1. Report No. FHWA/TX-91/1235-1	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle **TRAFFIC LOAD FORECASTING FOR PAVEMENT DESIGN**		5. Report Date **August 1991**
		6. Performing Organization Code
7. Author(s) Anthony J. Vlatas and George B. Dresser		8. Performing Organization Report No. **Research Report 1235-1**
9. Performing Organization Name and Address Texas Transportation Institute The Texas A&M University System College Station, TX 77843-3135		10. Work Unit No.
		11. Contract or Grant No. **2-10-90-1235**
12. Sponsoring Agency Name and Address Texas Department of Transportation Transportation Planning Div., P. O. Box 5051, Austin, TX 78763		13. Type of Report and Period Covered **Interim - September 1990 - August 1991**
		14. Sponsoring Agency Code

15. Supplementary Notes Study was conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration. Research Study Title: Improving Transportation Planning Techniques.

16. Abstract

When a pavement structure fails prematurely, the constructing agency must pay millions of dollars in traffic control and construction costs to rehabilitate or reconstruct the pavement sooner than had the pavement survived its design life. The money required to rehabilitate or reconstruct the pavement could have been put to alternative uses during the remaining years of the pavement's design life; but because the money must be spent when the pavement actually ceases to provide adequate service, the opportunity to apply the much needed capital elsewhere is lost. A primary determinant of a pavement's actual service life is the traffic loading applied to the pavement. Consequently, an important consideration in pavement structural design is a forecast of the traffic loading expected to be applied to the pavement structure during its design life. This research evaluated the Texas State Department of Highways and Public Transportation's traffic load forecasting procedures. The research found that traffic load forecast accuracy could be improved by more than 30 percent from current levels by conducting 24-hour manual vehicle classification sessions at specific pavement project sites and by more than 85 percent by conducting week-long weigh-in-motion (WIM) sessions at specific pavement project sites. The research shows that if forecast accuracy was improved by the amounts indicated above, fewer pavements would typically fail prematurely; and, while some pavements would still fail prematurely despite improved forecasts, these pavements would have longer lives than under current practice. The research found that the cost to improve traffic load forecasts is justified by the benefits received in return for almost all pavement reconstruction projects and most major pavement rehabilitation projects.

17. Key Words Traffic Load, ESAL, Forecasting, Premature Pavement Failure, Economic Analysis, Traffic Variance, Pavement Life, Site-Specific Traffic Data	18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service Springfield, Virginia 22161.		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 231	22. Price

Form DOT F 1700.7 (8-69)

TRAFFIC LOAD FORECASTING FOR PAVEMENT DESIGN

Prepared by

Anthony J. Vlatas
Research Associate

and

George B. Dresser
Research Scientist

Research Study Number 2-10-90-1235

Sponsored by
Texas Department of Transportation

In cooperation with
U. S. Department of Transportation
Federal Highway Administration

Texas Transportation Institute
The Texas A&M University System
College Station, Texas

August 1991

METRIC (SI*) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol

LENGTH

Symbol	When You Know	Multiply By	To Find	Symbol
in	inches	2.54	centimetres	cm
ft	feet	0.3048	metres	m
yd	yards	0.914	metres	m
mi	miles	1.61	kilometres	km

AREA

Symbol	When You Know	Multiply By	To Find	Symbol
in²	square inches	645.2	centimetres squared	cm²
ft²	square feet	0.0929	metres squared	m²
yd²	square yards	0.836	metres squared	m²
mi²	square miles	2.59	kilometres squared	km²
ac	acres	0.395	hectares	ha

MASS (weight)

Symbol	When You Know	Multiply By	To Find	Symbol
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams	Mg

VOLUME

Symbol	When You Know	Multiply By	To Find	Symbol
fl oz	fluid ounces	29.57	millilitres	mL
gal	gallons	3.785	litres	L
ft³	cubic feet	0.0328	metres cubed	m³
yd³	cubic yards	0.0765	metres cubed	m³

NOTE: Volumes greater than 1000 L shall be shown in m³.

TEMPERATURE (exact)

Symbol	When You Know	Multiply By	To Find	Symbol
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol

LENGTH

Symbol	When You Know	Multiply By	To Find	Symbol
mm	millimetres	0.039	inches	in
m	metres	3.28	feet	ft
m	metres	1.09	yards	yd
km	kilometres	0.621	miles	mi

AREA

Symbol	When You Know	Multiply By	To Find	Symbol
mm²	millimetres squared	0.0016	square inches	in²
m²	metres squared	10.764	square feet	ft²
km²	kilometres squared	0.39	square miles	mi²
ha	hectares (10 000 m²)	2.53	acres	ac

MASS (weight)

Symbol	When You Know	Multiply By	To Find	Symbol
g	grams	0.0353	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams (1 000 kg)	1.103	short tons	T

VOLUME

Symbol	When You Know	Multiply By	To Find	Symbol
mL	millilitres	0.034	fluid ounces	fl oz
L	litres	0.264	gallons	gal
m³	metres cubed	35.315	cubic feet	ft³
m³	metres cubed	1.308	cubic yards	yd³

TEMPERATURE (exact)

Symbol	When You Know	Multiply By	To Find	Symbol
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F

```
        °F                                              °F
       -40        32        98.6                       212
        |40    0   |40    80  |   120    160    200|
   -40     -20    0     20    |40     60    80    100
        °C                     37                    °C
```
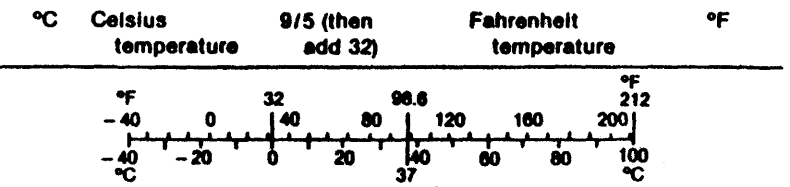
These factors conform to the requirement of FHWA Order 5190.1A.

* SI is the symbol for the International System of Measurements

ABSTRACT

When a pavement structure ceases to provide adequate service sooner than called for in its design, the constructing agency must pay millions of dollars in traffic control and construction costs to rehabilitate or reconstruct the pavement sooner than had the pavement survived its design life. The money required to rehabilitate or reconstruct the pavement could have been put to alternative uses during the remaining years of the pavement's design life; but because the money must be spent when the pavement actually ceases to provide adequate service, the opportunity to apply the much needed capital elsewhere is lost.

A primary determinant of a pavement's actual service life is the traffic loading applied to the pavement. Consequently, an important consideration in pavement structural design is a forecast of the traffic loading expected to be applied to the pavement structure during its design life. This research evaluated the Texas Department of Transportation's (TxDOT) traffic load forecasting procedures.

The research found that traffic load forecast accuracy could be improved by more than 30 percent from current levels by conducting 24-hour manual vehicle classification sessions at specific pavement project sites and by more than 85 percent by conducting week-long weigh-in-motion (WIM) sessions at specific pavement project sites.

The research found that if forecast accuracy was improved by the amounts indicated above, pavements could be designed and built better. As a result, fewer pavements would typically fail prematurely; and, while some pavements would still fail prematurely despite improved forecasts, these pavements would have longer lives than under current forecasting procedures.

The research found that the cost to improve traffic load forecasts is justified by the benefits received in return, for almost all pavement reconstruction projects and most major pavement rehabilitation projects.

DISCLAIMER

TABLE OF CONTENTS

vii

LIST OF TABLES

LIST OF FIGURES

EXECUTIVE SUMMARY

When a pavement structure fails prematurely (i.e., ceases to provide adequate service sooner than called for in its design), the constructing agency must pay millions of dollars in traffic control and construction costs to rehabilitate or reconstruct the pavement sooner than had the pavement survived its design life. The money required to rehabilitate or reconstruct this failed pavement could have been put to alternative uses (e.g., could have been used to fund other pavement projects) during the remaining years of the failed pavement's design life; but, because the money must be spent when the pavement actually ceases to provide adequate service, the opportunity to apply the much needed capital elsewhere is lost.

A primary determinant of a pavement's actual service life is the traffic loading applied to the pavement. Consequently, an important consideration in pavement structural design is a forecast of the traffic loading expected to be applied to the pavement structure during its design life. This research has evaluated the Texas Department of Transportation's (TxDOT) traffic load forecasting procedures.

The research found that the traffic load forecast components, most responsible for forecast variability at present, were "site-specific" characteristics of the traffic stream. As a result, the improvement in forecast accuracy that could be realized by sampling the traffic stream at specific pavement project locations was investigated. The research found that traffic load forecast accuracy could be improved by more than 30 percent from current levels by conducting 24-hour manual vehicle classification sessions at specific pavement project sites and that traffic load forecast accuracy could be improved by more than 85 percent by conducting week-long weigh-in-motion (WIM) sessions at specific project sites. (Vehicle classification data are automatically collected during portable WIM sessions).

The research found that if traffic load forecast accuracy was improved by the amounts shown above, pavements could be designed and built better. As a result, fewer pavement structures would fail prematurely; and, while some pavements would still fail prematurely despite improved forecasts, these pavements would generally have longer service lives than under current forecasting procedures.

The cost to make improvements in traffic load forecasts would be incurred in the

design stage of projects, but the benefits would be realized over time. In order to compare future benefits with present costs, it is necessary to express future benefits in terms of their present value. For example, the research found that for a typical pavement reconstruction project, the present value of the benefits resulting from conducting a 24-hour manual vehicle classification session at the pavement project site is approximately $109,000. This means that, on average, each time TxDOT conducts a 24-hour manual vehicle classification session at a pavement reconstruction project site, TxDOT will have effectively created for itself a $109,000 investment which will accumulate interest over time; this $109,000 plus interest will be available to TxDOT for use on other projects in the future. The cost to conduct a 24-hour manual vehicle classification session is approximately $550; this is the amount TxDOT must actually spend today to realize the payoff of $109,000 plus interest in the future. This indicates a typical benefit-to-cost ratio for 24-hour manual classification sessions of more than 198 to 1. The break-even project size for 24-hour manual counts is approximately $248,000; any time a pavement project is worth more than this amount, the cost to conduct a 24-hour manual count is justified by the benefits received in return.

The present value of the benefits resulting from conducting a week-long WIM session at a typical reconstruction project site is approximately $267,000. The cost to conduct a week-long WIM session is approximately $2,790. This indicates a typical benefit-to-cost ratio for week-long WIM sessions of more than 95 to 1. The break-even project size for week-long WIM sessions is approximately $543,000; for pavement projects worth more than this amount, conducting site-specific week-long WIM sessions is cost-effective.

The report recommends that TxDOT conduct a site-specific 24-hour manual vehicle classification session for any pavement project worth more than $248,000 and that TxDOT conduct a site-specific 24-hour manual vehicle classification session or, preferably, a site-specific week-long WIM session for any pavement project worth more than $543,000. Almost all pavement reconstruction projects and most major pavement rehabilitation projects meet even the $543,000 cutoff.

For projects where TxDOT elects not to collect site-specific traffic data, the report recommends that TxDOT use a modified percent trucks prediction model and, otherwise, continue to use current forecasting procedures.

CHAPTER I
INTRODUCTION

INTRODUCTION

When a pavement structure fails prematurely (i.e, ceases to provide an adequate level of service sooner than called for in its design), the constructing agency must pay millions of dollars in traffic control and construction costs to rehabilitate or reconstruct the pavement sooner than had the pavement survived its design life. The money required to rehabilitate or reconstruct this failed pavement could have been put to alternative uses (e.g., could have been used to fund other pavement projects) during the remaining years of the failed pavement's design life; but, because the money must be spent when the pavement actually ceases to provide adequate service, the opportunity to apply the much needed capital elsewhere is lost.

LOAD EQUIVALENCE

A primary determinant of a pavement's actual service life is the traffic loading applied to the pavement. Consequently, an important consideration in pavement structural design is a forecast of the traffic loading expected to be applied to the pavement structure during its design life (generally 20 years). For pavement design purposes, the traffic loading applied to the pavement by axles of different weights and/or configurations (e.g., single, tandem, tridem, etc.) is equated with the loading applied by an arbitrarily chosen reference axle, an 18,000 pound single axle [1].

A **load equivalence factor** is defined as the ratio of the number of repetitions of an 18,000 pound single axle which are required to cause a given level of pavement damage to the number of repetitions of an axle of some other weight and/or configuration which are required to cause the same given amount of damage [2]. The load equivalence factor may be defined algebraically as shown in Equation 1.1 [2].

$$LEF_{wc} = N_{18s} / N_{wc} \tag{1.1}$$

where:

LEF_{wc} = the load equivalence factor for an axle of weight "w" and configuration "c"

N_{18s} = the number of repetitions of an 18,000 single axle load required to cause a specified amount of damage

N_{wc} = the number of repetitions of an axle of weight "w" and configuration "c" required to cause the specified amount of damage

For example, if 16 repetitions of a 9,000-pound single axle are required to do the same amount of pavement damage as 1 repetition of an 18,000-pound single axle, the 9,000-pound axle would have a load equivalence factor of 1/16 or 0.0625:

LEF_{9s} = 1/16

= 0.0625

Conversely, if one repetition of a 36,000-pound single axle does as much damage to the pavement as 16 repetitions of the 18,000-pound single axle, then the 36,000-pound single axle load would have a load equivalence factor of 16/1 or 16:

LEF_{36s} = 16/1

= 16

The examples above imply that the relationship between axle weight and load equivalence factor is exponential - i.e., an increase (decrease) in axle weight causes a greater than proportional increase (decrease) in load equivalence factor. Figure 1 shows the relationship between axle weight and load equivalence factor identified using empirical data collected at the 1958-60 AASHO Road Test.

LOAD EQUIVALENCE FACTORS AND TRAFFIC LOAD FORECASTING

The load equivalence factor for a given axle is a complex function of many variables, including axle weight, axle configuration (i.e., single, tandem, etc.), pavement type (rigid, flexible), pavement layer thicknesses, tire contact area, tire contact pressure, environmental conditions, and soil support [2].

However, for traffic load forecasting purposes, the load equivalence factor for a given axle weight, configuration, pavement type, etc., is taken as given. The goal in traffic load forecasting is to develop the best possible estimate of the number of axles of each configura-
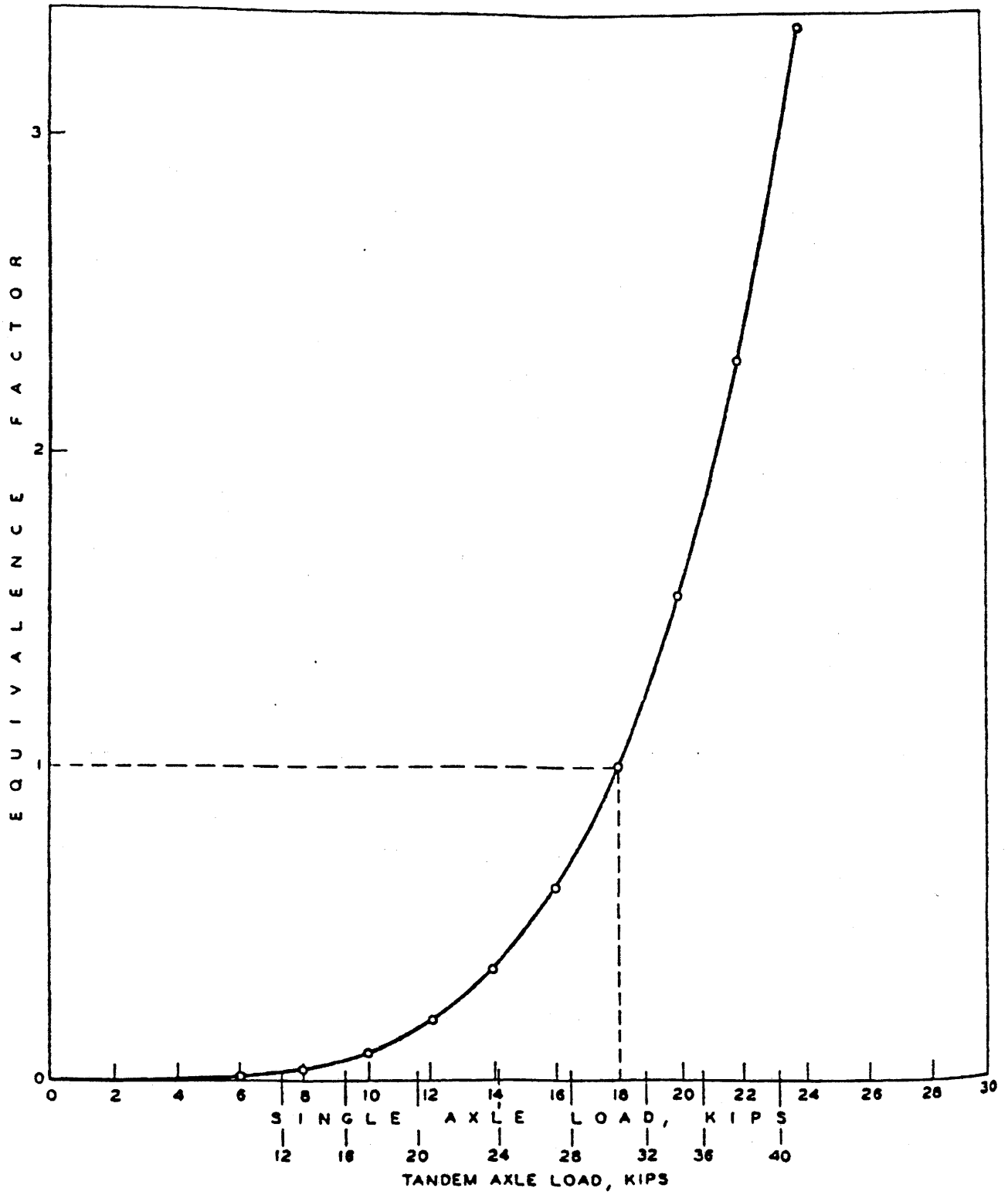
Source: [3]
Figure 1: Relationship between Axle Weight and Load Equivalence Factor

3

ation in each weight category expected at the project site over the design period. Given the expected number of axles of each configuration in each weight category, the load equivalence factor for each axle configuration and weight category is used to convert the axle weights to **equivalent single axle loads (ESALs)**. The ESALs contributed by axles of each axle configuration in each weight category are then summed to arrive at a cumulative ESAL forecast for use in pavement design.

PURPOSE, SCOPE, AND ORGANIZATION OF REPORT

The purpose of this report is to evaluate and recommend improvements to TxDOT's ESAL forecasting procedures. This is accomplished by:

1) documenting current TxDOT ESAL forecasting procedures (Chapters II and III);

2) evaluating the accuracy associated with each procedure, in isolation (Chapter IV);

3) assessing the sensitivity of an ESAL forecast to errors introduced by individual procedures (Chapter IV);

4) determining the cumulative accuracy of an ESAL forecast, given the accuracies of the individual procedures used to make the forecast (Chapter IV);

5) identifying the relative responsibility of individual procedures for any cumulative error in resulting ESAL forecasts (Chapter IV);

6) determining the impact of ESAL forecast accuracy on pavement life (Chapter V); and

7) assessing the monetary benefits and costs of two strategies to improve ESAL forecast accuracy (Chapters VI and VII).

Most pavement projects in undertaken in Texas involve rehabilitation and reconstruction of existing pavement facilities [4]; in addition, the number of projects involving new facility construction in Texas is declining [4]. As a result, the research focuses on evaluating and improving ESAL forecasting procedures for existing pavement facilities.

CHAPTER II
THE COMPONENTS OF AN ESAL FORECAST

INTRODUCTION

The purpose of this chapter is 1) to identify the components of an ESAL forecast under current TxDOT practice; 2) to identify the procedures used to assign values to the ESAL forecast components; and 3) to identify any assumptions explicitly or implicitly made concerning the components by using these procedures. The first section of the chapter discusses the components supplied by D-10. The second section discusses the components supplied by D-8.

COMPONENTS SUPPLIED BY D-10

Average Daily Traffic Growth Rate

The average daily traffic (ADT) growth rate is the expected annual percentage growth in ADT over the design period. The design period is the block of time (generally 20 to 30 years) following pavement reconstruction during which the pavement facility is designed to provide adequate service. D-10 determines an ADT growth rate for each ESAL forecast based on historical traffic volume data collected at or near the pavement project site. The growth rate is determined by performing a linear regression on the historical volume data. The output of the linear regression is an equation of the form:

$$ADT(t) = GR * t + ADT(0) \tag{2.2}$$

where:

$ADT(t)$	= the average daily traffic at a point in time, t
GR	= the ADT growth rate, measured in vehicles per year (vpy)
t	= time, measured in years (t = 0 corresponds to the first year of historical volume data used in the analysis)
$ADT(0)$	= the "t = 0" ADT identified by the regression, measured in vehicles per day (vpd)

An annual percentage ADT growth rate, GF_{ADT}, is found by dividing GR by ADT(0). For example, if the regression equation yields:

$$ADT(t) = 50 \text{ vpy} * t + 1000 \text{ vpd}$$

a percentage growth is obtained by dividing 50 vpy by 1000 vpd; this results in a 5 percent per year ADT growth rate for the example equation.

This procedure assumes that traffic growth follows a linear model.

Base Year ADT

The **base year** is the first year of the design period. **Base year ADT** is the two-directional average daily traffic volume expected at the pavement facility during the base year. Base year ADT is determined by projecting one to two years ahead the **current year ADT** at the project site. The ADT growth rate is used to make the projection.

D-10 determines a current year ADT for each ESAL forecast based on traffic count(s) taken at or near the pavement project site. The traffic counts used in the analysis may have come from an automatic traffic recorder (ATR) or a 24-hour coverage count. If the project encompasses two or more existing count locations, the current year ADT used in the analysis is a weighted average of the different locations' ADTs. The weights are determined by the length of road for which each ADT is applicable.

Equation 2.1 shows the relationship between base year ADT, current year ADT, and the ADT growth rate:

$$ADT_o = ADT_{current} * (1 + GF_{ADT} * T) \tag{2.1}$$

where:

ADT_o	= base year ADT
$ADT_{current}$	= current year ADT
GF_{ADT}	= ADT growth rate
T	= the number of years from the current year to the base year

Percent Trucks

Percent trucks is the percentage of heavy trucks in the traffic stream. Percent trucks includes dual-rear-tire pickup trucks and buses. D-10 determines the percent trucks for each ESAL forecast based on vehicle classification data.

