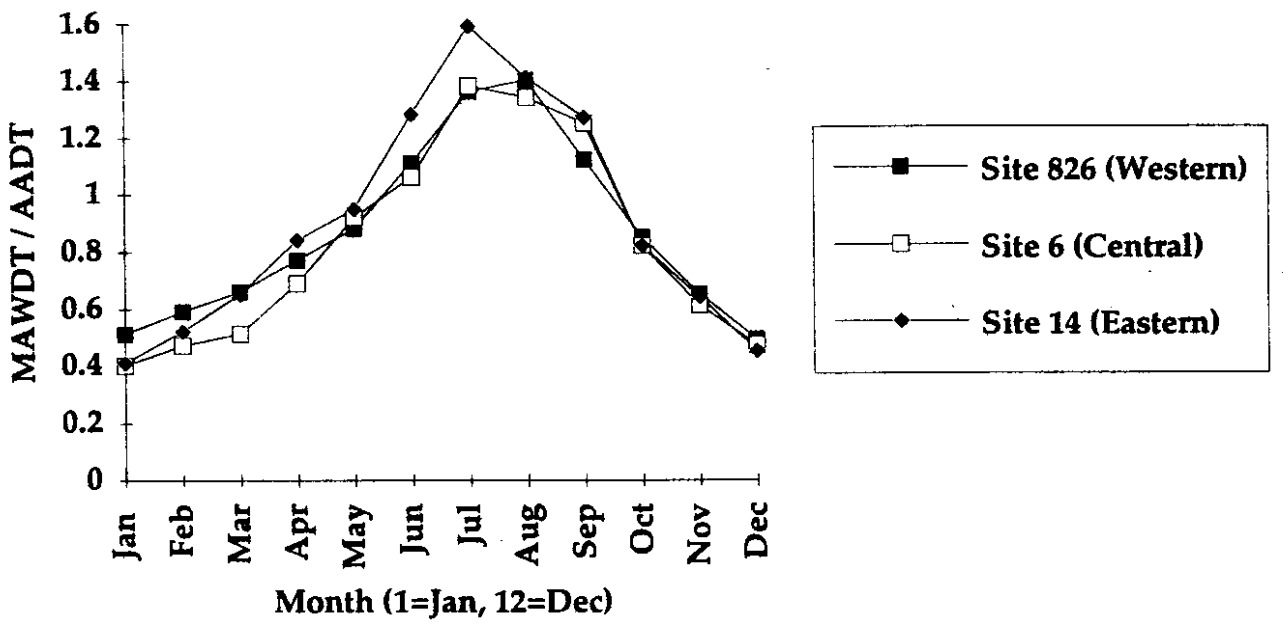
Comparison of Weekday Travel Patterns For Length Bin 3 on I-5 at Marysville



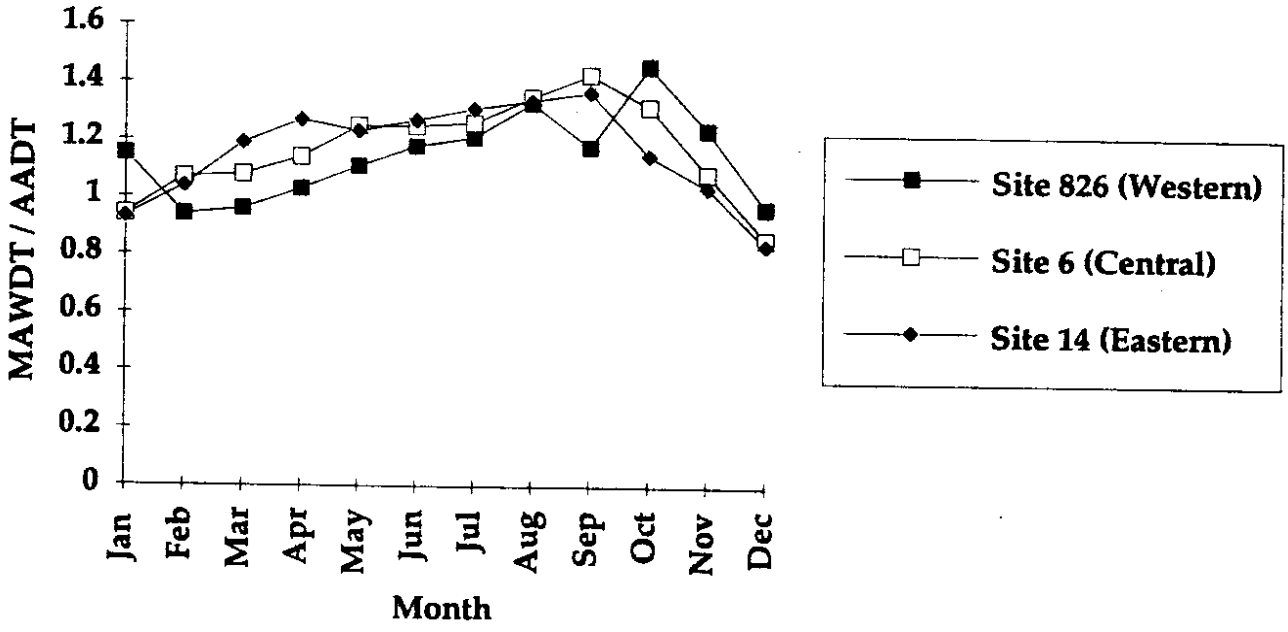
Comparison of Weekday Seasonal Patterns, Length Bin 1, For 3 Sites on I-90



Comparison of Weekday Length Bin 2 Travel Patterns For 3 Sites on I-90 in 1991



Comparison of Weekday Travel Patterns For Length Bin 3 on I-90 in 199



Comparison of Length Bin 4 Travel Patterns For Weekdays on I-90 In 1991