If a manual vehicle classification site is located within the pavement project limits,

classification data from the manual classification site are used to determine percent trucks. If a manual classification site is located on the same highway as the project site but outside the project limits, vehicle classification data from the manual class site are used to determine percent trucks at the project site; the determination is based on the ADTs at the two sites. If the ADT at the project site is higher than the ADT at the manual classification site, the percent trucks at the project site is assumed to be lower than at the classification site and vice versa. This adjustment of percent trucks from the manual classification site to the project site is accomplished using a "1/2-growth model" (i.e., a model in which truck volume grows [declines] between the two sites at 1/2 the rate total volume grows [declines] between the two sites). For example, given 10,000 ADT and 10 percent trucks at the data collection site and 12,500 ADT at the project site, percent trucks at the project site is found as follows:

1) subtract $ADT_{data\ collection\ site}$ from $ADT_{project\ site}$: 12,500 - 10,000 = 2,500 additional vehicles;

2) multiply the additional vehicles by $PCT_{data\ collection\ site}$: 2,500 * 0.10 = 250 trucks;

3) multiply this number of trucks by 1/2: 250*(1/2) = 125 additional trucks;

4) add the number of additional trucks at the project site to the number of trucks at the data collection site: 125 trucks + (10,000 vehicles * 10 percent trucks) = 1,125 trucks at the project site;

5) divide the number of trucks at the project site by total vehicles at the project site: 1,125 trucks/12,500 vehicles = 9.0 percent trucks at the project site.

The number of trucks has increased from 1,000 at the data collection site to 1,125 at the project site; but the percent trucks has decreased from 10 percent at the data collection site to 9 percent at the project site.

If there is no manual classification site on the same highway as the project site, classification data from another highway in the same geographic region as the project site are used in the analysis. Effort is made to identify a classification site on the same highway system (i.e., Interstate, U.S./State, FM) as the project site for this purpose. The percent trucks will be adjusted based on the ADTs at the two sites using the 1/2-growth model described above.

Percent trucks is assumed to remain constant throughout the design period. This implies an assumption that truck traffic grows at the same rate as overall traffic.

Percent Single Axles

Percent single axles is the percent of total truck axles passing the project site that are single axles. A tandem axle is treated as one axle to calculate percent single axles. To illustrate, a 3-S2 (e.g.,a typical 18-wheeler), which has one single axle and two tandem axles, has a percent single axles of 33.33 percent. D-10 determines the percent single axles for each pavement project based on classification data obtained as described for "percent trucks" above.

Note, however, that when classification data from another site on the same highway or from another highway in the same geographic region as the project site are used in the analysis, percent single axles is not adjusted based on ADT. Percent single axles is determined by the truck traffic stream makeup (i.e.,the proportions of individual truck types in the truck traffic stream), not the overall number of trucks. The truck traffic stream makeup is assumed to be approximately the same at the data collection and project sites.

Percent single axles is assumed to remain constant throughout the design period. This implies an assumption that the truck traffic stream makeup remains constant during the design period.

Axle Factor

The **axle factor** is the average number of axles per truck passing the site. A tandem axle is treated as one axle for axle factor calculation purposes. D-10 determines an axle factor for each pavement project based on classification data obtained as described for "percent trucks" above.

When classification data from another site on the same highway or from another highway in the same geographic region as the project site are used in the analysis, the axle factor is not adjusted based on ADT. Like percent single axles, the axle factor is determined by the truck traffic stream makeup. The truck traffic stream makeup is assumed to be approximately the same at the data collection and project sites.

The axle factor is also assumed to remain constant throughout the design period. This implies an assumption that the makeup of the truck traffic stream remains constant during the design period.

Axle Weight Distribution Table

An axle weight distribution table gives the percentage of single and tandem axles weighed in different weight categories. An axle weight distribution table is shown Table 1. Table 1 reads, for example, that 0.213 percent of all axles weighed at WIM station 501 were single axles between 0 and 2,000 pounds; there were no tandem axles that weighed between 0 and 2,000 pounds.

A separate axle weight distribution table is produced for each of the state's permanent weigh-in-motion (WIM) stations each year. Six of these stations weigh trucks continuously throughout the year; trucks are weighed during three 48-hour sessions per year at each of the remaining seven sites. In addition to the individual WIM station axle weight distribution tables, a statewide average axle weight distribution table is calculated by combining data from all permanent WIM sites.

If a pavement project is located on the same highway as a WIM site, the most recent year's axle weight distribution from that WIM site is used in the analysis. If there is no WIM site on the same highway as the project site, the statewide average axle weight distribution is used.

The axle weight distribution is assumed to remain constant throughout the design period.

This completes the list of ESAL forecast components supplied by D-10. D-10 uses the RDTEST68 computer program to generate a **Total ESAL** forecast based on these components. The Total ESAL covers all lanes and both directions of travel at the project site. D-10 provides the Total ESAL to D-8.

Table 1
Example of an Axle Weight Distribution Table

STATION 501, 1981-1983

Upper Weight Limit (pounds)	Single Axles		Tandem Axles (Percent)
	Percent	Cumulative Percent	
2,000	0.213	0.213	0.000
3,000	0.419	0.632	0.017
4,000	1.625	2.257	0.000
5,000	2.344	4.601	0.000
6,000	2.729	7.330	0.068
7,000	3.268	10.598	0.119
8,000	4.978	15.577	0.231
9,000	7.460	23.037	0.727
10,000	9.291	32.328	1.411
11,000	7.161	39.489	2.369
12,000	3.413	42.902	2.669
13,000	1.890	44.792	2.190
14,000	1.069	45.861	2.318
15,000	0.710	46.571	2.173
16,000	0.761	47.332	1.942
17,000	0.496	47.828	1.719
18,000	0.248	48.076	1.557
19,000	0.419	48.495	1.488
20,000	0.308	48.803	1.488
21,000	0.325	49.128	1.206
22,000	0.136	49.264	1.009
23,000	0.231	49.495	0.958
24,000	0.136	49.631	0.761
25,000	0.077	49.708	1.060
26,000	0.059	49.767	0.744
27,000	0.017	49.784	0.941
28,000	0.077	49.861	1.060
29,000	0.017	49.878	1.240
30,000	0.017	49.895	1.240

(CONTINUED)

Table 1 (Continued)

Upper Weight Limit (pounds)	Single Axles		Tandem Axles (Percent)
	Percent	Cumulative Percent	
31,000	0.017	49.912	1.206
32,000	0.000	49.912	1.522
33,000	0.000	49.912	1.377
34,000	0.000	49.912	1.736
35,000	0.000	49.912	1.488
36,000	0.000	49.912	1.454
37,000	0.000	49.912	1.437
38,000	0.000	49.912	1.377
39,000	0.000	49.912	1.274
40,000	0.000	49.912	1.112
41,000	0.000	49.912	0.812
42,000	0.000	49.912	0.658
43,000	0.000	49.912	0.462
44,000	0.000	49.912	0.427
45,000	0.000	49.912	0.316
46,000	0.000	49.912	0.145
47,000	0.000	49.912	0.179
48,000	0.000	49.912	0.102
49,000	0.000	49.912	0.145
50,000	0.000	49.912	0.085
51,000	0.000	49.912	0.000
52,000	0.000	49.912	0.017
53,000	0.000	49.912	0.017
54,000	0.000	49.912	0.000
55,000	0.000	49.912	0.000
56,000	0.000	49.912	0.000

COMPONENTS SUPPLIED BY D-8

Pavements in Texas are designed based on the traffic loadings expected in the highway's **design lane.** A highway's design lane is the lane expected to experience the greatest number of ESALs over the design period. The design lane for many highways is the right-hand lane; but on some highways (e.g., urban freeways) the design lane is the second lane from the right. To identify the **Design Lane ESAL** it is necessary to distribute the Total ESAL between the two directions of travel and among the lanes in each direction. This accomplished using a **directional distribution factor** and a **lane distribution factor.**

Directional Distribution Factor

The directional distribution factor applied by D-8 is an expected average directional distribution for the entire design period. D-8 generally assigns 50 percent of D-10's total ESAL forecast to each direction of travel on the highway. If there is strong reason to believe that trucks at the site travel loaded in one direction and unloaded in the other, D-8 may assign a greater percentage of ESALs to the "loaded" direction.

Lane Distribution Factor

The lane distribution factor applied by D-8 is an expected average lane distribution for the entire design period. D-8 currently assigns 100 percent of the **One-Directional ESAL** to the design lane for highways with four or less lanes, 80 percent to the design lane for highways with six lanes, and 70 percent to the design lane for highways with eight lanes. D-8 describes these lane distribution factors as "conservative" indicating that the factors may tend to overestimate the design lane ESAL percentage.

This completes the list of ESAL forecast components supplied by D-8.

Example Total ESAL and Design Lane ESAL calculations are provided in Chapter III.

CHAPTER III
EXAMPLE ESAL CALCULATIONS

INTRODUCTION

The purpose of this chapter is to illustrate how the individual ESAL forecast components combine to generate a Design Lane ESAL forecast. The first section of the chapter identifies the assumptions used in the example. The second and third sections demonstrate the Total ESAL and Design Lane ESAL calculations, respectively. The fourth section discusses the results of the example ESAL calculations and presents a simplified Design Lane ESAL formula for use throughout the remainder of the report.

ASSUMPTIONS

The example ESAL calculations are based on the following assumptions:

Base Year ADT - 1,000 vpd

ADT Growth Rate - 5 percent per year

Percent Trucks - 10 percent

Percent Single Axles - 45 percent

Axle Factor - 2.75 axles per truck

Axle Weight Distribution Table - shown in Table 2 (a condensed table has been used for simplicity)

Directional Distribution Factor - 50 percent to each direction

Lane Distribution Factor - 80 percent of one-directional ESALs to the design lane (i.e., the example site is a 6-lane road)

Design Period - 20 years

Table 2
Condensed Axle Weight Distribution

Weight Group	Singles (percent)	ESALs/ Axle	Contribution to Average ESAL/Axle
0 - 10K	35	0.010	0.00350
10 - 20K	9	0.500	0.04500
20 - 30K	1	3.500	0.03500
30 - 40K	-	-	-
40 - 54K	-	-	-
Percent Singles	45%		
Total Contribution by Single Axles			0.08350

	Tandems (percent)	ESALs/ Axle	Contribution To Average ESAL/ Axle
0 - 10K	6	0.001	0.00006
10 - 20K	22	0.055	0.01210
20 - 30K	12	0.350	0.04200
30 - 40K	10	1.250	0.12500
40 - 54K	5	3.900	0.19500
Percent Tandem	55%		
Total Contribution By Tandem Axles			0.37416

AVG ESAL PER AXLE (0.0835 + 0.37416)	0.45766

TOTAL ESAL CALCULATION

The Total ESAL calculation is performed by D-10 using the RDTEST68 computer program. The steps are as follows:

Step I

The Base Year ADT, ADT Growth Rate, and Percent Trucks components are used to calculate **Total Vehicles, Total Trucks,** and **Total Other Vehicles.** Total Vehicles is the total number of vehicles expected to use the pavement facility during the design period. Total Trucks and Total Other Vehicles are, respectively, the total number of trucks and total number of non-trucks expected to use the pavement facility during the design period. Total Vehicles is calculated using the following equation:

$$\text{Total Vehicles} = T * 365 * ADT_o * (2 + GF_{ADT} * T)/2 \qquad (3.1)$$

where:

$$T \quad = \quad \text{the length of the design period (years)}$$

$$ADT_o \qquad = \text{Base Year ADT (vpd)}$$

$$GF_{ADT} \qquad = \text{ADT Growth Rate (percent volume growth per year)}$$

Given ADT_o = 1000 vpd, GF_{ADT} = 5 percent per year, and T = 20 years:

$$\text{Total Vehicles} = 365 * 20 * 1000 * (2 + 0.05 * 20)/2 = 10,950,000$$

Total Trucks is found by multiplying Percent Trucks times Total Vehicles:

$$\text{Total Trucks} = \text{Total Vehicles} * \text{Percent Trucks} \qquad (3.2)$$

Given 10,950,000 Total Vehicles and Percent Trucks = 10.0 percent:

$$\text{Total Trucks} = 10,950,000 * 0.10 = 1,095,000$$

Total Other Vehicles is found by subtracting Total Trucks from Total Vehicles:

$$\text{Total Other Vehicles} = \text{Total Vehicles} - \text{Total Trucks} \qquad (3.3)$$

Given Total Vehicles = 10,950,000 and Total Trucks = 1,095,000:

$$\text{Total Other Vehicles} = 9,855,000$$

Step II

Total Trucks and Total Other Vehicles are used in combination with an **Average Load Equivalency Factor per Truck** and an **Average Load Equivalency Factor per Other**

Vehicle, respectively, to calculate the Total ESAL. An Average Load Equivalency Factor per Other Vehicle, **AVG ESAL$_{OV}$**, of 0.000626 is built into the RDTEST68 program. The total number of ESALs attributable to Total Other Vehicles, **Total ESAL$_{OVs}$**, is given by:

$$\text{Total ESAL}_{OV_s} = \text{Total Other Vehicles} * \text{AVG ESAL}_{OV} \qquad (3.4)$$

$$\text{Given Total Other Vehicles} = 9,855,000 \text{ and AVG ESAL}_{OV} = 0.000626:$$

$$\text{Total ESAL}_{OV_s} = 9,855,000 * 0.000626 = 6,169 \text{ ESALs}$$

The Average Load Equivalency Factor per Truck is calculated by RDTEST68 for each ESAL forecast using the Axle Weight Distribution Table, Percent Single Axles, and Axle Factor. Table 2, the condensed Axle Weight Distribution Table, indicates that 35 percent of the axles passing the hypothetical WIM site are single axles which weigh between 0 and 10,000 pounds. In addition, each of these 0 to 10,000 pound single axles imparts an average of 0.01 ESALs to the pavement. In all, these 0 to 10,000 pound single axles contribute 0.0035 ESALs (i.e., 0.35 * 0.01 ESALs) to the **Average Load Equivalency Factor per Truck Axle (AVG ESAL$_{axle}$)**. AVG ESAL$_{axle}$ is found by summing the contribution of all single and tandem axle weight groups. In this case, AVG ESAL$_{axle}$ is 0.4577 ESALs per axle. Note the relationship between AVG ESAL$_{axle}$ and the percent single axles in Table 2: percent single axles effectively weights the contributions of single axles to the AVG ESAL$_{axle}$ while (1 - percent single axles), that is, percent tandems, weights the contribution of tandem axles to AVG ESAL$_{axle}$. As a result, given the same relative proportions of single axles among single axle weight groups (i.e., (35/45)*100 percent or 77.8 percent of single axles weigh between 0 and 10,000 pounds, and (9/45)*100 percent or 20 percent of single axles weight between 10,000 and 20,000 pounds, etc.) and tandem axles among tandem axle weight groups, a higher percent single axles will lead to a higher weighting of single axles and a lower weighting of tandem axles in AVG ESAL$_{axle}$. Because the average load equivalency factor per tandem axle at a site is generally much larger than the average load equivalency factor per single axle at the site, a higher weighting of single axles will lead to a lower AVG ESAL$_{axle}$ for the site and vice versa.

The **Average Load Equivalency Factor per Truck, AVG ESAL$_{Truck}$**, is found by multiplying AVG ESAL$_{axle}$ by the Axle Factor:

$$\text{AVG ESAL}_{Truck} = \text{AVG ESAL}_{axle} * \text{Axle Factor} \qquad (3.5)$$

16

Given an Axle Factor of 2.75 axles/truck:

$$\text{AVG ESAL}_{\text{Truck}} = 0.4577 \text{ ESALs/axle} * 2.75 \text{ axles/truck} = 1.26 \text{ ESALs}$$

This Average Load Equivalency Factor per Truck is then multiplied by Total Trucks to determine the total number of ESALs attributable to Trucks, **Total ESAL**$_{\text{Trucks}}$:

$$\text{Total ESAL}_{\text{Trucks}} = \text{Total Trucks} * \text{AVG ESAL}_{\text{Truck}} \qquad (3.6)$$

Given Total Trucks = 1,095,000 and Average ESAL Per Truck = 1.26:

$$\text{Total ESAL}_{\text{Trucks}} = 1,095,000 * 1.26 = 1,379,700 \text{ ESALs}$$

Step III

The Total ESAL is the sum of Total ESAL$_{\text{Trucks}}$ and Total ESAL$_{\text{OVs}}$:

$$\text{Total ESAL} = \text{Total ESAL}_{\text{Trucks}} + \text{Total ESAL}_{\text{OVs}} \qquad (3.7)$$

Given Total ESAL$_{\text{Trucks}}$ = 1,379,700 ESALs and Total ESAL$_{\text{OVs}}$ = 6,169 ESALs:

$$\text{Total ESAL} = 1,379,700 + 6,169 = 1,385,869 \text{ ESALs}$$

DESIGN LANE ESAL CALCULATION
Step I

D-8 uses the Total ESAL in combination with the directional distribution factor (D) to generate a One-Directional ESAL.

$$\text{One-Directional ESAL} = \text{Total ESAL} * D \qquad (3.8)$$

Given Total ESAL = 1,385,869 ESALs and D = 50 percent:

$$\text{One-Directional ESAL} = 1,385,869 * 0.50 = 692,935 \text{ ESALs}$$

Step II

D-8 then uses the One-Directional ESAL and the lane distribution factor, LF, to generate the Design Lane ESAL.

$$\text{Design Lane ESAL} = \text{One-Directional ESAL} * LF \qquad (3.9)$$

Given One-Directional ESAL = 692,935 ESALs and LF = 0.80:

$$\text{Design Lane ESAL} = 692,935 \text{ ESALs} * 0.80 = 554,348 \text{ ESALs}$$

17

DISCUSSION AND SIMPLIFIED DESIGN LANE ESAL FORMULA

In addition to demonstrating the Design Lane ESAL calculation process, the preceding example illustrates the great disparity in a typical ESAL calculation between the percentage of ESALs contributed by trucks versus other vehicles. In this case, 99.6 percent of Design Lane ESALs were contributed by trucks. This is caused by 1) the exponential relationship between axle weights and equivalent axle loads described in Chapter I; and, to a lesser extent, 2) the fact that trucks generally have more axles per vehicle than non-trucks. These causes are discussed below.

Truck axles typically weigh much more than non-truck axles; however, differences in axle weights are magnified by a power of approximately four in the conversion from axle weight to equivalent axle load. For example, if a truck axle weighs five times as much as a non-truck axle, all other things being equal, one repetition of the truck axle is equivalent, from a pavement damage perspective, to approximately 5^4 or 625 repetitions of the non-truck axle. In the example ESAL calculation, the average load equivalency factor per truck axle, 0.4577 ESALs, is more than 1,400 times greater than the average load equivalency factor per non-truck axle, 0.000313 ESALs.

In addition, trucks generally have greater numbers of axles per vehicle than non-trucks. In this case, the truck axle factor is 2.75 axles per vehicle while the non-truck axle factor is always 2 axles per vehicle.

These two factors combine to create an average load equivalency factor per truck that is much, much larger than the average load equivalency factor per non-truck. In this example the average load equivalency factor per truck, 1.26 ESALs, was more than 2,000 times greater than the average load equivalency factor per non-truck, 0.000626 ESALs. As a result, even though there were nine times as many non-trucks as trucks, the non-trucks contributed almost nothing to the Design Lane ESAL.

Even in a case of extremely high non-truck volumes relative to truck volumes, the contribution of non-trucks to total ESALs is negligible. For example, given Base Year ADT = 100,000 vpd, ADT Growth Rate = 5 percent per year, and Percent Trucks = 1 percent:

Total Vehicles	=	1,095,000,000
Total Trucks	=	10,950,000

Total Other Vehicles　　=　　1,084,050,000

Given $AVG\ ESAL_{Trucks}$ = 1.26 and $AVG\ ESAL_{OV}$ = 0.000626 from the previous example:

Total $ESAL_{Trucks}$　　=　　13,797,000

Total $ESAL_{OVs}$　　=　　678,615

Total ESAL　= Total $ESAL_{Trucks}$ + Total $ESAL_{OVs}$　　　　　(3.8)

　　　　= 13,797,000 + 678,615

　　　　= 14,475,615 ESALs

The directional and lane distribution factors do not change the percentage of Design Lane ESALs contributed by trucks versus non-trucks. Hence, even in this extreme example, non-truck traffic contributes only 4.7 percent of Design Lane ESALs.

If Total $ESAL_{OVs}$ had been completely ignored in this example (i.e., if the Design Lane ESAL had been underestimated by 4.7 percent), an "error" of less than 1/16th inch in pavement thickness would result [5]. Pavement contractors are not expected to control pavement thicknesses to better than 1/4 inch [6]. As a result, a 1/16 inch error is not significant from a pavement design perspective.

Given the relative unimportance of non-truck ESALs for ESAL forecasting purposes, the Design Lane ESAL can be expressed in the following simplified form:

$$w_T = 365 * T * ADT_o * [(2 + GF_{ADT}*T) / 2] * PCT * EF * D * LF \quad (3.10)$$

where:

w_T　　　　= cumulative design lane ESALs

T　　　　= design period, years

ADT_o　　　　= base year ADT

GF_{ADT}　　　　= ADT growth factor

PCT　　　　= percent trucks

EF　　　　= average load equivalency factor per truck (based on axle weight distribution table, percent single axles, and axle factor)

D　　　　= directional distribution

LF　　　　= lane factor

In this formulation, adopted from Cunagin [7], non-truck ESALs are ignored as negligible.

19

CHAPTER IV
ANALYSIS OF CURRENT TXDOT ESAL FORECASTING PROCEDURES
INTRODUCTION

In this chapter TxDOT's current ESAL forecasting procedures are evaluated. The first section of the chapter identifies the accuracy measures used in the analysis. The second section analyzes the individual component accuracies and, where possible, evaluates any assumptions made regarding components under current practice. The third section evaluates the sensitivity of the ESAL forecast to errors in individual components. The fourth section assesses overall ESAL forecast accuracy.

MEASURES OF ACCURACY

As used in this analysis, the general term "accuracy" encompasses the terms "precision" and "bias." To say that a procedure generates precise component estimates implies that repeated component estimates made using the procedure would vary little from one estimate to the another. To say that a procedure generates unbiased component estimates implies that repeated component estimates made using the procedure would not consistently over- or under-estimate the component's actual value.

For pavement design purposes, ESAL forecast precision is measured by the variance of the logarithm of the ESAL forecast [1,2,8]. This statistic is commonly referred to as traffic variance or $Var(log_{10} w_T)$ [2,7,8]. The traffic variance assessment framework used here is based on the work of Darter and Hudson [8]. Appendix A, Part III demonstrates that, given the simplified Design Lane ESAL formula (Equation 3.10), traffic variance may be found using Equation 4.1:

$$Var(log_{10} w_T) = 0.4343^2 * \{CV(ADT_o)^2 + CV(PCT)^2 + CV(EF)^2 + CV(D)^2 + CV(LF)^2 + [T^2*CV(GF_{ADT})^2/(2/GF_{ADT} + T)^2]\}$$

$$(4.1)$$

where:

$Var(log_{10} w_T)$ = traffic variance

$CV(ADT_o)$ = base year ADT coefficient of variation

$CV(PCT)$ = percent trucks coefficient of variation

CV(EF)	=	average load equivalency factor per truck coefficient of variation
CV(D)	=	directional distribution coefficient of variation
CV(LF)	=	lane distribution coefficient of variation
$CV(GF_{ADT})$	=	ADT growth rate coefficient of variation
GF_{ADT}	=	ADT growth rate

Equation 4.1 assumes independence between Design Lane ESAL forecast components; this assumption will be discussed in the "OVERALL FORECAST ACCURACY" section below. Equation 4.1 shows that traffic variance may be identified using the **coefficient of variation** of each forecast component. As a result, the statistic used to measure individual component precision will be the coefficient of variation. A component's coefficient of variation is defined as its **standard deviation** divided by its **expected value** [9]. Approximately 68 percent of the values a component may take on are encompassed within the range: *expected value ± one standard deviation* [9]. This implies that the 68 percent **confidence limits** of a component estimate are defined by the range: *expected value ± one coefficient of variation of the expected value*. For example, given a 1,000 vpd base year ADT estimate with a 10 percent coefficient of variation, there is a 68 percent chance that the actual ADT will fall within the range: *1,000 vpd ± 0.10 * 1,000 vpd ⇒ 1,000 vpd ± 100 vpd*. The 95 percent confidence limits of a component estimate are defined by the range: *expected value ± two coefficients of variation of the expected value* [9].

The bias associated with a procedure is the average percent of a component's actual value by which component estimates under- or over-estimate that actual value.

INDIVIDUAL COMPONENT ACCURACIES

The analysis of each component is organized as follows: 1) the definition of the component and the procedures used to assign it a value are briefly summarized; 2) any assumptions made regarding that component are stated and examined; and 3) the component's precision and, if applicable, bias, given each of its alternative sources, are evaluated. A summary of findings concerning component accuracies is provided following

21

the analysis below.

ADT Growth Rate

Under current TxDOT practice, the ADT growth rate is determined by performing a linear regression on historical traffic data collected at or near the pavement project site. This procedure assumes that traffic growth follows a linear model. This assumption was evaluated by performing a linear regression on 16 years of historical ADTs collected at each of 56 rural Texas ATR sites [10]. Six sites were located on Interstate Highways, 27 on U.S. Highways, 13 on State Highways, and 10 on Farm to Market roads. The sites were chosen because they had 16 years of continuous traffic history; it is assumed that these sites are representative of rural sites around the state.

The explanatory power (i.e., the appropriateness) of the linear model may be evaluated using the **coefficient of determination** of the regression equation, the " $r_{X,Y}^2$ " statistic [11]. The $r_{X,Y}^2$ for any regression equation may range from 0.0 to 1.0 [11]. The value $r_{X,Y}^2 * 100$ percent is interpreted to be the percentage of variation in the dependent variable, Y, explained by variation in the independent variable, X [11]. In this case, ADT is the dependent variable; time is the independent variable. The higher the $r_{X,Y}^2$, the more appropriate the linear model.

Figure 2 shows the frequency distribution of $r_{T,ADT}^2$s at the 56 sites. The median $r_{T,ADT}^2$ was 86.6 percent. The average $r_{T,ADT}^2$ was 70.2 percent. At 35 of the 56 sites (i.e., 62.5 percent of the sites) the linear model produces an $r_{T,ADT}^2$ of greater than 80 percent. At these sites, the linear assumption is considered appropriate. At 7 of 56 sites (i.e., 12.5 percent of the sites) the $r_{T,ADT}^2$ is between 50 and 80 percent. At these sites the linear assumption is considered marginal. At the remaining 14 of 56 sites (i.e., approximately 25 percent of the sites) the $r_{T,ADT}^2$ is less than 50 percent. At these sites, the linear model is considered inappropriate. Table 3 shows the average $r_{T,ADT}^2$ for locations on each highway system.
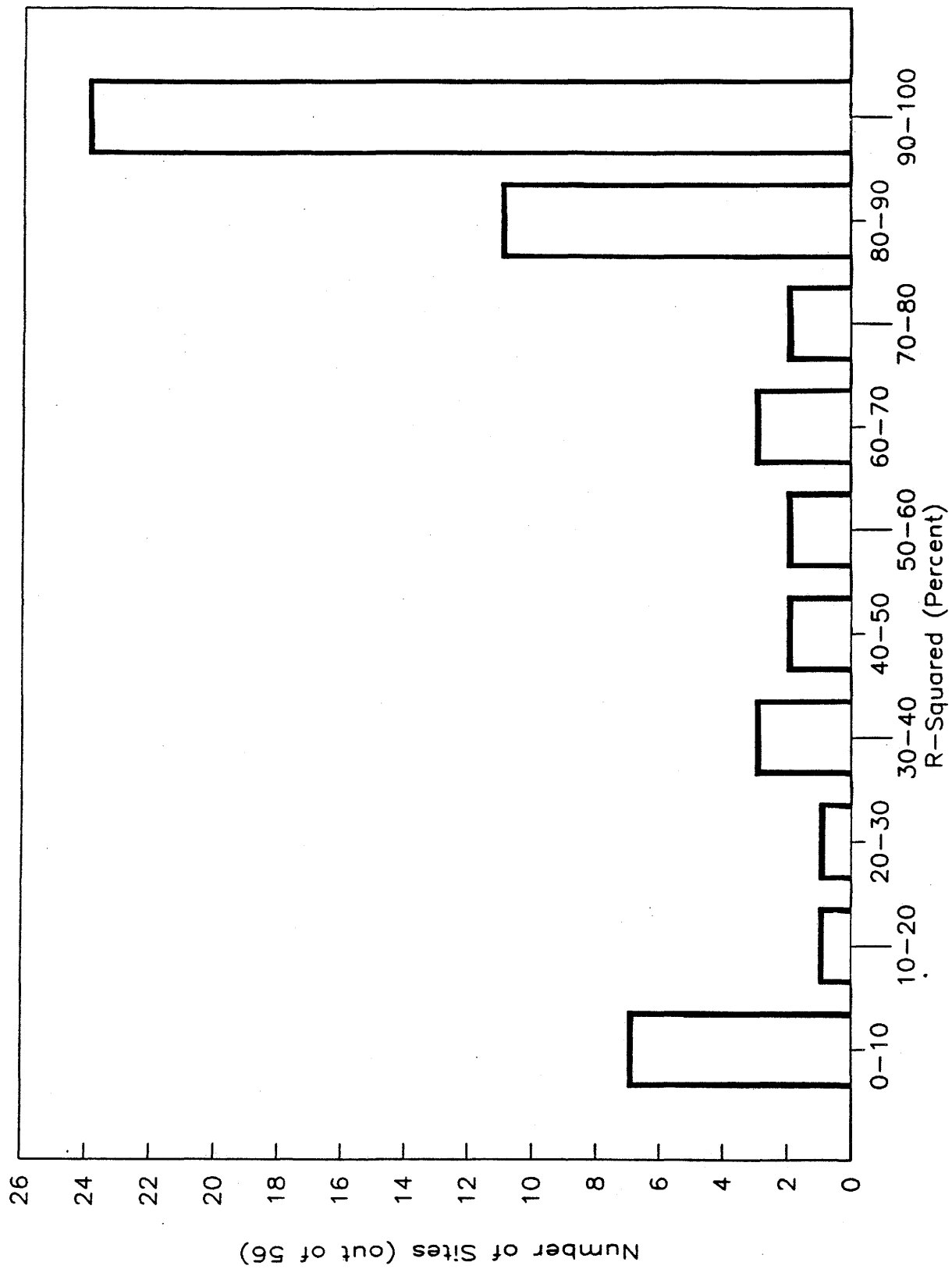
Figure 2: Frequency Distribution of $r_{T,ADT}^2$

R-Squared (Percent)

Number of Sites (out of 56)

0-10 10-20 20-30 30-40 40-50 50-60 60-70 70-80 80-90 90-100

26 24 22 20 18 16 14 12 10 8 6 4 2 0

23

Table 3
Average $r_{T,ADT}^2$ for Linear Model at Rural Texas Sites

Highway System	Average $r_{T,ADT}^2$	Number of Sites
Interstate	90.1%	6
U.S.	62.3%	27
State	71.2%	13
F.M.	78.1%	10
Overall	70.2%	56

Other researchers have attempted to model rural ADT using econometric methods. Neveu [12] found the following $r_{ECON,ADT}^2$s using econometric methods: interstates — 65 percent; principal arterials — 77 percent; and minor arterials and major collectors — 20 percent. Saha, et al [13], found the following $r_{ECON,ADT}^2$s: interstates — 65.8 percent; principal arterials — 69 percent; minor arterials — 72.7 percent; and major collectors — 83.7 percent.

Appendix A, Part IV shows that, given a linear annual traffic growth model, the ADT growth rate coefficient of variation may be found using the Equation 4.2:

$$CV(GF_{ADT}) = [CV(GR)^2 + CV(ADT(0))^2 - 2*r_{GR,ADT(0)}*CV(GR)*CV(ADT(0))]^{1/2}$$

(4.2)

where:

$CV(GF_{ADT})$	=	the ADT growth rate coefficient of variation
$CV(GR)$	=	the parameter GR's coefficient of variation
$CV(ADT(0))$	=	the parameter ADT(0)'s coefficient of variation
$r_{GR,ADT(0)}$	=	the coefficient of correlation between GR and ADT(0)

Equation 4.2 shows that to find $CV(GF_{ADT})$, it is necessary to know $CV(GR)$, $CV(ADT(0))$, and $r_{GR,ADT(0)}$.

1. CV(GR) and CV(ADT(0))

The parameters GR and ADT(0) were defined in Chapter II in connection with Equation 2.2, the equation used to find an ADT growth rate. That equation and the definitions of GR and ADT(0) are repeated here:

$$ADT(t) = GR * t + ADT(0) \tag{2.2}$$

where:

ADT(t) = the average daily traffic at a point in time, t

GR = the ADT growth rate, measured in vehicles per year (vpy)

t = time, measured in years (t = 0 corresponds to the first year of historical volume data used in the analysis)

ADT(0) = the "t = 0" ADT identified by the regression, measured in vehicles per day (vpd)

An annual percentage ADT growth rate, GF_{ADT}, is found, using Equation 2.2, by dividing GR by ADT(0).

As defined previously, a parameter's coefficient of variation is its standard deviation divided by its expected value. The expected values of GR and ADT(0) for any regression equation are the values assigned those parameters by the regression model (i.e., the **parameter estimates**). Because the parameters GR and ADT(0) follow the "Student's t" distribution [11], the standard deviation of each parameter must be found in terms of its **standard error**. The standard error takes into account the number of observations (i.e., the number of years of historical ADT) on which the regression parameters are based. The greater the number of underlying observations, the smaller the standard errors of the regression parameters, all other things being equal. Equation 4.3 shows the relationship between the standard error and standard deviation [11].

$$\text{Standard Deviation} = N^{1/2} * \text{Standard Error} \tag{4.3}$$

where:

N = the number of observations used to estimate the parameter

In practice, the parameter estimates may be based on 10 or more years of historical volume data. In this analysis, the parameters GR and ADT(0) were

25

estimated using 16 years of historical data. As a result, each parameter's coefficient of variation is given by the relationship:

$$CV(parameter) = 4.0 * Standard\ Error/Parameter\ Estimate \qquad (4.4)$$

$CV(GR)$ and $CV(ADT(0))$ were identified using Equation 4.4 and the regression output for each of the 56 locations.

2. $r_{GR,ADT(0)}$

The statistic $r_{GR,ADT(0)}$ is called the **coefficient of correlation** between the parameters, GR and ADT(0) [11]. The $r_{GR,ADT(0)}$ statistic may range from -1 to 1 depending on the relationship between GR and ADT(0). An $r_{GR,ADT(0)}$ greater than 0 indicates a positive correlation between GR and ADT(0) (i.e., if higher levels of traffic growth (measured in vehicles per year) are observed at sites with higher levels of year 0 historical traffic volume, then GR and ADT(0) are positively correlated). An $r_{GR,ADT(0)}$ less than 0 indicates a negative correlation between GR and ADT(0) (i.e., if higher levels of traffic growth (measured in vehicles per year) are observed at sites with lower levels of year 0 historical traffic volume, then GR and ADT(0) are negatively correlated). An $r_{GR,ADT(0)}$ close to 0 indicates little or no correlation between TK and ADT.

The magnitude of the statistic $r_{GR,ADT(0)}$ is simply square root of the $r_{GR,ADT(0)}{}^2$ obtained by regressing GR against ADT(0) [11]. The sign of $r_{GR,ADT(0)}$ may be found by examining a plot of GR versus ADT(0) to determine whether a positive or negative correlation is indicated or by referring to the sign of the constant assigned to the dependent variable by the regression (e.g., a positive relationship would be indicated by a positive constant and vice versa) [11].

A linear regression was performed on the 56 pairs of GR and ADT(0) values identified by the regressions of historical ADT against time at each ATR site. The $r_{GR,ADT(0)}{}^2$ identified by the regression of GR against ADT(0) was 0.6083; in addition, the relationship between GR and ADT(0) was positive. This indicates an observed $r_{GR,ADT(0)}$ of approximately $+(0.6083)^{1/2} = +0.7788$.

The significance of this $r_{GR,ADT(0)}$ may be evaluated using Equations 4.5 and 4.6 [9].

$$LB = \{(1+R)-(1+R)*exp(2*Z_{\alpha/2}/[(n-3)^{1/2}])\}/\{(1+R)+(1+R)*exp(2*Z_{\alpha/2}/[(n-3)^{1/2}])\}$$

(4.5)

$$UB = \{(1+R)-(1+R)*exp(-2*Z_{\alpha/2}/[(n-3)^{1/2}])\}/\{(1+R)+(1+R)*exp(-2*Z_{\alpha/2}/[(n-3)^{1/2}])\}$$

(4.6)

where:

LB = the lower bound of the $(1-\alpha)*100$ percent confidence limit for r

UB = the upper bound of the $(1-\alpha)*100$ percent confidence limit for r

R = the observed coefficient of correlation

$Z_{\alpha/2}$ = the value of the standard normal deviate corresponding to the $(1-\alpha)*100$ percent level of significance (e.g. $Z_{0.05/2}$ corresponds to the $(1-0.05)*100$ or 95 percent significance level).

n = the number of observations used to estimate R

These equations give, respectively, the lower and upper bounds of the $(1-\alpha)*100$ percent confidence limits of the observed $r_{GR,ADT(0)}$. The bounds are used to test the null hypothesis, H_o: $r_{GR,ADT(0)}$ = 0.0; i.e., the bounds are used to determine whether the observed r value is different enough from 0.0, given the number of underlying observations, to conclude with some level of confidence, that the actual value of $r_{GR,ADT(0)}$ between the two variables is not 0.0. If both bounds are greater than 0.0 or both bounds are less than 0.0, it may be concluded with $(1-\alpha)*100$ percent confidence that the observed r is not equal to zero. The 95 percent significance level will be used; this indicates a $Z_{0.05/2}$ = 1.96.

Substituting $r_{GR,ADT(0)}$ = +0.7799, n = 56, and $Z_{0.05/2}$ = 1.96 into Equations 4.5 and 4.6 yields a lower bound of 0.6504 and an upper bound of 0.8654. Both bounds are greater than 0.0. As a result, the null hypothesis may be rejected and $r_{GR,ADT(0)}$ = +0.78 will be used below.

The CV(GR) and CV(ADT(0)) for each ATR site were entered into Equation 4.2 along with $r_{GR,ADT(0)}$ = +0.78 to find the each location's ADT growth rate coefficient of variation, $CV(GF_{ADT})$. Figure 3 shows the frequency distribution of $CV(GF_{ADT})$ over the 56 sites. The median $CV(GF_{ADT})$ at the 56 sites was 29.3 percent.

Note that Equation 4.2 actually identifies the coefficient of variation associated with estimating a site's historical ADT growth rate using linear regression. This analysis uses this historical $CV(GF_{ADT})$ as an approximation for the $CV(GF_{ADT})$ associated with the growth rate used to forecast future ADT. Because the historical $CV(GF_{ADT})$ is essentially a measure of the appropriateness of the linear annual traffic growth model in the past at the site, using the historical $CV(GF_{ADT})$ to approximate the future $CV(GF_{ADT})$ implies an assumption that the appropriateness of the linear model at the site will not change over time.

Since growth rates are usually discussed in percentage terms, a growth rate coefficient of variation (also expressed in percentage terms) can be misleading. To illustrate, assume that a regression equation yields a 4 percent per year ADT growth rate with a 25 percent coefficient of variation. This does not imply a 68 percent probability that the actual growth rate will be within the range: *4 percent ±25 percent ⇒ -21 percent to 29 percent per year.* Rather, it implies a 68 percent probability that the actual growth rate will be within the range: *4 percent ± (25 percent of 4 percent) ⇒ 3 percent to 5 percent per year.*

Figure 4 shows the frequency distribution of linear annual percentage growth rates at the 56 sites. The median ADT growth rate, GF_{ADT}, at the 56 locations surveyed was 3.3 percent per year.
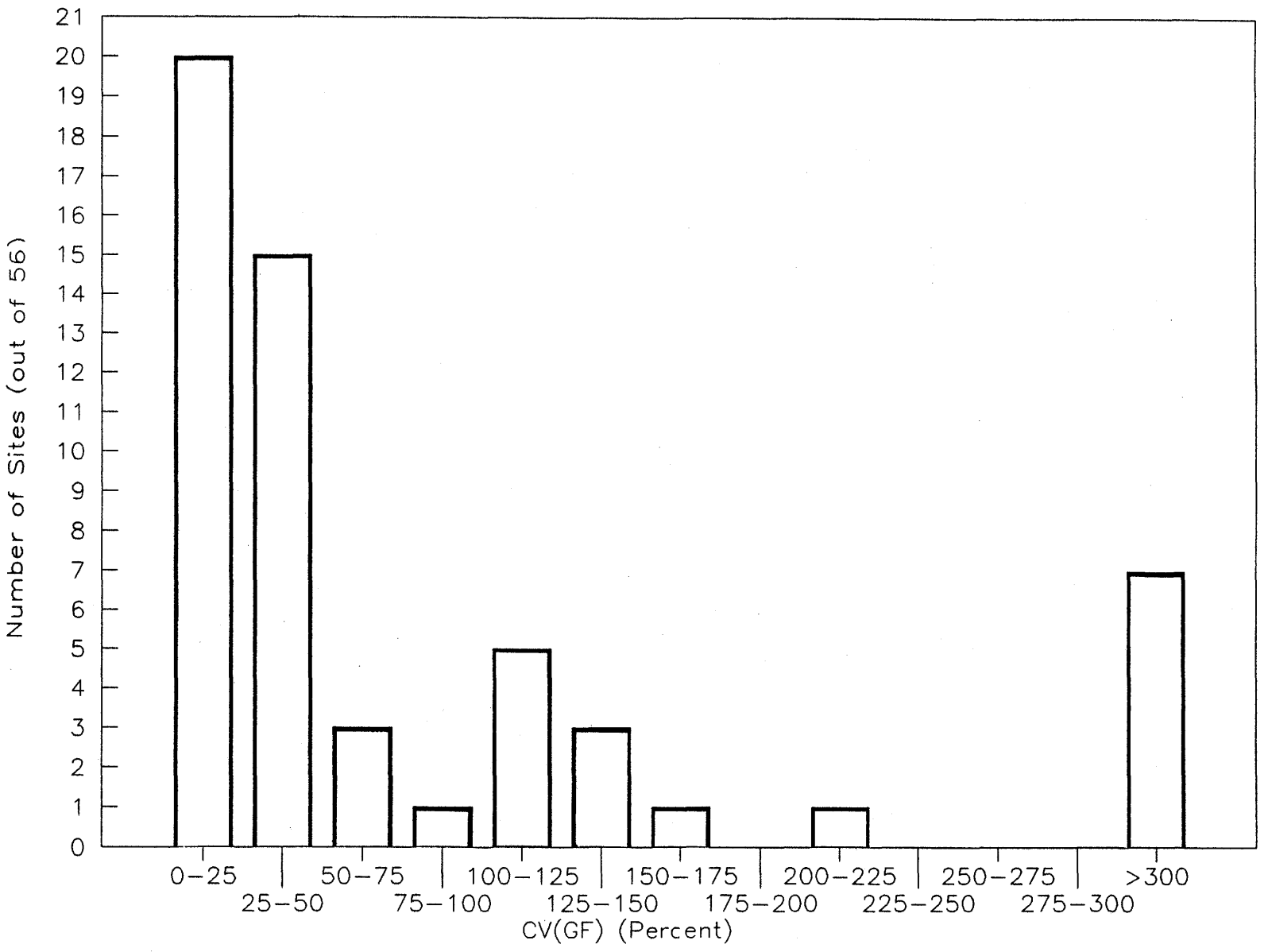
Figure 3: Frequency Distribution of CV(GF_{ADT})

29
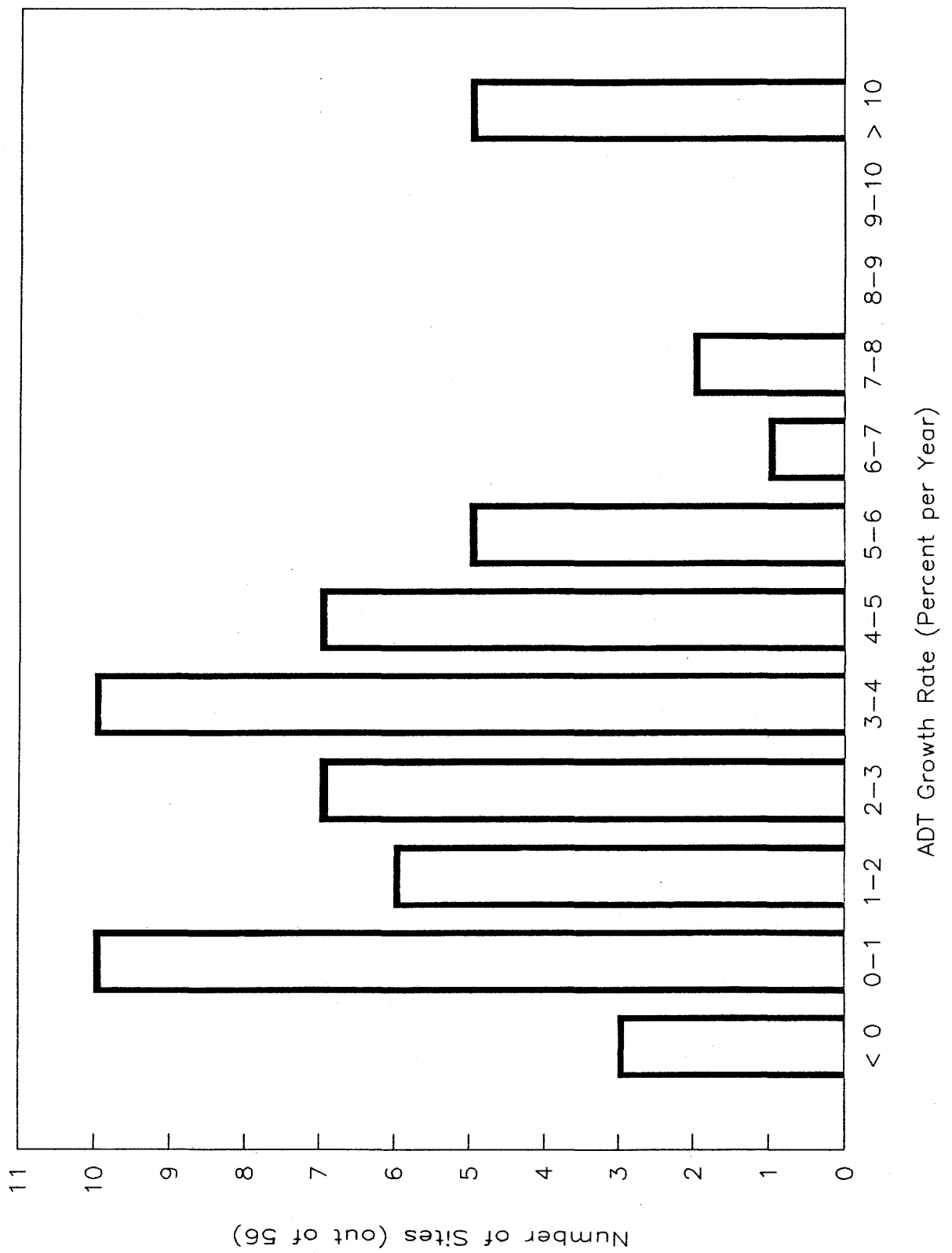
Figure 4: Frequency Distribution of GF$_{ADT}$

Base Year ADT

A pavement project's base year ADT is determined by projecting current year ADT ahead one to two years, to the first year of the design period, using the ADT growth rate.

Appendix A, Part V demonstrates that the base year ADT coefficient of variation may be determined using Equation 4.7:

$$CV(ADT_o) = \{ CV(ADT_{current})^2 + [T^2 * CV(GF_{ADT})^2 / (1/GF_{ADT} + T)^2] \}^{1/2} \tag{4.7}$$

where:

$CV(ADT_o)$ = base year ADT coefficient of variation

$CV(ADT_{current})$ = current year ADT coefficient of variation

T = time from the current year to the base year

$CV(GF_{ADT})$ = ADT growth rate coefficient of variation

GF_{ADT} = ADT growth rate (measured in percent per year)

Equation 4.7 shows that to identify $CV(ADT_o)$, it is necessary to know: $CV(ADT_{current})$, $CV(GF_{ADT})$, GF_{ADT}, and T. Equation 4.7 assumes that GF_{ADT} and $ADT_{current}$ at a site are not correlated (i.e., $r_{GF,ADT} \approx 0.0$).

1. $r_{GF,ADT} \approx 0.0$

   The correlation between GF_{ADT} and $ADT_{current}$ was evaluated by regressing GF_{ADT} versus $ADT_{current}$ values at the 56 rural ATR sites referenced previously. The regression yielded an $r_{GF,ADT}^2$ of 0.0490 and an $r_{GF,ADT}$ of +0.2215. The significance of this $r_{GF,ADT}$ value was evaluated using Equations 4.5 and 4.6. Substituting $r_{GF,ADT} = +0.2215$, $n = 56$, and $Z_{0.05/2} = 1.96$ into Equations 4.5 and 4.6 yields a lower bound, for the 95 percent confidence limits, of -0.0440 and an upper bound of 0.4578. Since the point 0.0 is included within the 95 percent confidence band, the null hypothesis, $r_{GF,ADT} = 0.0$, may not be rejected and independence between GF_{ADT} and $ADT_{current}$ is assumed.

2. $CV(GF_{ADT})$ and GF_{ADT}

$CV(GF_{ADT})$ and GF_{ADT} were examined in the "ADT Growth Rate" section above. That examination identified a median $CV(GF_{ADT})$ = 29.3 percent and a median statewide GF_{ADT} of 3.3 percent; these values for GF_{ADT} and $CV(GF_{ADT})$ will be used here.

3. T

T, the number of years from the current year to the base year, is known for each forecast. A value of T = 2 years will be used here.

4. $CV(ADT_{current})$

Current year ADT may be based on ATR data or on 24-hour coverage count data collected within the project limits. $CV(ADT_{current})$ differs depending on which situation applies.

a) Current Year ADT from an ATR: When current year ADT is based on data from an ATR within the project limits, there are two potential sources of error: 1) the operating error of the ATR; and 2) any error due to imputation of missing data points.

Data imputation error could not be quantified. This source of error is ignored.

TxDOT's tolerance limits for ATR precision are ±2 percent deviation from volumes observed during observation periods [14]. This analysis will assume that ADT estimates based on ATR volumes are unbiased and are precise to within ±2 percent of actual ADT in 95 percent of cases. This assumption implies that the 95 percent confidence limits of an ADT estimate based on ATR data are defined by the range: *estimated ADT ±2 percent*. The "Measures of Accuracy" section above pointed out that the 95 percent confidence limits of a component estimate are based on moving two coefficients of variation in either direction from the expected value. In this case, the expected value is the current year ADT produced by the ATR; two coefficients of variation equal 2 percent. Thus, when $ADT_{current}$ is based on ATR data, $CV(ADT_{current})$ = 1 percent.

Substituting $CV(ADT_{current})$ = 1 percent, $CV(GF_{ADT})$ = 29.3 percent, GF_{ADT} = 3.3 percent, and $T = 2$ into Equation 4.2:

$$CV(ADT_o) = \{ 0.01^2 + 2^2 * 0.293^2 / (1/0.033 + 2)^2 \}^{1/2}$$
$$= 0.0207$$

Hence, the coefficient of variation of a base year ADT estimate determined using ATR data collected within the project limits is approximately 2.1 percent.

b) Current Year ADT Based on a 24-Hour Coverage Count: In Texas, the raw coverage count produced by the counting device is an axle count. The axle count is adjusted to represent an annual average volume (i.e., an ADT) using an **axle correction factor** and a **monthly adjustment factor**. The axle correction factor accounts for the presence in the traffic stream of vehicles with more than two axles and converts the raw axle count to a vehicle count. The monthly adjustment factor adjusts the vehicle count for seasonal variations in traffic volumes at the coverage count site. Each coverage count location is assigned to a **monthly factor group** for adjustment purposes. Monthly factor groups are groups of ATRs which exhibit similar patterns in monthly variation.

Appendix A, Part VI presents the derivation of the formula used by Bodle [15] to assess the coefficient of variation of a current year ADT estimate based on a coverage count. That formula is:

$$CV(ADT_{current}) = [CV(CC)^2 + CV(MF)^2]^{1/2} \qquad (4.3)$$

where:

$CV(CC)$ = the coverage count coefficient of variation

$CV(MF)$ = the monthly factor coefficient of variation

Equation 4.3 shows that to identify $CV(ADT_{current})$, it is necessary to know $CV(CC)$ and $CV(MF)$. Equation 4.3 assumes no correlation between the monthly adjustment factor used at the site and the coverage count volume observed at the site. The $CV(CC)$ term in Equation 4.3 measures the variability of 24-hour weekday volume samples about the monthly mean

33

volume for a site. The monthly factor that will be used to adjust the coverage count volume observed at the site is the same whether the observed volume under- or over-estimates the monthly mean volume. As a result, even though the monthly factor used at the site may vary from the "true" monthly factor for the site, the monthly factor variation is unrelated to the coverage count variation.

Note that CV(CC) in Equation 4.3 reflects the variability in 24-hour **vehicle counts**, not 24-hour **axle counts**. The variability associated with a vehicle count under Texas practice necessarily incorporates any errors in the 24-hour axle count and the axle correction factor used to obtain the vehicle count. Review of the literature revealed no information concerning the day-to-day variability of 24-hour axle counts. As a result, the error in a vehicle count based on an axle count and an axle correction factor could not be identified directly. The literature review, however, did reveal a study [15] which evaluated the variability of 24-hour volume samples within one-month periods. Since Texas practice is based on a monthly adjustment factor system, results from this study will be used to approximate the precision of a vehicle count under Texas practice.

Bodle calculated CV(CC) using data from 386 rural ATRs in five states. Only 40 of these ATRs had ADTs of less than 500 vehicles per day. Excluding these low volume ATRs from the analysis did not change the results appreciably. Bodle found the coefficient of variation of 24-hour monthly ADT estimates to range between 9.7 percent and 12.4 percent of the estimate. The lower value was achieved by limiting the days for taking 24-hour coverage counts to Monday through Thursday. The higher value resulted when Friday counts were included. Texas practice excludes Friday counts; as a result, CV(CC) = 9.7 percent will be used in the analysis.

CV(MF) in Equation 4.3 measures the variability of monthly adjustment factors within a monthly factor group. Cunagin [14] calculated CV(MF) for different Texas monthly factor groups. He found the coefficient

34

of variation for the rural interstate group, for example, to be 4.5 percent; this value for CV(MF) will be used here.

Substituting CV(CC) = 9.7 percent and CV(MF) = 4.5 percent into Equation 4.3:

$$CV(ADT_{current}) = (0.097^2 + 0.045^2)^{1/2}$$
$$= 0.1069$$

Thus, the coefficient of variation of a current year ADT estimate based on a 24-hour coverage count is approximately 10.7 percent.

Substituting $CV(ADT_{current})$ = 10.7 percent, $CV(GF_{ADT})$ = 29.3 percent, GF_{ADT} = 3.3 percent, and T = 2 into Equation 4.2:

$$CV(ADT_o) = \{ 0.107^2 + 2^2 * 0.293^2 / (1/0.033 + 2)^2 \}^{1/2}$$
$$= 0.1085$$

Hence, the coefficient of variation of a base year ADT estimate determined using 24-hour coverage count data is approximately 10.9 percent.

Note that Equation 4.7, used to calculate $CV(ADT_o)$, evaluates only the variability associated with predicting the ADT that would occur in the base year at the facility currently in place at the project site. Because the new facility may attract traffic that would not use the facility currently in place at the site, $CV(ADT_o)$ may actually be higher than the $CV(ADT_o)$ estimates identified above.

Bodle's research did not confirm or deny bias in seasonally-adjusted, 24-hour coverage count-based ADT estimates. Albright [16] found minimal bias associated with non-seasonally adjusted, 24-hour coverage count-based ADT estimates.

Percent Trucks, Percent Single Axles, and Axle Factor

These components will be evaluated together because they all depend on vehicle classification data.

The percent trucks, percent single axles, and axle factor components are all assumed to remain constant over the design period. This implies two additional assumptions: 1) that truck volumes grow at the same rate as overall ADT; and 2) that the makeup of the truck traffic stream (i.e., the individual truck type percentages) remains constant during the design period. Not enough information was available to thoroughly evaluate these assumptions. The information that was available is summarized here.

Middleton [17] studied vehicle classification data collected at 54 Texas sites from 1977 to 1983. He found that during this period, percent trucks at most of the 54 sites remained relatively constant over time. This implies that at these sites from 1977 to 1983, the assumption that truck traffic grows at the same rate as overall traffic was valid. Middleton also found that from 1977 to 1983, the makeup of the truck traffic stream at most sites did not change appreciably. This implies that at these 54 sites from 1977 to 1983, the assumption of a constant axle factor and constant percent single axles was valid. A study of seven years of data, however, is not conclusive as to whether or not the percent trucks, percent single axles, or axle factor components typically remain constant over a 20 year period (a typical pavement design period).

Using nationwide data provided by the FHWA, Cunagin [7] found that during the period from 1970 to 1985, the percent of single-unit trucks using rural interstates did not change; however, the percentage of multi-unit trucks on rural interstates grew at approximately a 6.6 percent linear annual rate ($r^2 \approx 90.5$ percent, found by performing a linear regression on Cunagin's data). Cunagin's data suggest that the nationwide percent trucks on rural interstates increased from 1970 to 1985 and that the nationwide trend can be modeled linearly. The finding that the multi-unit truck percentage was increasing while the single-unit percentage remained constant indicates that nationwide, axle factors were increasing while percent single axles was decreasing. Based on these findings, no conclusion can be drawn concerning the validity of the constant percent trucks, constant percent single axles, and constant axle factor assumptions for sites on various highway systems over a 20-

year period in Texas.

As described in Chapter I, the manual classification data for a project may have been collected at or very near the project site, at another point on the same highway as the project site, or on another highway in the same geographic region on the same highway system as the project site. The error in the percent trucks, percent single axles, and axle factor estimates differs depending on which situation applies.

Manual classification sessions are 24 hours long. When the classification data for a project are collected at or very near the project site, there are two sources of error associated with resulting component estimates. These are 1) human error; and 2) error resulting from differences between the sampled and actual percent trucks, axle factor, and percent single axles at the site.

No quantitative information was available concerning human error. The anecdotal evidence [18,19] supports the conclusion that the quality of the resulting count is entirely dependent on the quality of the observer. Human error is ignored in this analysis.

Concerning sampling error, Appendix A, Part VII shows that the coefficient of variation of a percent trucks estimate based on a sample may be found using Equation 4.7:

$$CV(PCT) = [CV(TK)^2 + CV(ADT)^2 - 2*r_{TK,ADT}*CV(TK)*CV(ADT)]^{1/2} \qquad (4.7)$$

where:

CV(PCT)	= percent trucks coefficient of variation
CV(TK)	= truck volume coefficient of variation
CV(ADT)	= total volume coefficient of variation
$r_{TK,ADT}$	= the coefficient of correlation between truck and total volumes at individual sites (explained below)

Equation 4.7 reflects the fact that the percent trucks observed on a day of the year depends on the truck volume and total volume at the site on that day; and that if 24-hour truck and total volumes are positively correlated, the day-to-day variability of percent trucks is made lower in proportion to the degree of positive correlation between TK and ADT. Equation 4.7 shows that to find CV(PCT), it is necessary to know: CV(TK), CV(ADT), and $r_{TK,ADT}$.

37

1. $r_{TK,ADT}$

The $r_{X,Y}^2$ statistic, for a regression equation, times 100 percent is interpreted to be the percentage of variation in the dependent variable, Y, which is explained or accounted for by variation in the independent variable, X. In addition, the magnitude of $r_{X,Y}$, the coefficient of correlation between X and Y, is the square root of the $r_{X,Y}^2$ statistic.

In a case in which weekday, 24-hour, truck volumes are not correlated with weekday, 24-hour, non-truck volumes and CV(TK) is comparable in magnitude to CV(ADT), the parameter $r_{TK,ADT}$ may be approximated using Equation 4.8.

$$r_{TK,ADT} \approx +(PCT)^{1/2} \tag{4.8}$$

where:

$r_{TK,ADT}$ = the coefficient of correlation between truck volume and total volume

PCT = percent trucks at the site

Equation 4.8 implies that $r_{TK,ADT}^2$ for a site equals the percent trucks at the site. To illustrate the relationship between $r_{TK,ADT}^2$ and percent trucks, consider a site at which 24-hour, weekday truck and non-truck volumes are not correlated (i.e., at which the number of trucks on the road during a 24-hour, weekday period at a site is not related to the number of non-trucks on the road during that period at the site) and at which truck volumes and total volumes each vary by 10 percent from day to day. First, given the assumption that weekday truck and non-truck volumes are uncorrelated and the fact that total volume is the sum of truck and non-truck volumes, the relationship between truck volume and total volume is necessarily positive. Second, if the percent trucks at this site is very small, say 1 percent, a 10 percent variation in the number of trucks on a given day would have only a 0.1 percent (i.e., 10 percent variation in truck volume * 1 percent trucks) impact on total volume; if total volume varies by 10 percent from day to day as was assumed, then 0.1 of that 10 percent total volume variation or 1 percent of total volume variation is accounted for by the variation in truck volumes. If percent trucks at the site is very large, say 50 percent, then

a 10 percent variation in the number of trucks would have a 5 percent (10 percent variation in truck volume * 50 percent trucks) impact on total volume; again, if total volume varies by 10 percent from day to day as assumed, then 5 of the 10 percent or exactly 50 percent of total volume variation is accounted for by variation in truck volumes.

The literature review found that CV(TK) and CV(ADT) are comparable in magnitude. (Specific values for each are presented and discussed below.) This analysis assumes that weekday, 24-hour, truck and non-truck volumes, throughout the year at a site, are not correlated (note: weekday truck and non-truck volumes during shorter periods such as the peak period may be negatively correlated). Percent trucks data, collected in 1988, from 925 Texas road sections were available for use in the study [20]. The average percent trucks on these sections was 15.6 percent. Substituting this value into Equation 4.8 yields an average $r_{TK,ADT} = 0.156^{1/2} = 0.4$. This value for $r_{TK,ADT}$ will be used here.

2. CV(TK)

A 1989 Strategic Highway Research Program [SHRP] study [21] evaluated the precision of 3-S2 volume estimates based on 24-hour samples. The SHRP study used data collected continuously at four sites, including two interstates, a principal arterial, and a minor arterial. Four years of data were available for one of the interstate sites and the principal arterial site. One year of data was available for the other interstate site and the minor arterial site.

The SHRP study found the following coefficients of variation for 3-S2 volume estimates based on seasonally-adjusted 24-hour samples: 1) median coefficient of variation at all sites in all years — 9.52 percent; and 2) range of coefficients of variation at all sites in all years — 5.95 percent to 15.65 percent.

In a telephone conversation [22], the SHRP study's principal investigator pointed out that during some years at some sites, data points were missing due to equipment malfunction or other reasons. These missing values were imputed by averaging actual observations collected before and after the missing days. Such a procedure would have the effect of reducing the variability of the data set.

As a result, the coefficients of variation above may tend to underestimate the actual coefficients of variation associated with 3-S2 average daily volume estimates based on seasonally-adjusted 24-hour truck counting sessions.

In addition, manual classification counts in Texas are not seasonally adjusted; the coefficients of variation in the SHRP study reflect precision achieved with seasonal adjustment. If seasonal adjusting does consistently improve classification count precision, the median 24-hour truck count coefficient of variation from the SHRP study will tend to underestimate the variability associated with Texas practice.

Finally, the SHRP study evaluated the precision of 3-S2 volume samples, not total truck volume samples. To use the SHRP coefficients of variation as representative of an overall truck volume coefficient of variation, it is necessary to assume that overall truck volumes are not more or less variable than 3-S2 volumes. Literature review revealed no study which evaluated the relative variability of 3-S2 versus overall truck volumes. This research assumes that 3-S2 volume variability is comparable to overall truck volume variability. Hence, the median SHRP coefficient of variation, 9.52 percent, will be used to approximate CV(TK).

3. CV(ADT)

Since Texas manual classification counts are not seasonally adjusted, the appropriate CV(ADT) is one that reflects the variability of weekday traffic volumes throughout the entire year. Albright [16] studied the variability of weekday traffic volumes throughout the year. Albright expressed this variability in terms of the percentage of the annual average daily weekday traffic (AAWDT) spanned by the 90 percent confidence range. For the 24 rural locations used in the analysis, the percentage of AAWDT spanned by the 90 percent confidence range was approximately 46 percent. To convert this range to a coefficient of variation, it necessary to assume that 24-hour weekday volumes at the sites used in the study follow a normal distribution. Albright used the difference between the median and mean volumes at the sites as a measure of bias in the

40

distribution. A large difference between the median and mean volumes would indicate a high bias; a high bias would, in turn, call into question the assumption of a normal distribution. Albright found minimal bias, lending credence to the assumption of a normal distribution [16,23].

Given the normal distribution, the 90 percent confidence limits of an estimate are defined by the range: *estimate ±1.645 coefficients of variation of the estimate* [9]. In this case, the 90 percent confidence limits span 46 percent of the estimate, 23 percent to either side. This yields a CV(ADT) value of 13.98 percent (i.e., 23 percent/1.645).

As stated previously, CV(TK) (9.5 percent) is comparable in magnitude to CV(ADT) (14.0 percent).

Substituting CV(TK) = 9.5 percent, CV(ADT) = 14.0 percent, and $r_{TK,ADT}$ = 0.4 into Equation 4.7:

$$CV(PCT) = (0.095^2 + 0.14^2 - 2*0.4*0.095*0.14)^{1/2}$$
$$= 0.1341$$

Hence, when percent trucks is based on a 24-hour classification count taken within the project limits, the percent trucks coefficient of variation, CV(PCT), is approximately 13.4 percent.

The axle factor and percent single axles depend on the proportions of different trucks types in the truck traffic stream. The literature review revealed no information concerning the day-to-day variability of these individual truck type proportions. However, analysis below of the precision of percent single axles and axle factor estimates based on classification data collected at another point on the same highway or on another highway in the same geographic region on the same highway system as the project site finds CV(PSA) ≈ 19.7 percent and CV(AF) ≈ 10.8 percent. It is unlikely that percent single axles and axle factor estimates based on data collected at the project site are less precise than estimates of these parameters based on data from other sites. Hence, axle factor and percent single axles estimates based on 24-hour classification counts taken at the project site should lead to CV(PSA) ≤ 19.7 percent and CV(AF) ≤ 10.8 percent.

When the vehicle classification data for a project are collected at another point on

the same highway or a point on another highway in the same geographic region on the same highway system as the project site, current practice is to determine percent trucks using the ADT based 1/2-growth model. Equation 4.9 shows the 1/2-growth model.

$$PCT_{proj} = \{PCT_{data}*ADT_{data} + [PCT_{data}*(ADT_{proj} - ADT_{data})*(GC)]\}/ADT_{proj} \qquad (4.9)$$

where:

PCT_{proj}	= Percent trucks at the project site
PCT_{data}	= Percent trucks at the data collection site
ADT_{proj}	= ADT at the project site
ADT_{data}	= ADT at the data collection site
GC	= the growth constant (i.e., when $GC = 1/2$, the model becomes a 1/2-growth model; setting $GC = 1/2$ implies an assumption that truck volume grows (declines) at 1/2 the rate total volume grows (declines) between the control and prediction sites)

The accuracy of percent trucks predictions made using a control percent trucks and ADT from the same highway as the project site was evaluated using 1988 Texas manual vehicle classification data. The procedure used was to identify highways with multiple count locations, then use the percent trucks and ADT at each site on a highway as a control to predict the percent trucks at the next count site in each direction on the highway from the control site. Count sites on highways IH 10, IH 20, IH 35, US 67, US 82, US 90, SH 6, SH 35, and SH 71 were analyzed in this manner. These highways were selected because they had relatively large numbers of manual count sections (eight to 17 per highway) in 1988. The analytical framework resulted in a total of 155 predictions.

Given the set of predicted versus actual values, the prediction errors were made comparable by finding the ratio of actual to predicted percent trucks for each prediction. Figure 5 shows the frequency distribution of the ratios; this distribution is skewed to the right. Figure 6 shows the frequency distribution of the base 10 logarithms of the ratios; this distribution exhibits bias to the left, indicating that the 1/2-growth model tends to over-predict percent trucks (i.e., log(actual) is consistently less than log(predicted)). Figure 7 shows a plot of log(actual/predicted) percent trucks as a function of traffic volume at the project (i.e., prediction) site. Figure 7 shows that the half-growth model tends to over-

42

predict percent trucks, specifically, at relatively low volume (< 3,500 vpd) and high volume (> 45,000 vpd) sites. The average prediction at sites with volumes greater than 45,000 vpd was 1.267 times or 26.7 percent greater than the actual percent trucks at the site. The average prediction at sites with volumes less than 3,500 vpd was 1.268 times or 26.8 percent greater than the actual percent trucks at the site. Further investigation revealed that many of the low-volume over-predictions resulted because total volumes had declined from the control to the prediction site and truck volumes had declined at faster than 1/2 the rate of total volume decline; hence, a higher growth constant was indicated. Evaluation of higher GC's determined that bias at low volume sites could be reduced to only 1.5 percent by using GC = 10/11. Further investigation of the high-volume over-predictions revealed that many of these resulted because total volumes had increased from the control to the prediction site and truck volumes had increased at slower than 1/2 the rate of total volume increase; hence, a lower growth constant was indicated. Evaluation of lower GC's determined that bias at high-volume sites could be reduced to 0.0 percent by using GC = 1/8.

The precision of percent trucks predictions, made using classification data from another point on the same highway as the project site, was evaluated using the coefficient of variation of the ratio of actual to predicted percent trucks. Appendix A, Part II, shows that the coefficient of variation of a log-normally distributed variable may be expressed as shown in Equation 4.10.

$$CV(X) = STD[\log_{10}(X)]/0.4343 \tag{4.10}$$

where:

$CV(X)$ = the coefficient of variation of the variable X

$STD[\log_{10}(X)]$ = the standard deviation of the base 10 logarithm of X

The sample standard deviation for the distribution of $\log_{10}$(Actual/Predicted) percent trucks using the 1/2-growth model at all volumes was 0.1755. This indicates a population standard deviation of 0.1761 and a coefficient of variation for these predictions of CV(PCT) = 40.5 percent. When the composite model was used (i.e., GC = 10/11 for ADT_{proj} < 3,500; GC = 1/2 for 3,500 ≤ ADT_{proj} ≤ 45,000; and GC = 1/8 for ADT_{proj} > 45,000) the resulting CV(PCT) was 34.6 percent.

The accuracy of percent trucks predictions made using a control percent trucks and

ADT from a point in the same geographic region on the same highway system as the project site was also evaluated using 1988 Texas manual vehicle classification data. The procedure used was to identify multiple count locations on a highway system within an TxDOT district, then use the percent trucks and ADT at each site on the highway system in the district as a control to predict the percent trucks at all other count locations on the highway system in the district. Interstate Highway sites in districts 2, 4, 18, and 20 were evaluated; U.S. Highway sites in districts 1, 8, 14, and 17 were evaluated; and State Highway sites in districts 6, 9, 11, and 13 were evaluated. The districts for Interstate sites were chosen because they contained the greatest number of Interstate count sections in 1988: six, four, eight, and four, respectively. Many count sections were available in almost every district for U.S. and State system highways; as a result, the districts for the U.S. and State highway systems were randomly selected. The analytical framework resulted in a total of 2616 predictions.

Given a set of predicted versus actual values, the prediction errors were made comparable by finding the ratio of actual to predicted percent trucks for each prediction. Figure 8 shows the frequency distribution of the ratios; Figure 9 shows the frequency distribution of the base 10 logarithm of the ratios; and Figure 10 shows a plot of log(actual/predicted) percent trucks as a function of traffic volume at the project (i.e., prediction) site. Figure 10, again, shows the tendency toward over-prediction at low-volume sites. (The data set used to evaluate predictions based on classification data from the same geographic region and highway system did not contain any prediction sites with volumes greater than 45,000 vpd; while this was not intentional, it is realistic in that TxDOT has at least one classification count at some point on almost all roads with high volume sections). The average prediction at sites with volumes of less than 3,500 vpd was 1.195 or 19.5 percent greater than the actual value. Increasing the growth constant to 10/11 reduced the average prediction for these sites to 1.07 times or 7 percent greater than the actual value.

The sample standard deviation for the distribution of the logarithms, using GC = 1/2 at all volumes, was 0.2718. This indicates a population standard deviation of 0.2719 and, using Equation 4.10, a percent trucks coefficient of variation of 0.626 or CV(PCT) = 62.6 percent. Using the composite model (i.e., GC = 10/11 for ADT_{proj} < 3,500, and GC = 1/2 for 3,500 ≤ ADT_{proj} ≤ 45,000), the resulting CV(PCT) was 47.5 percent.

44
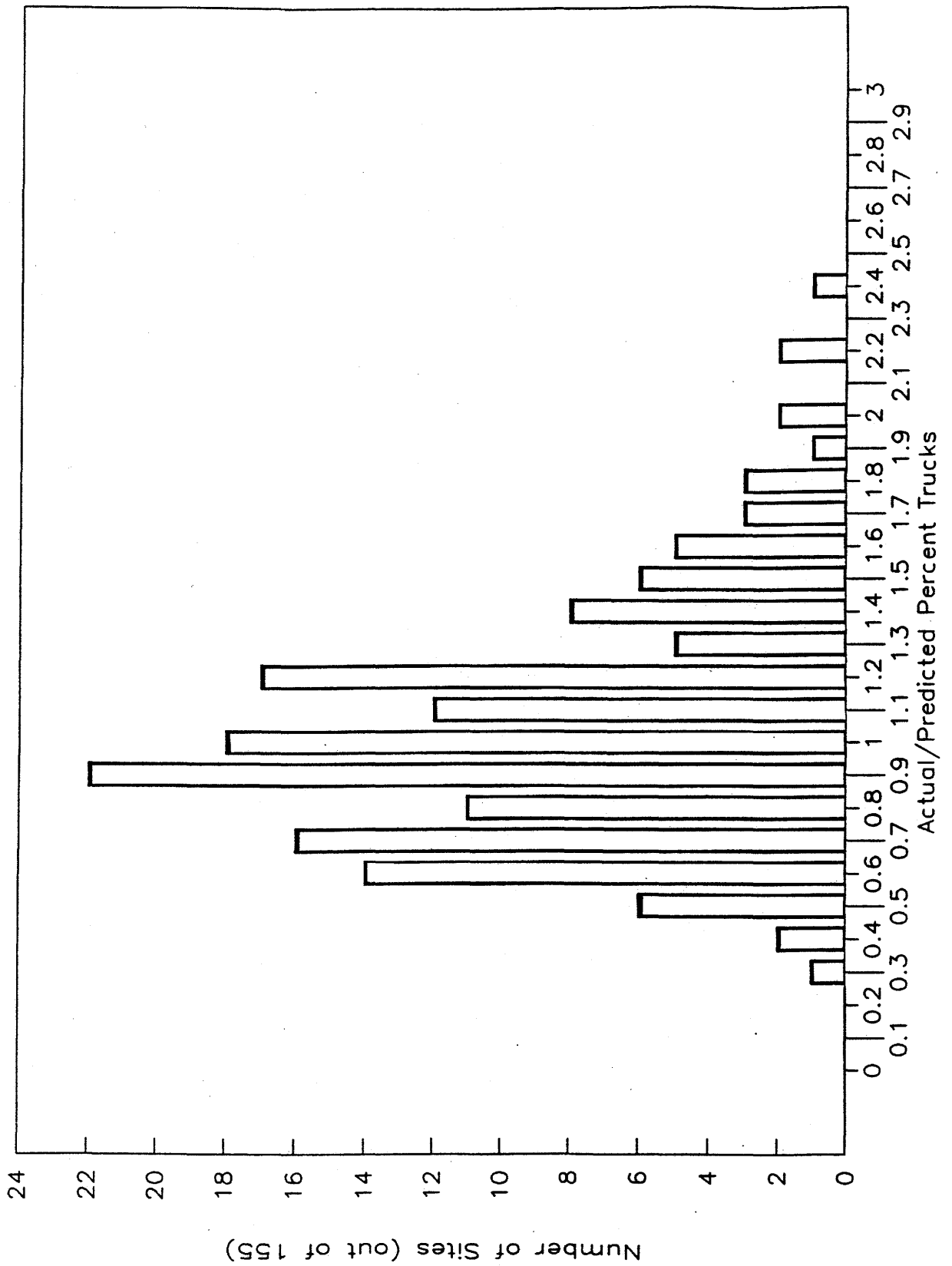
Figure 5: Distribution of (Actual/Predicted) Percent Trucks, Data from Same Highway
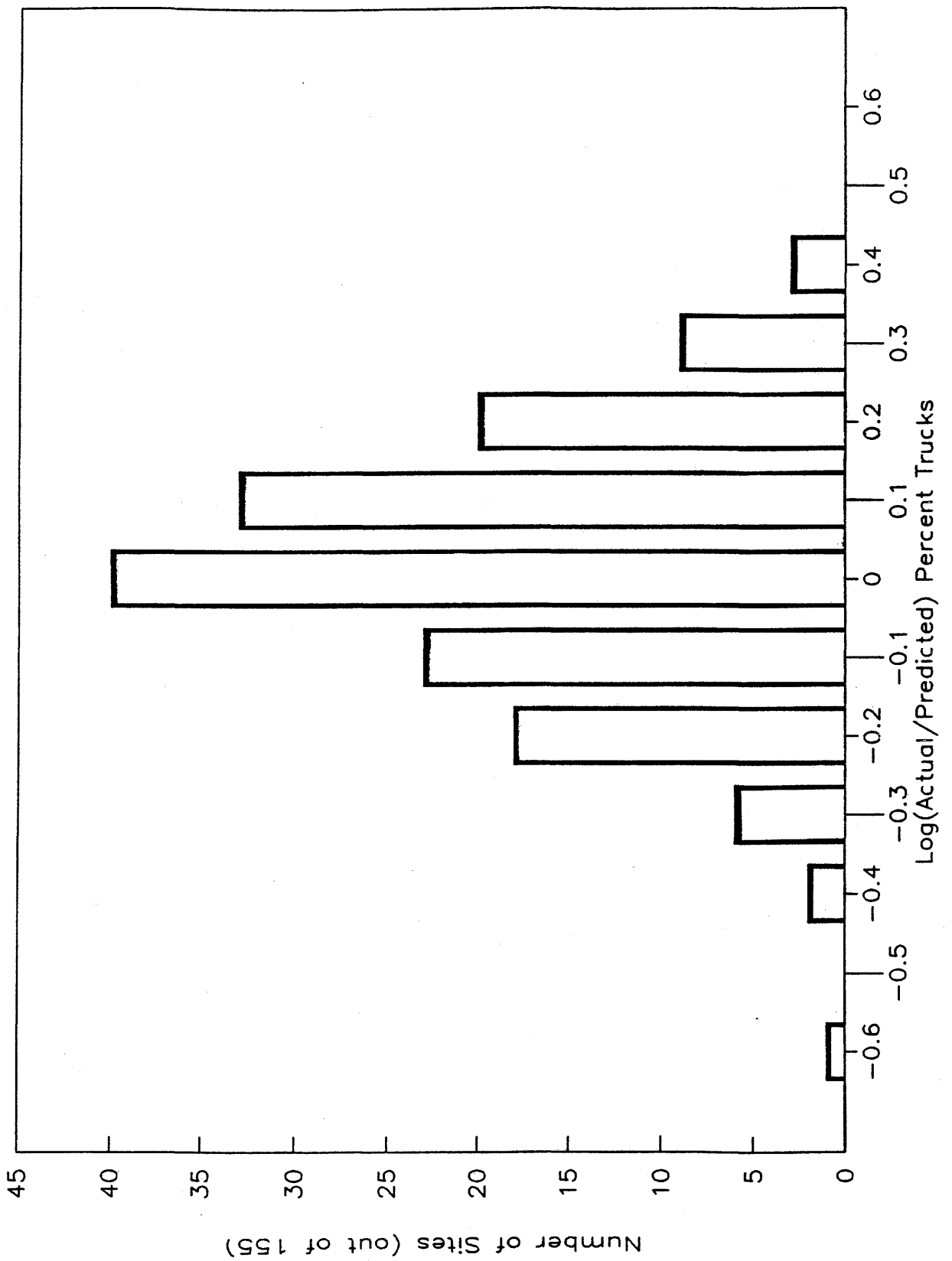
Figure 6: Distribution of Log(Actual/Predicted) Percent Trucks, Data from Same Highway
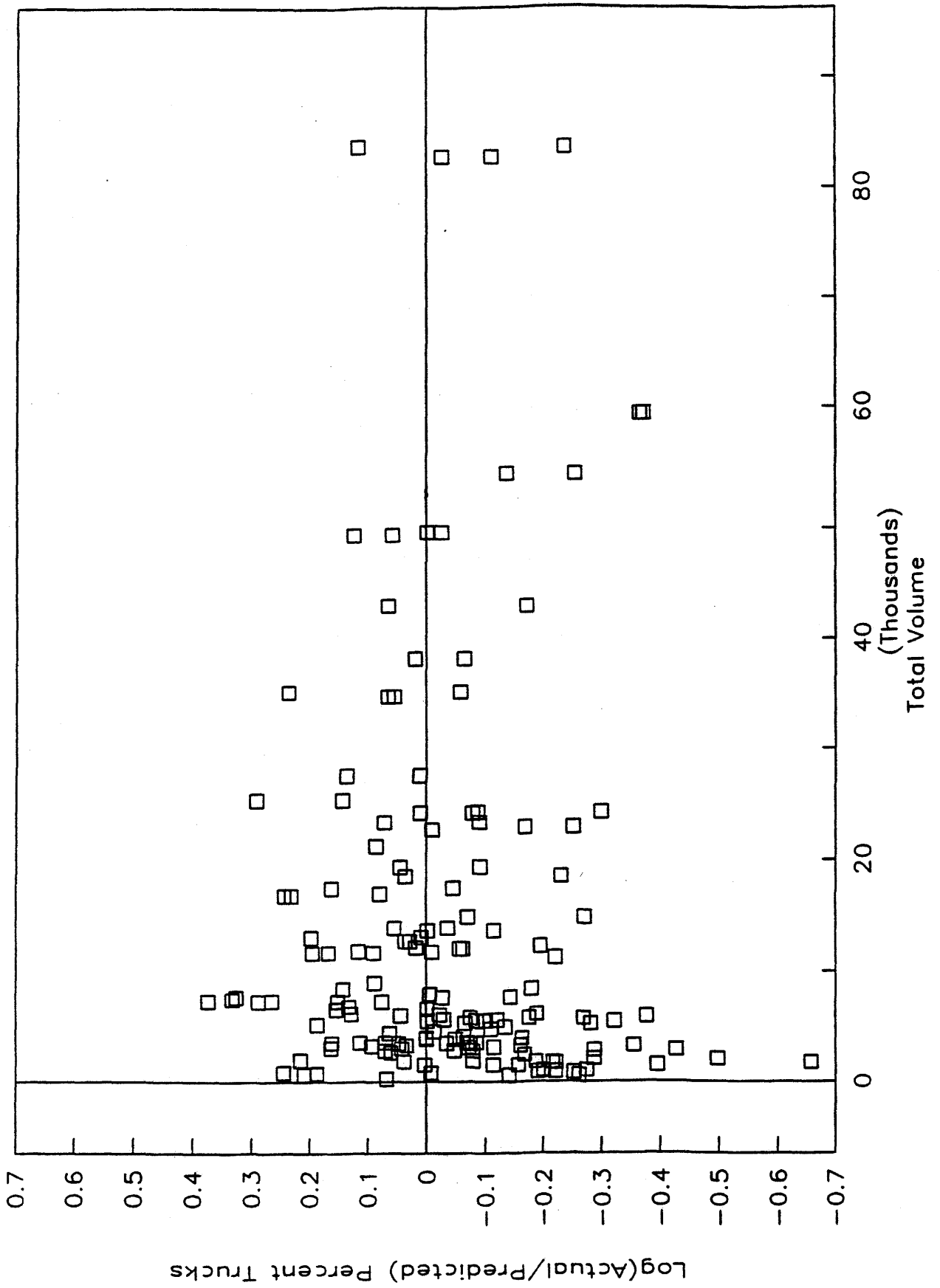
Figure 7: Log(Actual/Predicted) versus ADT, Data from Same Highway

47
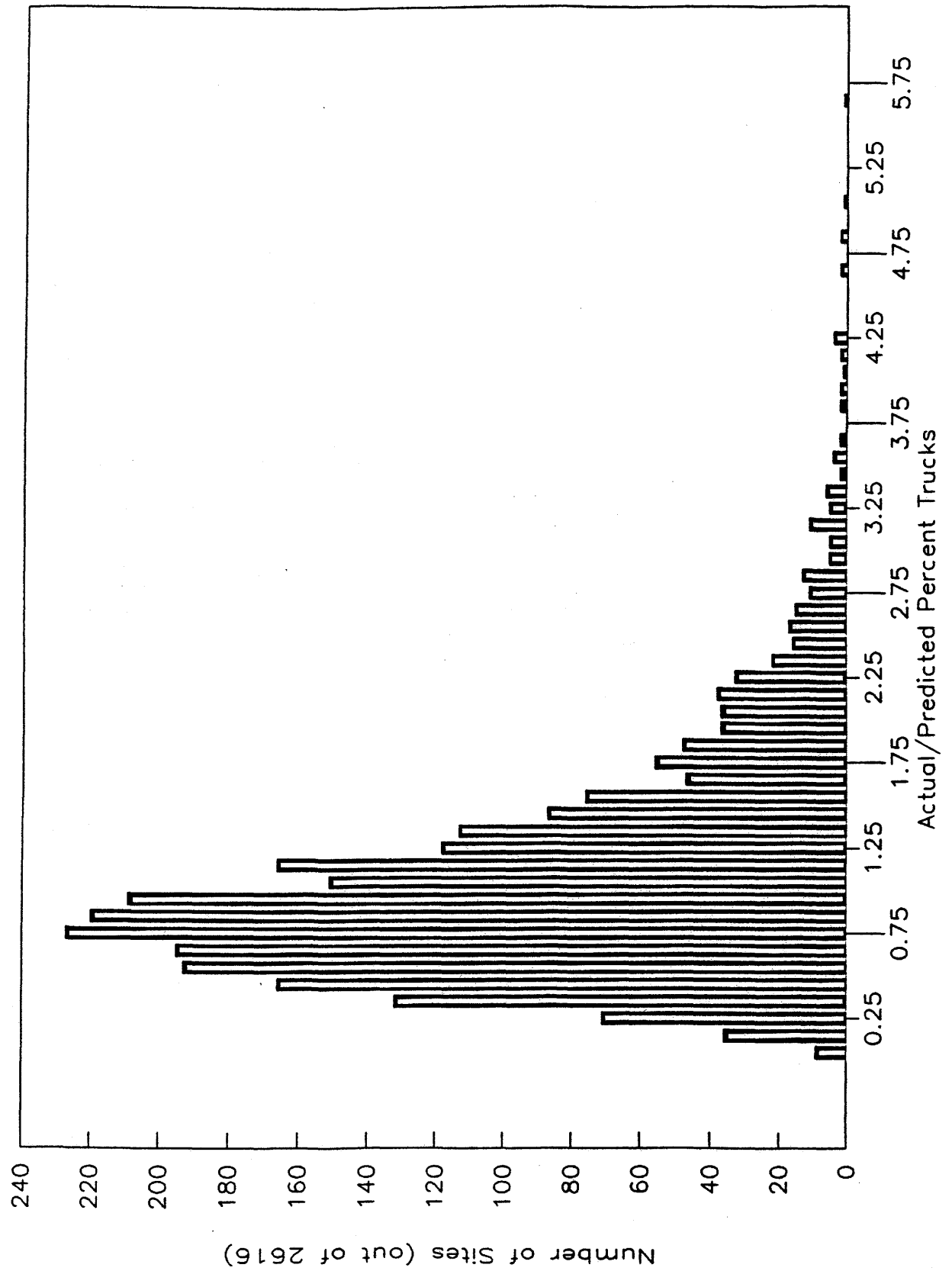
Figure 8: Distribution of (Actual/Predicted) Percent Trucks, Data from Same Region

48
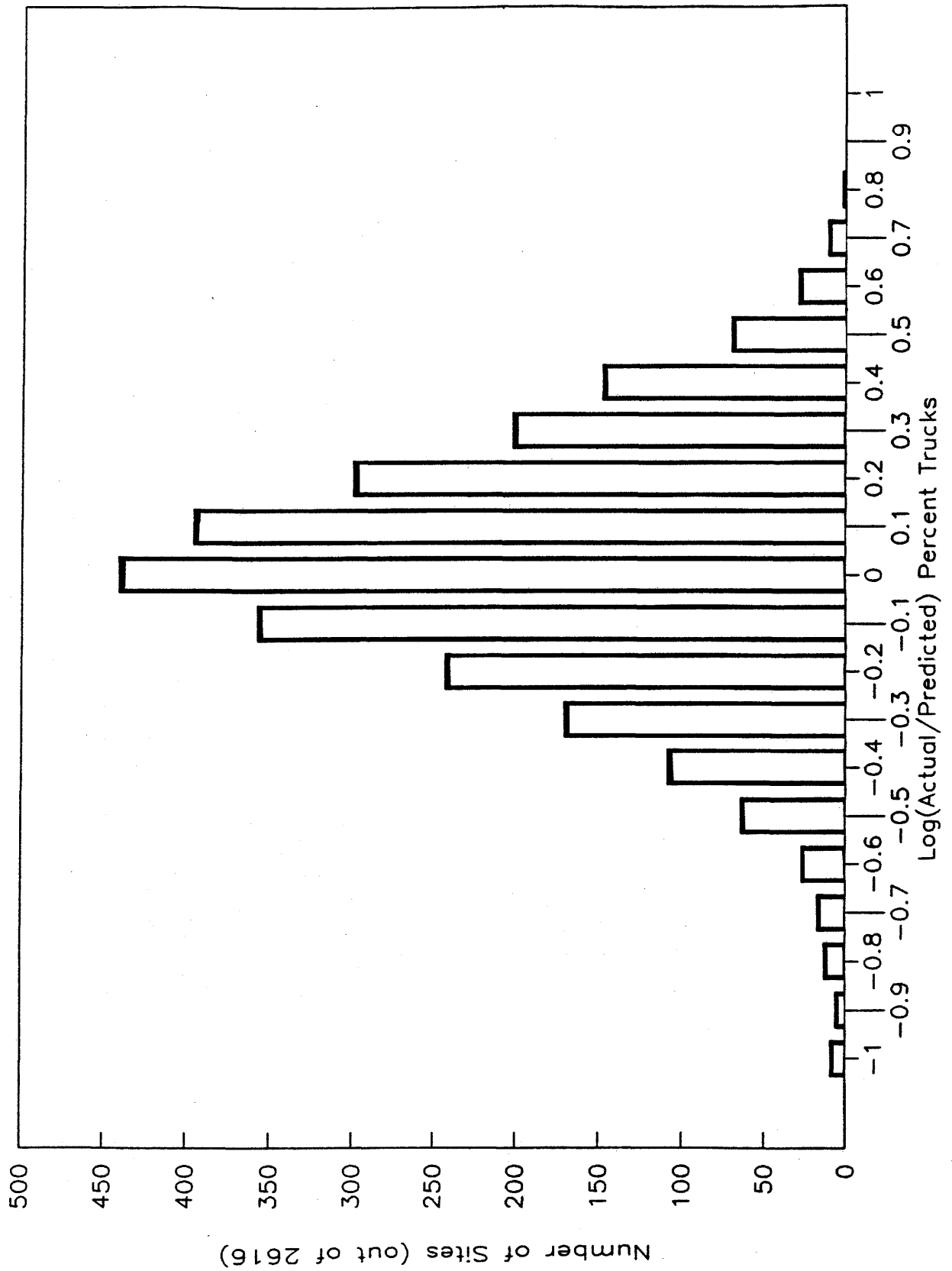
Figure 9: Distribution of Log(Actual/Predicted) Percent Trucks, Data from Same Region
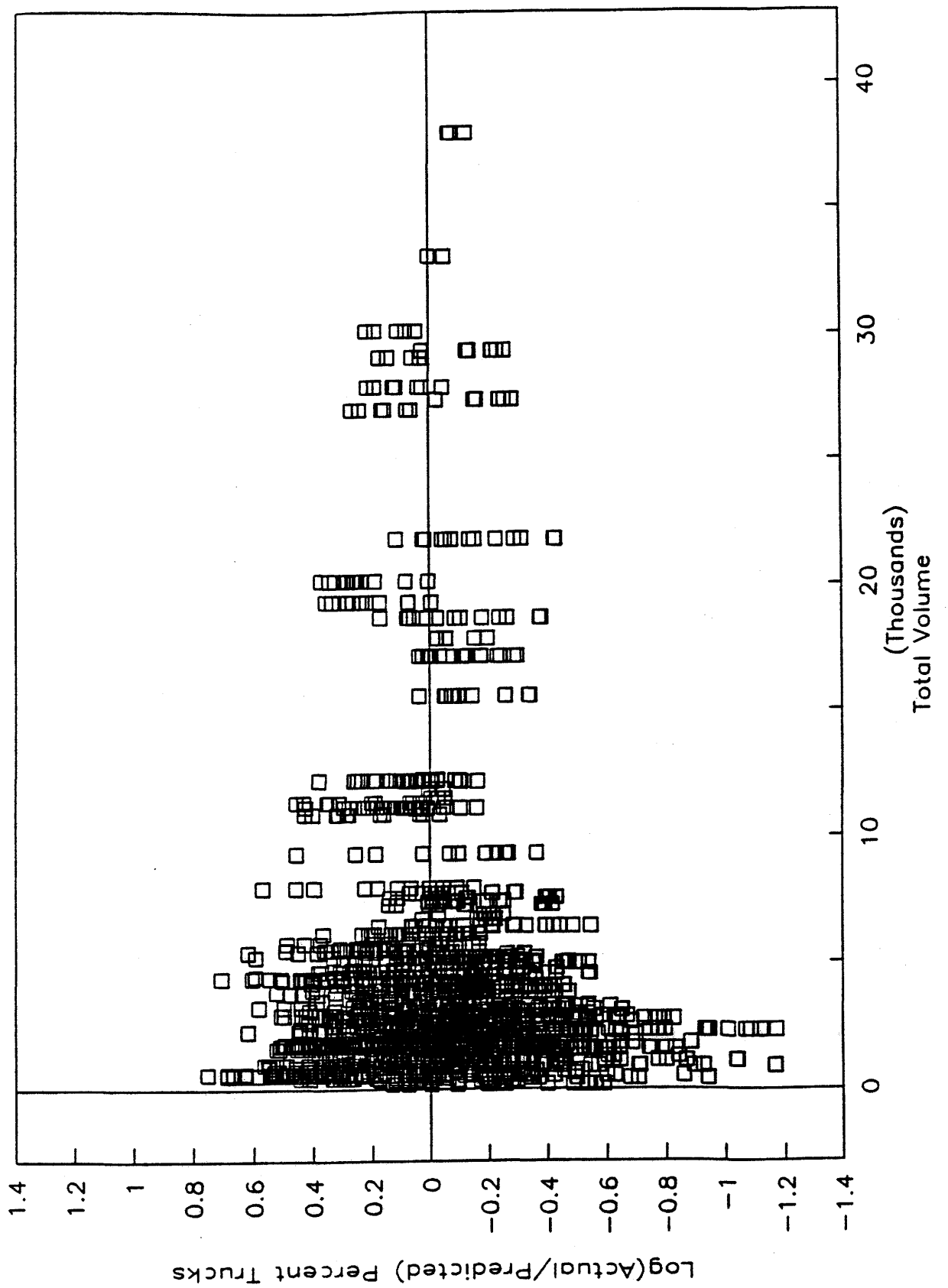
Figure 10: Log(Actual/Predicted) versus ADT, Data from Same Region

When the vehicle classification data for a project are collected at another point on the same highway or on another highway in the same geographic region on the same highway system as the project site, current practice is to use the axle factor and percent single axles from the data collection site without adjustment at the project site.

The axle factor and percent single axles are determined by the proportion of different truck types in the truck traffic stream. In his study of Texas truck traffic from 1977 to 1983, Middleton found that these proportions are "location-specific" and are unrelated to ADT, highway system, or geographic region. This indicates that categorizing projects by individual highway or by highway system and geographic region, for axle factor and percent single axles prediction purposes, does not enhance the precision of predictions beyond that achieved by selecting axle factor and percent single axles values from the statewide distributions of these components. The coefficient of variation of selections from the statewide distributions are the statewide standard deviations divided by the statewide averages. The average axle factor at 925 manual classification sections in 1988 was 2.69; the standard deviation of this value was 0.29. This indicates an axle factor coefficient of variation, CV(AF), of approximately 10.8 percent. The average percent single axles at the sections was 64 percent. The standard deviation was 12.6 percent. This indicates a percent single axles coefficient of variation, CV(PSA), of approximately 19.7 percent.

Hence, when classification data from another point on the same highway or another highway in the same geographic region on the same highway system as the project site are used to estimate percent single axles and the axle factor, the resulting coefficients of variation are: CV(AF) $\approx$ 10.8 percent, and CV(PSA) $\approx$ 19.7 percent.

Axle Weight Distribution Table (Average Load Equivalency Per Truck)

The example Total ESAL calculation in Chapter III showed that the axle weight distribution table, percent single axles, and axle factor components are converted into an average load equivalency factor per truck for ESAL forecasting purposes. Errors in these resulting average load equivalency factors per truck are analyzed below. This approach to axle weight distribution table analysis is used by Cervenka and Walton [24].

The axle weight distribution table, percent single axles, and axle factor are all

assumed to remain constant throughout the design period. As a result, the average load equivalency per truck is assumed to remain constant over the design period. Not enough information was available to thoroughly evaluate this assumption. The information that was available is summarized below.

Cervenka and Walton studied Texas truck weight data collected between 1976 and 1983. During this period, Cervenka and Walton found "[no] significant upward or downward trend in [average load equivalency factors per axle for individual vehicle types at a site];" these authors did, however, note "significant year-to-year variations, possibly due to small sample sizes." Cunagin [7] studied historical WIM data collected between 1975 and 1985 at permanent WIM sites in nine states. Cunagin concluded that average load equivalency factors for individual vehicle types are "approximately constant" over time at most sites.

Note that Cunagin and Cervenka and Walton studied individual vehicle type load equivalencies, not the average load equivalency factor per truck, at a site. To conclude that the average load equivalency factor per truck at most sites is constant over time, Cunagin's and Cervenka and Walton's findings that individual vehicle type load equivalencies remain constant must be combined with a finding that the mix of vehicles in the traffic stream at most sites also remains constant. If, for instance, the percentage of multiple-unit vehicles (i.e., vehicles with relatively high average load equivalencies) in the traffic stream increases while the percentage of single unit trucks (i.e., vehicles with relatively low load average load equivalencies) stays constant, the overall average load equivalency per truck at the site would increase despite the fact that the individual vehicle type load equivalencies remain constant.

As pointed out in the "Percent Trucks, Percent Single Axles, and Axle Factor" analysis above, Middleton found that the individual vehicle type percentages at 54 Texas sites remained approximately constant from 1977 to 1983. Cunagin found that nationwide, the percentage of multiple-unit vehicles on rural interstates grew at a 6.6 percent linear annual rate while the percentage of single-unit trucks did not change. Based on these findings, no conclusion can be drawn regarding the constant average load equivalency per truck assumption for sites on various highway systems over a 20-year period in Texas.

The axle weight distribution table for a project may come from a permanent WIM

52

station at or very near the project site; from a permanent WIM station at another point on the same highway as the project site; or, if there is no permanent WIM site on the same highway as the project site, the statewide average axle weight distribution is used. Two types of permanent WIM stations operate in Texas. At one station type, axle weight data are collected continuously throughout the year; at the other type, axle weight data are collected during three 48-hour sampling sessions each year. The accuracy of the average load equivalency factor per truck estimate depends on the source of the axle weight data.

When the axle weight data for a forecast come from a continuously operating permanent WIM site at or very near the project site, there are two sources or error: 1) equipment error and 2) data imputation error. The latter source of error is ignored.

Cunagin [25] evaluated the accuracy of TxDOT's continuous WIM equipment (PAT Bending Plate WIM systems). He found that the PAT system measured individual axle weights to within ±4 to ±8 percent of actual static weight. He did not find, however, that the device consistently over- or under-weighs axles. As a result, even if the machine randomly over- or under-weighs individual axles, the distribution of axle weights over a large number of axles should be very close to the actual axle weight distribution at the site [26]. Since the average load equivalency per truck depends not on any individual axle weight, per se, but on the overall distribution of axle weights, the average load equivalency per truck produced by the PAT system should be almost identical to the actual average load equivalency factor per truck. Hence, assuming negligible error associated with the percent single axles and axle factor estimates for the site, the average load equivalency factor per truck coefficient of variation, CV(EF), for this situation, is approximately 0.0.

When the axle weight distribution table for a forecast comes from a seasonally-operating permanent WIM site at or very near the project site, there are two sources of error: 1) equipment error; and 2) error due to differences between the sampled and actual axle weight distribution at the site.

Cunagin [25] also evaluated the accuracy of TxDOT's seasonally-operating permanent WIM equipment (Radian WIM systems). Cunagin found that the device measured individual axle weights to within ±4 to ±8 percent of actual static weights. He reported no evidence that the device consistently over- or under-weighs axles. Hence, even if the

53

machine randomly over- or under-weighs individual axles, over a large number of axles, the sampled average load equivalency factor per truck should be very close to the actual value for the sampling period.

Since the seasonal WIM sites operate only during three 48-hour sessions per year, the average load equivalency factor per truck weighed during the sampling sessions may differ from the average load equivalency factor per truck during the entire year. The precision of an average load equivalency factor truck estimate based on three 48-hour WIM sessions per year has not been studied, per se. However, the 1989 SHRP study referenced previously evaluated the precision of average load equivalency factor per 3-S2 estimates based on seasonally-adjusted single 48-hour WIM samples. Again, the SHRP study used data taken from four sites, including two interstates, a principal arterial, and a minor arterial. Four years of data were available for one of the interstate sites and the principal arterial site. One year of data was available for the other interstate site and the minor arterial site.

The SHRP study found the following coefficients of variation for average load equivalency factor per 3-S2 estimates based on seasonally-adjusted single 48-hour samples: 1) median coefficient of variation at all sites in all years -- 8.2 percent; and 2) range of coefficients of variation at all sites in all years -- 3.2 percent to 16.5 percent.

The SHRP study's principal investigator pointed out that during some years at some sites, data points were missing due to equipment malfunction or other reasons. These missing values were imputed by averaging actual observations collected before and after the missing days. Such a procedure would have the effect of reducing the variability of the data set. As a result, the coefficients of variation above may tend to underestimate the actual coefficients of variation associated with single 48-hour WIM sessions.

In addition, the SHRP study evaluated the precision of average load equivalency factor per 3-S2 estimates, not average load equivalency factor per truck estimates. To use the SHRP coefficients of variation as representative of the average load equivalency factor per truck coefficient of variation, it is necessary to assume that average load equivalency factors per truck are not more or less variable than average load equivalency factors per 3-S2. This research assumes that average load equivalency factors per 3-S2 are comparable

in variability to average load equivalency factors per truck. Hence, assuming negligible error associated with the percent single axles and axle factor estimates for the site, CV(EF) is approximately 8.2 percent.

When the axle weight distribution table for a project comes from either a continuous or seasonal WIM station located at another point on the same highway as the project site, there are two sources of error: 1) error due to differences between the average load equivalency factor per truck at the data collection and project site; and 2) error associated with the percent single axles and axle factor used in the forecast.

In 1989, three permanent WIM stations operated on Interstate 10. The average load equivalency factors per truck at the stations were 1.32 ESALs per truck, 1.94 ESALs per truck, and 2.07 ESALs per truck. While these values do not provide a basis upon which to calculate a meaningful coefficient of variation, they do indicate that the average load equivalency factor per truck may vary substantially from one point to another on the same highway.

The CV(EF) which results from using the statewide average axle weight distribution at a site is analyzed below and is determined to be approximately 23.1 percent; this value includes the variability introduced by the percent single axles and axle factor components. It is unlikely that axle weights are, on average, more variable at different points on the same highway than they are at points on different highways. If, in fact, axle weights at different points on the same highway are no more variable than axle weights at points on different highways, the average load equivalency factor per coefficient of variation, CV(EF), should be less than or equal to approximately 23.1 percent.

When the statewide average axle weight distribution is used, there are two sources of error: 1) error due to differences between the statewide average axle weight distribution and the actual axle weight distribution at the project site; and 2) error associated with the percent single axles and axle factor estimates used in the forecast.

The error resulting from using the statewide average axle weight distribution at specific sites depends on the statewide variability of axle weights. If there is large variation in axle weights at sites across the state, there is potentially large error associated with using the statewide average distribution at a specific site and vice versa.

55

If variability in axle weights among TxDOT's permanent WIM sites is representative of the variability of axle weights at sites throughout the state, the variability introduced into an ESAL forecast by using the statewide average axle weight distribution may be identified by evaluating the variability of axle weights among permanent WIM stations. The representativeness of the state's WIM stations was not evaluated as part of this research; however, all but one of the state's permanent WIM sites are located on the Interstate highway system. As a result, while the findings concerning the statewide variability of average load equivalency factors presented below may be valid for Interstate sites, they may not be valid for sites on other highway systems. In addition, the HPMS Truck Weight Case Study [27] found that truck "weights and equivalent axle loads were highly dependent on functional class." This implies that using an axle weight distribution, based almost exclusively on Interstate-based WIM data, at a non-Interstate site may lead to biased average load equivalency factor per truck estimates. However, since only Interstate-system average load equivalencies were available for analysis, bias could not be quantitatively evaluated.

The average load equivalency factor per truck at a site may be calculated using Equation 4.11:

$$EF = AF*[PSA*SA + (1-PSA)*TA] \qquad (4.11)$$

where:

EF = average load equivalency factor per truck

AF = axle factor

PSA = percent single axles

SA = average load equivalency factor per single axle

TA = average load equivalency factor per tandem axle

Given Equation 4.11, Appendix A, Part VIII shows that the average load equivalency factor per truck coefficient of variation may be found using Equation 4.12:

56

$$CV(EF) = \{[PSA*(SA-TA)+(1-PSA)*TA]^2*[AF*CV(AF)]^2$$
$$+ [AF*(SA-TA)]^2*[PSA*CV(PSA)]^2$$
$$+ [AF*PSA]^2*[SA*CV(SA)]^2$$
$$+ [AF*(1-PSA)]^2*[TA*CV(TA)]^2\}^{1/2} \; / \; \{AF*[PSA*SA+(1-PSA)*TA]\}$$

$$(4.12)$$

where:

CV(EF)	= average load equivalency factor per truck coefficient of variation
SA	= average load equivalency factor per single axle
TA	= average load equivalency factor per tandem axle
PSA	= percent single axles
AF	= axle factor
CV(PSA)	= percent single axles coefficient of variation
CV(AF)	= axle factor coefficient of variation
CV(SA)	= average load equivalency factor per single axle coefficient of variation
CV(TA)	= average load equivalency factor per tandem axle coefficient of variation

Equation 4.12 shows that to find CV(EF), it is necessary to know AF, CV(AF), SA, TA, PSA, CV(PSA), CV(SA), CV(TA). Equation 4.12 assumes no correlations between pairs of Equation 4.11 components.

1. Assumption of independence between pairs of Equation 4.11 components.

The data required to evaluate the assumption of independence between all pairs of Equation 4.11 components, values of PSA, AF, SA, and TA, from a representative sample of Texas road sections, were not available for use in the study. As a result, independence between component pairs is assumed.

2. SA, TA, CV(SA) and CV(TA)

Table 4 shows the average load equivalency factor per single axle and tandem axle on flexible and rigid pavements at Texas permanent WIM stations [28]. Values from sites 501 through 512 are 1989 observations, while values from stations 513 and 514 are 1990 observations. The average load equivalency factors are based on the AASHTO Guide's load equivalence factors for flexible and rigid pavements assuming a 2.0 terminal serviceability index. Values for SA, TA, CV(SA), and CV(TA), for flexible and rigid pavements, are shown at the bottom of Table 4.

3. PSA, AF, CV(PSA), and CV(AF)

Analysis in the "Percent Trucks, Percent Single Axles, and Axle Factor" section above found an average PSA of 64 percent and an average AF of 2.69 in 1988; analysis above found CV(PSA) = 19.7 percent and CV(AF) = 10.8 percent in 1988. These values will be used here.

Substituting the values for PSA, AF, CV(PSA), and CV(AF) along with the flexible pavement values for SA, TA, CV(SA), and CV(TA) into Equation 4.12 yields a CV(EF) for flexible pavements of 20.2 percent. Substituting the values of PSA, AF, CV(PSA), and CV(AF) along with the rigid pavement values for SA, TA, CV(SA), and CV(TA) into Equation 4.12 yields a CV(EF) for rigid pavements of 26.0 percent. The average of the flexible and rigid pavement CV(EF)'s, 23.1 percent, will be used throughout the remainder of this analysis.

Hence when the statewide average axle weight distribution is used in a forecast, the average load equivalency factor per truck coefficient of variation, CV(EF) is approximately 23.1 percent; this value incorporates the variability associated with estimates of the axle factor and percent single axles components but does not incorporate any variability associated with component correlations.

58

Table 4
ESAL per Truck on Flexible and Rigid Pavements

Station Number	Average Load Equivalency Factors for Flexible Pavement (SN = 3)		Average Load Equivalency Factors for Rigid Pavement (Slab = 8 inches)	
	Single Axles (SA)	Tandem Axles (TA)	Single Axles (SA)	Tandem Axles (TA)
501	0.310	0.817	0.295	1.439
502	0.256	0.654	0.242	1.148
503	0.312	1.075	0.297	1.897
504	0.318	0.754	0.303	1.325
505	0.247	0.697	0.234	1.224
507	0.299	0.717	0.284	1.260
508	0.293	0.851	0.280	1.499
509	0.410	0.868	0.392	1.528
510	0.392	0.992	0.375	1.751
511	0.347	0.965	0.331	1.699
512	0.289	0.741	0.276	1.303
513	0.341	0.723	0.325	1.272
514	0.400	0.962	0.383	1.694
Average	0.324	0.832	0.309	1.465
Sample Standard Deviation	0.050	0.127	0.049	0.226
Population Standard Deviation	0.052	0.132	0.051	0.235
Coefficient of Variation	16%	15.9%	16.3%	16.1%

Directional Distribution

D-8 currently assigns 50 percent of D-10's Total ESAL to each direction of travel. If there is strong reason to believe that trucks at the site travel loaded in one direction and unloaded in the other, D-8 may assign a greater percentage of ESALs to the loaded direction. The directional distribution applied by D-8 is an expected average directional distribution for the entire design period.

Lin, et al, [29] reported the percentage of total pavement distress occurring in each direction of travel on 12 Texas interstate sections. Table 5 shows the results of Lin's research. Concerning his findings, Lin stated: "Field surveys of [pavement] distress as evidenced by cracking, spalling, punch-outs, and patching in continuously reinforced concrete pavements in Texas have shown that considerably more distress exists in one direction than in the other. This can, in all probability, be attributed almost entirely to heavier traffic loading as all other conditions at the sites were virtually identical." The sample standard deviation of Lin's directional distress percentages from D-8's 50 percent average directional split is 16.45 percent. This yields a population standard deviation of 17.18 percent and a directional distribution coefficient of variation, CV(D), of 34.4 percent. Note, however, that pavement distress may become manifest over relatively short periods of time; as a result, the fact that significantly more distress is present in one directional of travel than the other, at a point in time, does not, necessarily, indicate that loadings in the direction with more distress are consistently higher than loadings in the other direction [2]. For this reason, this value for CV(D) is an approximation.

A high CV(D) is consistent with the findings of Hage [30] and Basson [26]. Hage reported large differences in the average load equivalency per 3-S2 in different directions of travel at sites in Minnesota. He first noted that the average load equivalency per truck ranged from 0.62 ESALs to 1.46 ESALs at different weigh stations in Minnesota in 1979. He then stated: "The range of values is even more pronounced when the factors are analyzed by direction. For example, on Trunk Highway 2 . . . the loaded direction [equivalency] factor [per 3-S2] averaged 1.95 ESALs [while the unloaded factor averaged] 0.34 ESALs." Hage also found that at 13 of 15 sites where truck weight data were collected in both 1977 and 1979, the loaded direction remained unchanged over the two-year period.

Hage concluded: "To reduce the likelihood of early pavement failures, design load estimates should be based on the loaded-direction [equivalency] factor rather than the two way average." Hage did not provide enough data to calculate a directional distribution coefficient of variation based on load equivalency factors per truck. Basson studied truck weights on 56 roads in Southern Africa; he reported "directional effects ...at certain sites and at one particular site the average [load equivalency] factor [per truck] travelling in one direction was 17 times that for trucks travelling in the opposite direction."

Lane Distribution

D-8 currently assigns 100 percent of the one-directional ESAL to the design lane for highways with four or fewer lanes, 80 percent to the design lane for highways with six lanes, and 70 percent to the design lane for highways with eight lanes.

Research by Darter [31] and Cunagin [32] suggests that the D-8 factors may typically overestimate the design lane ESAL percentage. Darter used regression analysis to develop lane distribution equations. These equations allow the user to predict the proportion of trucks traveling in different lanes of the highway based on one-directional average daily traffic volume. Darter developed an equation for use 4-lane highways and another for use on 6-or-more-lane highways. The equations were calculated based on truck lane distributions at 129 sites in six states.

Cunagin compared Darter's lane distribution equations to design lane truck percentages observed in Texas. Figure 11, taken from Cunagin's report, shows Darter's 4- and 6-or-more-lane equations and Cunagin's observed Texas design lane percentages. D-8's lane distribution factors have been superimposed on the graph. The horizontal axis of Figure 11 is labeled "Total Daily Traffic" as it was in Cunagin's report. Cunagin used the term "Total Daily Traffic" to mean "One-Way Average Daily Traffic."

Note that Darter's and Cunagin's findings relate to design lane volume proportions rather than design lane ESAL proportions. The goal of a lane distribution system is to distribute ESALs rather than volumes across the lanes of a multi-lane highway. If trucks in each lane of the highway are equally heavily loaded, a volume-based lane distribution system will correctly distribute ESALs as well. Limited evidence from the 1989 SHRP study

61

Table 5
Directional Distribution of Observed
Distress on Continuously Reinforced Concrete Pavements, 1979

			Percent of Total Observed Distress	
			NB* or EB	SB or WB
Location	Length	Direction		
Interstate 10 (from Luling to US Highway 77)	39.9	E-W	30	70
Interstate 10 (From US Highway 77 to SH Highway 71)	22.6	E-W	30	70
Interstate 10 (US Highway 71 to end of research sections)	14.7	E-W	31	69
Interstate 10 (Winnie to Port Arthur)	17.4	N-S	31	69
Interstate 10 (Van Horn to Reeves County)	48.2	E-W	34	66
Interstate 20 (Kaufman County to SH 19)	10.0	E-W	55	45
Interstate 20 (SH 19 to SH 69)	33.0	E-W	57	43
Interstate 20 (SH 69 to US 271)	15.2	E-W	61	39
Interstate 20 (US 271 to SH 135)	13.0	E-W	76	24
Interstate 20 (SH 135 to Longview)	12.2	E-W	35	65
Interstate 35 East (CFHR Sections 906, 903)	9.6	N-S	32	68
Interstate 35 (CFHR Sections, 910, 909, 908, 907, 905, 904)	6.9	N-S	43	57

*Northbound direction of traffic, etc. Source: [29]
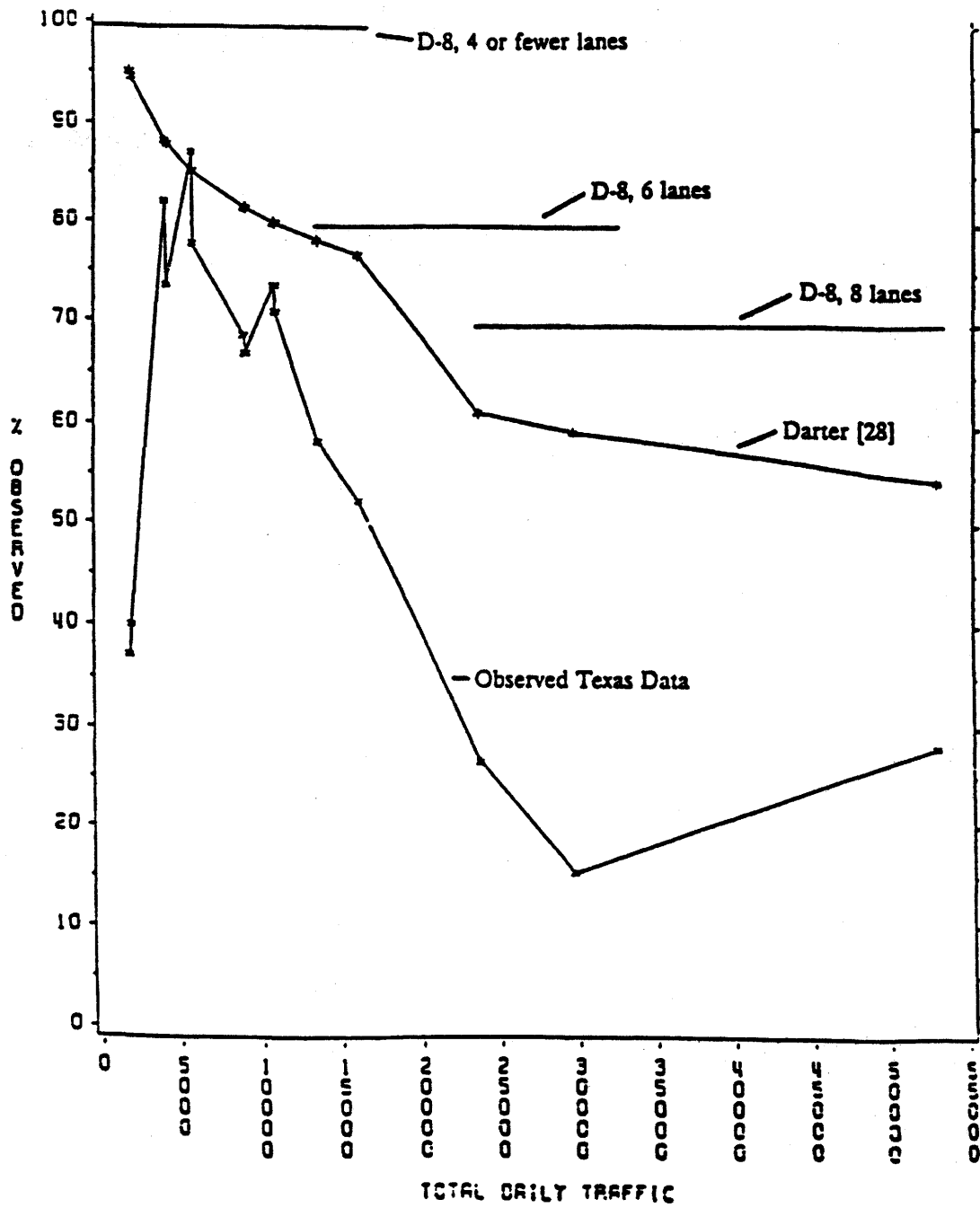
Source: [32]
Figure 11: Lane Distribution Factors

suggests that the average load equivalency factor per 3-S2 in the right lane of a 2-lane highway may be higher than the average load equivalency per 3-S2 in the left lane. In the single case cited in the study, the average load equivalency per 3-S2 in the design (right) lane of a 4-lane highway was 1.15 ESALs/vehicle. The average load equivalency per 3-S2 in the left lane was 0.95 ESALs/vehicle. If design lane trucks are generally more heavily loaded than trucks in other lanes, a lane distribution system based on volumes rather than ESALs will underestimate the percentage of ESALs in the design lane. This would indicate that the D-8 factors do not overestimate design lane ESALs by as much as is shown above.

Alexander and Graves [33] studied truck lane distributions in Georgia. Table 6 shows average, standard deviation, and resulting coefficient of variation of the design lane truck percentage for different facility types. The results are based on truck lane distributions observed in both directions of travel at 34 4-lane rural locations, 44 4-lane urban locations, and 31 6-lane urban locations.

Table 6
Percentage of Trucks in the Design Lane

Facility Type	Average Percent Trucks In Design Lane	Standard Deviation	Coefficient of Variation
4-lane rural	93.5	3.0	3.2 percent
4-lane urban	88.1	5.8	6.6 percent
6-lane urban	60.2	8.0	13.3 percent

Source: Alexander and Graves [33]

The averages are, again, based on volumes rather than ESALs and may tend to overstate the amount by which D-8's factors over-estimate design lane ESALs. The average of Alexander and Graves' three coefficients of variation, 7.7 percent, will be used to approximate the lane distribution coefficient of variation, CV(LF).

SUMMARY OF COMPONENT ACCURACIES

Base Year ADT

   a) When based on an ATR at or very near the project site: $CV(ADT_o) = 2.1$ percent.

   b) When based on a 24-hour coverage count at or very near the project site: $CV(ADT_o) = 10.9$ percent.

ADT Growth Rate

   a) Based on historical traffic volume data collected at or very near the project site: $CV(GF_{ADT}) = 29.3$ percent.

Percent Trucks

   a) When based on a 24-hour classification count taken at or very near the project site: $CV(PCT) = 13.4$ percent.

   b) When based on an adjustment of percent trucks from a classification site at another point on the same highway as the project site: $CV(PCT) = 34.6$ percent.

   c) When based on an adjustment of percent trucks from a classification site on another highway in the same geographic region on the same highway system as the project site: $CV(PCT) = 47.5$ percent.

The composite percent trucks prediction model (i.e., $GC = 10/11$ for $ADT_{proj} < 3,500$; $GC = 1/2$ for $3,500 \leq ADT_{proj} \leq 45,000$; and $GC = 1/8$ for $ADT_{proj} > 45,000$) substantially eliminated the prediction bias associated with using the 1/2-growth model (i.e., $GC = 1/2$) at relatively low and high volume sites.

Percent Single Axles

   a) When based on a 24-hour classification count taken at or very near the project site: $CV(PSA) \leq 19.7$ percent.

   b) When based on the percent single axles from another point on the same highway or another highway in the same geographic region on the same highway system

as the project site: CV(PSA) $\approx$ 19.7 percent.

Axle Factor

a) When based on a 24-hour classification count taken at or very near the project site: CV(AF) $\leq$ 10.8 percent.

b) When based on the axle factor from another point on the same highway or another highway in the same geographic region on the same highway system as the project site: CV(AF) $\approx$ 10.8 percent.

Average Load Equivalency Factor per Truck

(Includes Axle Weight Distribution Table, Percent Single Axles, and Axle Factor variability)

a) When based on a continuous WIM site at or very near the project site: CV(EF) $\approx$ 0 percent.

b) When based on a seasonally-operating permanent WIM site at or very near the project site: CV(EF) = 8.2 percent.

c) When based on a WIM site at another point on the same highway as the project site: CV(EF) $\leq$ 23.1 percent.

d) When based on the statewide average axle weight distribution: CV(EF) = 23.1 percent.

The statewide average axle weight distribution is based on WIM data collected almost exclusively at Interstate WIM sites. As a result, CV(EF)'s c) and d), which were based on analysis of the statewide average axle weight distribution, may not be representative of the variability introduced into a forecast by using non-site-specific axle weight data, at sites on other highway systems. In addition, using the statewide average axle weight distribution at a non-Interstate site may lead to consistent over- or under-estimates of the average load equivalency factor per truck at non-interstate sites. But because only Interstate data were available for analysis, the magnitude and direction of any bias introduced by this practice could not be evaluated.

Directional Distribution

    a) Generally 50 percent of the Total ESAL to each direction of travel: CV(D) ≈ 34.4 percent.

Lane Distribution

    a) Generally 100 percent for 2- or 4-lane roads, 80 percent for 6-lane roads, and 70 percent for 8-lane roads: CV(LF) ≈ 7.7 percent. These lane distribution factors may tend to overestimate the design lane ESAL percentage.

ESAL FORECAST SENSITIVITY TO ERRORS IN INDIVIDUAL COMPONENTS

Equation 3.10, repeated below, shows the cumulative Design Lane ESAL formula under Texas practice:

$$w_T = 365 * T * ADT_o * [(2 + GF_{ADT}*T) / 2] * PCT * EF * D * LF \qquad (3.10)$$

where:

w_T	= cumulative design lane ESALs
T	= design period
ADT_o	= base year ADT
GF_{ADT}	= ADT growth factor
PCT	= percent trucks
EF	= average load equivalency factor per truck (based on axle weight distribution table, percent single axles, and axle factor)
D	= directional distribution
LF	= lane factor

In this formulation: 1) only ADT varies with time; 2) cumulative traffic growth follows a parabolic model (this results from the linear annual traffic growth assumption); and 3) non-truck ESALs are ignored as negligible.

Examination of Equation 3.10 shows that an error in any component except the ADT growth rate has a directly proportional effect on the resulting Design Lane ESAL. For example, if the average load equivalency factor per truck is 15 percent too great, but all the

other components are correct, the resulting ESAL estimate will be 15 percent too great.

An error in the ADT growth rate has a less than proportional effect on the resulting ESAL. To illustrate, assume that all inputs except the ADT growth rate are correct. If the growth rate used in the analysis is 4 percent per year and the actual growth rate is only 2 percent per year (i.e., indicating a 100 percent error in the growth rate) the resulting ESAL estimate will be 16.7 percent too great as a result.

OVERALL DESIGN LANE ESAL FORECAST ACCURACY
Forecast Bias

Three components were found to be potential sources of forecast bias: percent trucks, the average load equivalency factor per truck, and the lane distribution factor. Only the bias in percent trucks estimates could be quantitatively assessed; in addition, it was determined that this bias could be substantially eliminated by varying the growth constant used in TxDOT's percent trucks prediction model, as described in the "SUMMARY OF COMPONENT ACCURACIES" section, above.

Without more information regarding average load equivalency factor per truck and lane distribution factor bias, an empirical estimate of remaining forecast bias cannot be made.

Traffic Variance Formula Repeated

As described in the "Measures of Accuracy" section of this chapter, pavement designers measure ESAL forecast variability by the variance of the logarithm of the ESAL estimate (i.e., traffic variance or $Var(\log_{10} w_T)$). Equation 4.1, repeated below, shows that traffic variance may be calculated using the individual component coefficients of variation:

$$
\begin{aligned}
Var(\log_{10} w_T) \quad &= 0.4343^2 * \{CV(ADT_o)^2 + CV(PCT)^2 + CV(EF)^2 \\
&+ CV(D)^2 + CV(LF)^2 + [T^2*CV(GF_{ADT})^2/(2/GF_{ADT} + T)^2]\}
\end{aligned}
$$

(4.1)

where:

$Var(\log_{10} w_T)$ = traffic variance

$CV(ADT_o)$ = base year ADT coefficient of variation

68

CV(PCT)	=	percent trucks coefficient of variation
CV(EF)	=	average load equivalency per truck coefficient of variation
CV(D)	=	directional distribution coefficient of variation
CV(LF)	=	lane distribution coefficient of variation
CV(GF$_{ADT}$)	=	ADT growth rate coefficient of variation
GF$_{ADT}$	=	ADT growth rate

Assumption of Independence

Equation 4.1 assumes no correlation between all pairs of Design Lane ESAL forecast components. The data required to analyze this assumption, values of ADT$_o$, PCT, EF, D, LF, and GF$_{ADT}$ from a representative sample of Texas road sections, were not available for use in the study. As a result, independence between component pairs is assumed.

Component Combinations

Since a number of components have different coefficients of variation depending on their source, a number of different traffic variances are possible. Figure 12 shows the possible component combinations. The combinations are labeled Sets 1 through 6.

Figure 12 shows that when base year ADT is based on ATR data collected at or near the project site, there is no branch for "non-site-specific vehicle classification data"; this is because classification data are collected at every ATR station. When base year ADT is based on a coverage count and site-specific classification data are available, there is no branch for "continuous WIM"; this is because TxDOT's continuous WIM systems count traffic in all directions and all lanes (i.e., they are effectively ATRs as well as WIM systems). When base year ADT is based on a coverage count and no site-specific vehicle classification data are available, there are no branches for "continuous WIM" or "seasonal WIM"; this is because classification counts are taken at every WIM site. Finally, the ADT growth rate is based on historical traffic volume data collected at or near the pavement project site and the directional and lane distribution factors are set by D-8 as shown in the figure.

The numbers in parentheses next to each branch label reflect the approximate number of locations at which the situation described is applicable. There are currently 148

ATRs in place; coverage counts are taken at approximately 65,000 "on-system" locations (the "on-system" designation excludes county roads and urban streets). Manual classification data, which are being used for ESAL forecasting purposes as TxDOT makes the transition to automatic vehicle classification, are currently collected manually at approximately 300 stations; some of these stations are located at intersections where it is possible to collect data on more than one road section (i.e., on each leg of the intersection) at once; as a result, the number of distinct road sections for which current year classification data are available is approximately 900; because data collected in previous years may also be used in the analysis, site-specific manual classification data are available for a total of approximately 2,350 distinct road sections. Continuous WIM data are collected at six sites; seasonal WIM data are collected at seven sites.

Figure 12 shows that Set 6 is the situation most likely to occur. This is because the great majority of base year ADT estimates are based on coverage counts and because it is much more likely than not that the classification data for a project will have been collected at another point on the same highway or on another highway in the same geographic region as the project site.

Makeup of Traffic Variance

Table 7 shows the traffic variance associated with each component combination. The variances for Sets 1 through 5 are comparable, ranging from 0.0279 to 0.0401. The Set 6a (classification data from another point on same highway) and Set 6b (classification data from a point on another highway in the same geographic region on the same highway system) traffic variances, 0.0593 and 0.0793, respectively, are considerably larger than the Set 1 through 5 variances. This is due to the large difference in the site-specific versus non-site-specific percent trucks coefficient of variation (i.e., 13.4 percent for site-specific versus 34.6 percent or 47.5 percent for non-site-specific).

Table 8 shows the absolute and percentage contribution to traffic variance by each component for Sets 5, 6a, and 6b. These sets are used in the comparison because they differ only in their source of vehicle classification data. Table 8 shows that the percent trucks

Sources: [34,35,36,37,38]
Figure 12: Component Combinations

BASE YEAR ADT	PERCENT TRUCKS	LOAD EQUIVALENCY FACTOR PER TRUCK	ADT GROWTH RATE	DIRECTIONAL DISTRIBUTION	LANE DISTRIBUTION	

Site-Specific Classification Data (148)

Continuous WIM (6)

Historical Volume Data — 50/50 — Depending on the number of lanes: 100%, 80%, 70% — Set 1 (6)

Seasonal WIM (2)

Historical Volume Data — 50/50 — Depending on the number of lanes: 100%, 80%, 70% — Set 2 (2)

Non-Site-Specific WIM (140)

Historical Volume Data — 50/50 — Depending on the number of lanes: 100%, 80%, 70% — Set 3 (140)

ATR (148)

Coverage Count (65,000)

Site-Specific Classification Data (2202)

Seasonal WIM (5)

Historical Volume Data — 50/50 — Depending on the number of lanes: 100%, 80%, 70% — Set 4 (5)

Non-Site-Specific WIM (2197)

Historical Volume Data — 50/50 — Depending on the number of lanes: 100%, 80%, 70% — Set 5 (2197)

Non-Site-Specific Classification Data (62,798)

Non-Site-Specific WIM (62,798)

Historical Volume Data — 50/50 — Depending on the number of lanes: 100%, 80%, 70% — Set 6 (62,798)

Table 7
Contributions to Traffic Variance in Sets 1 through 6

Component	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6a	Set 6b
ADT_o	0.0001	0.0001	0.0001	0.0022	0.0022	0.0022	0.0022
PCT	0.0034	0.0034	0.0034	0.0034	0.0034	0.0226	0.0426
EF	0.0000	0.0013	0.0101	0.0013	0.0101	0.0101	0.0101
D	0.0223	0.0223	0.0223	0.0223	0.0223	0.0223	0.0223
LF	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011
GF_{ADT}	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
Traffic Variance	0.0279	0.0292	0.0380	0.0313	0.0401	0.0593	0.0793

Table 8
The Impact of Vehicle Classification Data Source on Forecast Precision

Component	Set 5	Percent of Total	Set 6a	Percent of Total	Set 6b	Percent of Total
ADT_o	0.0022	5.6%	0.0022	3.8%	0.0022	2.8%
PCT	0.0034	8.4%	0.0226	38.0%	0.0426	53.7%
EF	0.0101	25.1%	0.0101	17.0%	0.0101	12.7%
D	0.0223	55.6%	0.0223	37.6%	0.0223	28.1%
LF	0.0011	2.8%	0.0011	1.9%	0.0011	1.4%
GF_{ADT}	0.0010	2.5%	0.0010	1.7%	0.0010	1.3%
Traffic Variance	0.0401	100%	0.0593	100%	0.0793	100%

coefficient of variation contributes 0.0226 out of 0.0593 or 38.0 percent of traffic variance in Set 6a and 0.0426 out of 0.0793 or 53.7 percent of traffic variance in Set 6b. Set 5 traffic variance is approximately 32 percent smaller than Set 6a traffic variance and approximately

49 percent smaller than Set 6b traffic variance. This is due to the availability of site-specific vehicle classification data for Set 5 forecasts. This suggests that obtaining site-specific vehicle classification data greatly improves Design Lane ESAL forecast precision. This finding is consistent with findings of Middleton, who concluded his study of 1977-1983 Texas vehicle classification data by saying: "The findings also demonstrate a need for classification data at or very near the site being considered for redesign." Chapters V and VI, below, show the impact of site-specific classification data on pavement life and the monetary benefits and costs of obtaining site-specific classification data for use in pavement design, respectively.

The directional distribution factor is the second largest contributor to traffic variance in Sets 6a and 6b and the largest contributor in Set 5 (and all other sets). The average load equivalency factor per truck, which incorporates the variabilities associated with the axle weight distribution table, percent single axles, and axle factor components, is the only other significant contributor to traffic variance in Set 5.

Past studies also indicate that the directional distribution of traffic loadings [26,29,30] and the average load equivalency factor per truck [1,7,26,30]are site-specific traffic stream characteristics. The Set 1, 2, and 4 traffic variances shown in Table 7 are based on site-specific truck weight data; however, the directional and lane distribution factors, used in these forecasts to distribute loadings between the directions and among the lanes of the highway, are based on non-site-specific expected values. As a result, these variances do not reflect the full increase in precision associated with forecasts based on site-specific WIM data, only the increase in precision attributable to the average load equivalency factor per truck. Chapter VII, below, demonstrates the increase in Design Lane ESAL forecast precision which could be realized using truck weight data collected in the design lane of each travel direction, eliminating the need for lane and directional factors; Chapter VII then evaluates the monetary benefits and costs of obtaining site-specific truck weight data for use in pavement design.

The other ESAL forecast components contribute only small amounts to traffic variance in all sets. The ADT growth rate coefficient of variation is noteworthy because it has a substantial coefficient of variation ($CV(GF_{ADT})$ = 29.3 percent); but it contributes

73

only a small amount to traffic variance, 0.0010 in all sets; this is due to the mathematical relationship between the ADT growth rate and the other forecast components in Equation 3.10, the cumulative Design Lane ESAL formula. This indicates that improving ADT growth rate precision would have a negligible impact on overall forecast precision.

Lack-of-Fit Variance

Lack-of-fit variance is introduced into a traffic load forecast by the assumptions of the traffic load forecasting model on which the forecast is based. The key assumptions of TxDOT's traffic forecasting model are: 1) that annual traffic growth follows a linear model (and by implication, cumulative traffic growth follows a parabolic model); 2) that percent trucks remains constant over the design period; 3) that the truck traffic stream makeup remains constant over the design period; and 4) that the average load equivalency factor per truck remains constant over the design period. At a site where any of the model's assumptions is violated, traffic variance may be higher than the amounts shown above. For example, the "ADT Growth Rate" section of this chapter found that the assumption of a linear annual traffic growth model was appropriate at a majority of the rural Texas ATR sites operating continuously from 1974 to 1989. However, at a significant percentage of the sites, the linear model was inappropriate; at these sites, traffic variance for Set 5 forecasts might be 0.0401 + 0.0200; traffic variance for Set 6a forecasts might be 0.0593 + 0.0200; and traffic variance for Set 6b forecasts may be 0.0793 + 0.0200; the additional variance would be introduced by the lack-of-fit of the linear annual traffic growth model. Because the traffic load forecasting model's assumptions are not valid at every site, the most appropriate manner in which to compare the traffic variances shown above is to evaluate the differences between them, not their individual, absolute magnitudes.

74

CHAPTER V
THE IMPACT OF SITE-SPECIFIC CLASSIFICATION DATA ON PAVEMENT LIFE

INTRODUCTION

The purpose of this chapter is to demonstrate the impact of site-specific classification data on pavement life. The first section of the chapter explains the distinction between traffic variance and pavement variance. The second section uses an example to illustrate the respective impacts of traffic and pavement variance on pavement life. The third section introduces and informally defines the reliability concept as it is applied to pavement structures. The fourth section defines and explains two strategies which may be used to increase a pavement's reliability. The fifth section formally defines the reliability concept. The sixth section uses an example to illustrate how the reliability concept is used in pavement design. The seventh section illustrates how the reliability concept may be used to assess the impact of site-specific classification data on pavement life.

TRAFFIC AND PAVEMENT VARIANCE

Pavement life is influenced by many factors including the traffic loadings and environmental conditions that prevail at the project site over the design period and the properties of the materials used to construct the pavement. A designer cannot know with certainty during the design process how much traffic will eventually use a facility, how harsh or mild environmental conditions will actually be at the project site, or the exact properties of the materials that will be used to construct the pavement.

The sources of uncertainty regarding pavement life are grouped into two categories: traffic factors and pavement factors. For pavement design purposes, the magnitude of the uncertainty introduced by each set of factors is measured by its variance [1,2,8]. Hence, there is "traffic variance" and "pavement variance."

Traffic Variance

Traffic variance is a measure of the possible variation between predicted and actual design period traffic loadings. Chapter IV of this report has quantitatively assessed the magnitude of traffic variance under current TxDOT ESAL forecasting practice. The traffic

variance associated with a typical Design Lane ESAL forecast under current practice (i.e., Set 6a or 6b) ranges from 0.0593 to 0.0793, depending on whether the classification data used in the forecast was collected on the same highway or in the same region on the same highway system as the project site. When site-specific vehicle classification data are available for a forecast (i.e., Sets 1 through 5), traffic variance ranges from 0.0279 to 0.0401. The Set 5 and Set 6a traffic variances, 0.0401 and 0.0593, respectively, will be used below to illustrate the impact of site-specific classification data on pavement life.

Pavement Variance

Just as the traffic loadings that will actually be applied to the pavement during the design period may vary from predicted values, the loadings the pavement is actually strong enough to withstand may deviate from the pavement's design strength. Pavement variance measures the possible variation between design and actual pavement strength.

The AASHTO Guide's estimates of pavement variance for flexible and rigid pavements are:

1) Flexible-pavement pavement variance - 0.1938.

2) Rigid-pavement pavement variance - 0.1128.

These values include all non-traffic variances identified in the AASHTO Guide (e.g., design equation lack-of-fit variance is included). The AASHTO Guide cautions that these pavement variances are estimates. As a result, actual pavement variances may be greater or less than those above. Pavement variances will be taken as given in the AASHTO Guide throughout the remainder of this report. Note that AASHTO's pavement variances are greater than the traffic variances identified in this research. This indicates that uncertainty regarding actual pavement strength is greater than uncertainty regarding actual traffic loadings.

IMPACT OF UNCERTAINTY ON PAVEMENT LIFE

The following example describes the negative consequences for pavement life which may result due to uncertainty regarding traffic and pavement factors.

Role of Traffic Variance

The Design Lane ESAL forecast for a pavement reconstruction project is 10,000,000 ESALs. However, the number of trucks at the facility is actually substantially larger than forecast. As a result, the Design Lane ESAL forecast underestimated the actual design period traffic loadings at the site. The pavement experiences the predicted 10,000,000 ESALs in 12 rather than 20 years.

Role of Pavement Variance

The pavement's designer, aware that actual traffic loadings may exceed predicted loadings and that design pavement strength may exceed actual pavement strength, designed the pavement to carry 20,000,000 rather than 10,000,000 ESALs, over the design period. Because, however, environmental conditions at the project site were more harsh than anticipated, the pavement was actually strong enough to carry only 10,000,000 ESALs before failing. Since this pavement experienced 10,000,000 ESALs (its actual traffic loading capacity) in 12 years rather than 20, the pavement fails eight years prematurely.

INFORMAL DESCRIPTION OF THE RELIABILITY CONCEPT

In the example above, traffic loadings were greater than predicted and pavement strength was less than predicted. The opposite situation, i.e., traffic less than expected and pavement strength greater than expected, may also occur. In fact, as shown in Figure 13, it is possible to graphically depict the range of possible outcomes of actual traffic loadings and actual pavement strength [1,2,8],for a given design situation. Figure 13 is based on the design situation described in the pavement performance example above:

1) The design period traffic prediction is 10,000,000 ESALs. The distribution of actual traffic loadings is log-normal and the variance of the logarithm of a typical ESAL estimate (Set 6a) is 0.0593 as identified in this research.

2) The pavement design calls for a rigid pavement strong enough to carry 20,000,000 ESALs. The distribution of actual pavement strength is log-normal and the variance of the logarithm of rigid pavement strength is 0.1128 as given in the AASHTO Guide.

77
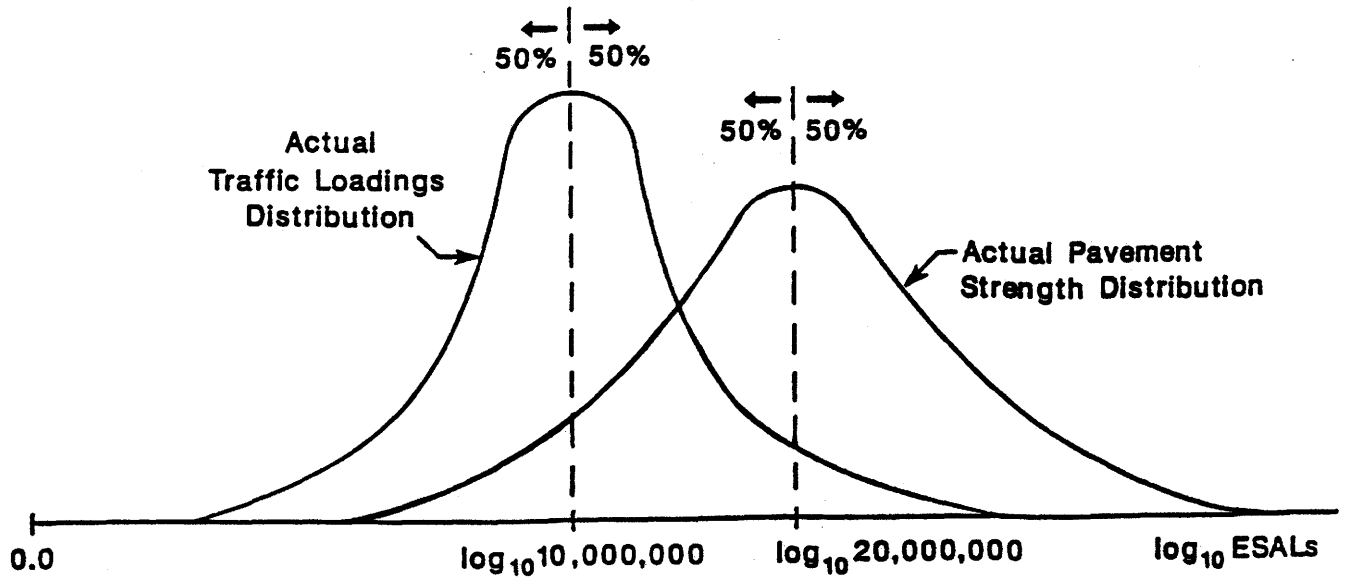
Figure 13. Possible Outcomes of Actual Pavement Strength and Actual Traffic Loadings

Possible Outcomes of Actual Pavement Strength and Actual Traffic Loadings

The two distributions in Figure 13 are **probability density functions**. A probability density function is interpreted by finding the area beneath the curve between two points on the horizontal axis. In the graph above, half the area beneath the traffic loadings distribution lies between the points 0.0 and $\log_{10}(10,000,000)$ $\log_{10}$ESALs on the horizontal axis. This means that there is a 50 percent probability that the actual design period traffic loading for pavements with a 10,000,000 ESAL predicted loading will be between 0.0 and $\log_{10}(10,000,000)$ $\log_{10}$ESALs. Similarly there is a 50 percent probability that the design period traffic loadings will be greater than $\log_{10}(10,000,000)$ $\log_{10}$ESALs. The point $\log_{10}(10,000,000)$ $\log_{10}$ESALs, the base 10 logarithm of the predicted traffic loading for this pavement, is defined as the mean value of the traffic loading distribution.

The mean value of the pavement strength distribution is $\log_{10}(20,000,000)$ $\log_{10}$ESALs, the base 10 logarithm of the design pavement strength. As in the traffic distribution, half the area beneath the pavement strength distribution is located on either side of its mean, $\log_{10}(20,000,000)$ $\log_{10}$ESALs. This implies there is a 50 percent chance that pavements designed to carry 20,000,000 ESALs will actually be strong enough to carry more or less than $\log_{10}(20,000,000)$ $\log_{10}$ESALs.

78

The dispersion of each distribution is determined by its variance. Since traffic variance is smaller than pavement variance, the traffic distribution is more tightly clustered and peaked than the pavement strength distribution.

Reliability

A pavement system's **reliability** may be defined as "the probability that the pavement system will perform its intended function over its design life (or time) and under the conditions (or environment) encountered during operation [1,8,39]." To find the reliability of a system of pavements built under the conditions used in the example, the two distributions in Figure 13 can be consolidated into a single **difference distribution** [1,2,8]. Points on the difference distribution correspond to differences between actual pavement strength and actual traffic loadings. When the difference between pavement strength and traffic loadings is greater than or equal to 0.0, actual design period pavement strength is greater than or equal to actual design period traffic loadings. Pavements with a difference greater than or equal to 0.0 do not fail prematurely. When the difference between pavement strength and traffic loadings is less than 0.0, actual traffic loadings exceed actual pavement strength. Pavements with a difference less than 0.0 do fail prematurely.

The difference distribution can be graphically depicted based on its mean and variance [1,2,8]. The difference distribution's mean, D_{bar}, is the difference between the mean pavement strength and the mean traffic loading [1,2,8]. In the example presented above, D_{bar} would be $\log_{10}(20,000,000) \log_{10} ESALs - \log_{10}(10,000,000) \log_{10} ESALs = 7.3 - 7.0 = 0.3 \log_{10} ESALs$.

D_{bar} can also be interpreted as the base 10 logarithm of the pavement strength/traffic loadings ratio. For the example pavement:

$$D_{bar} = \log_{10}(20,000,000) - \log_{10}(10,000,000)$$
$$= \log_{10}(20,000,000/10,000,000)$$

This implies:

$$10^{D_{bar}} = 20,000,000/10,000,000 = 2.0$$

And, in fact:

$$10^{0.3} = 2.0$$

The difference distribution's variance, S_o^2, is found by adding the traffic distribution's variance and the pavement strength distribution's variance [1,2,8]. In the example presented above, the difference distribution's variance is 0.0593 + 0.1128 = 0.1721. This variance is the **rigid pavement total variance.** Had the example pavement been a flexible rather than rigid pavement, the flexible-pavement pavement variance, 0.1938, would have been substituted for the rigid-pavement pavement variance in the total variance calculation. **Flexible pavement total variance,** then, is 0.0593 + 0.1938 = 0.2531.

The difference distribution for a pavement system designed under the conditions described in the example is graphically depicted in Figure 14 below.
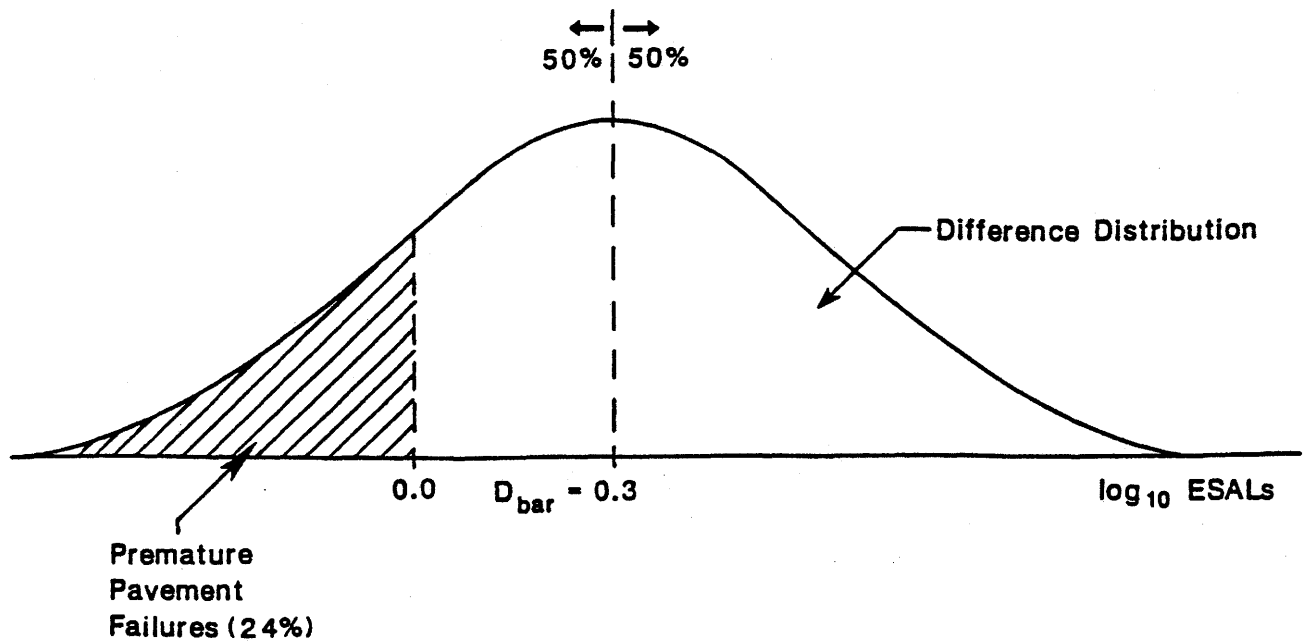
Figure 14. Reliability Difference Distribution

The difference distribution is centered at 0.3 $\log_{10}$ESALs, the average amount by which actual pavement strength exceeds actual traffic loadings for pavements of the type shown in the example. The part of the distribution which lies below 0.0 on the horizontal axis makes up approximately 24 percent of the total area under the curve. This implies that 24 percent of pavements built under the conditions used in the example fail prematurely. A system of pavements designed under the conditions in the example is 76 percent reliable (i.e., 100 percent - 24 percent reliable).

STRATEGIES TO INCREASE PAVEMENT RELIABILITY

In general, there are two ways to decrease the percentage of pavements which fall below 0.0 on the horizontal axis; that is, there are two ways to make the pavement system more reliable [8]:

1) design pavements to carry more ESALs, e.g., increase pavement layer thicknesses; or

2) decrease uncertainty regarding traffic or pavement factors, e.g., collect vehicle classification data at specific pavement project sites.

The effect of these strategies on the difference distribution is shown graphically in Figures 15 and 16 below.

Design Pavements to Carry More ESALs

To illustrate the effect of designing for more ESALs, a difference distribution based on a 21,000,000 ESAL design pavement strength has been superimposed on the original 20,000,000 ESAL design strength distribution. Due to the increase in average pavement strength, the difference distribution's mean increases from 0.3 $\log_{10}$ESALs to 0.32 $\log_{10}$ESALs.
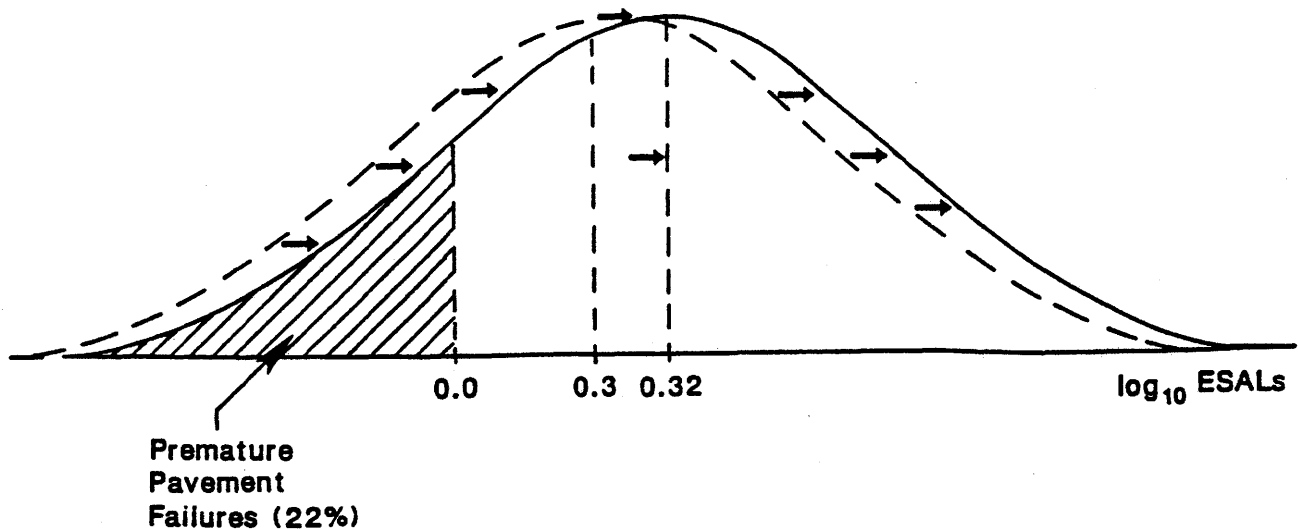
Figure 15. Increasing Pavement Reliability by Designing for More ESALs

81

Notice that this strategy does not change the shape of the difference distribution but, rather, has the effect of shifting the entire distribution to the right on the horizontal axis. Because the difference between actual average pavement strength and actual traffic loadings is, on average, greater than before, a smaller portion, now only approximately 22 percent, of the distribution lies below 0.0 on the horizontal axis.

Decrease Uncertainty Regarding Traffic or Pavement Factors

Figure 16 assumes that pavements are designed to carry 20,000,000 ESALs as in the original example. However, the difference distribution is based on the Set 5 rather than Set 6a traffic variance (i.e., the distribution is based on site-specific versus non-site-specific vehicle classification data). The reduction in traffic variance from 0.0593 to 0.0401 reduces total variance from 0.1721 to 0.1529.
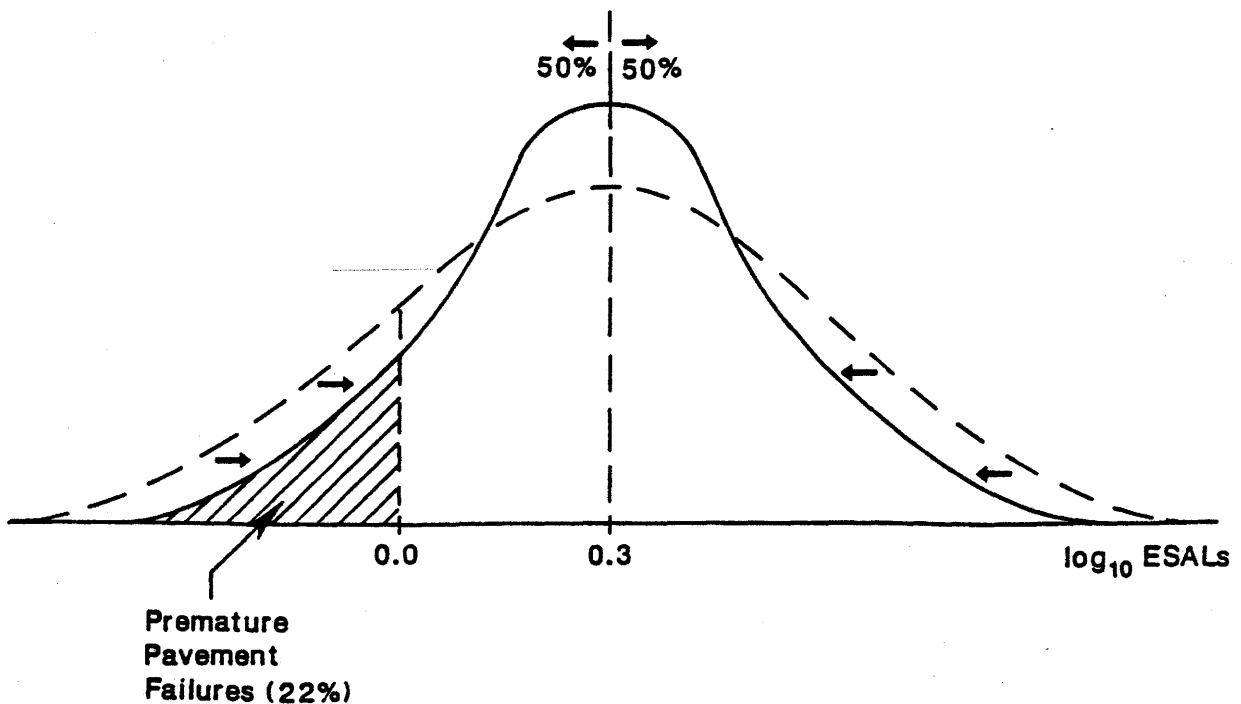
Figure 16: Increasing Reliability by Reducing Traffic Variance

Due to the reduction in total variance, the difference distribution is now narrower than before; and a smaller portion, again only 22 percent, of the distribution lies below 0.0 on the horizontal axis.

USE OF THE RELIABILITY CONCEPT IN DESIGN

The previous example identified a **resulting** reliability level based on predicted traffic loadings, design pavement strength, and total variance. As set forth in the AASHTO Guide and elsewhere [8], the formal reliability concept takes predicted traffic loadings and total variance as given, requires the designer to specify a **desired** reliability level, and provides the design pavement strength needed to achieve the desired reliability level.

In the AASHTO formulation, design pavement strength is a multiple of the predicted traffic loadings. This multiple is called the reliability factor. In the original example above, design pavement strength was 20,000,000 ESALs while predicted traffic loadings were 10,000,000 ESALs. The reliability factor implicit in this example was 2.0 (i.e., 20,000,000/10,000,000).

When reliability was increased by designing pavements to carry 21,000,000 ESALs instead of 20,000,000 ESALs, there was an implied increase in the reliability factor from 2.0 to 2.1. But when reliability was increased by reducing uncertainty, pavement's were still designed to carry 20,000,000 ESALs; i.e., there was no increase in the reliability factor. The reliability increase was due to the fact that higher than expected traffic loadings were made less likely to occur.

In the AASHTO formulation, the reliability factor is defined by the following equation:

$$F_R = 10^{-Z_r * S_o} \qquad (5.3)$$

where:

F_R = the reliability factor

Z_r = value of the standard normal deviate corresponding to the desired reliability level (values of the standard normal deviate for different reliability levels are shown in Table 9 below)

S_o = square root of the total variance (S_o^2)

Table 9
Values of the Standard Normal Deviate for
Different Desired Reliability Levels

Desired Reliability Level	Standard Normal Deviate
50%	-0.00
70%	-0.524
85%	-1.037
90%	-1.282
95%	-1.645

Source: [9]

Equation 5.3 has the following characteristics [1]:

1) A 50 percent desired reliability level (i.e., Z_r = 0.0) corresponds to a 1.0 reliability factor (i.e., F_R = 1.0). This property implies that half the pavements in a system of pavements designed to carry exactly their traffic predictions would survive the design period.

2) A greater than 50 percent reliability level (i.e., Z_r < 0.0) corresponds to a reliability factor greater than 1.0 (i.e., F_R > 1.0). This property implies that more than half the pavements in a system of pavements designed to carry more than their traffic predictions would survive the design period.

3) As total variance increases (i.e., as S_o^2 and S_o increase), F_R increases, for a given reliability level. This property implies that, to achieve the same percentage of design period survivors, a system of pavements built under conditions of greater uncertainty regarding traffic and pavement factors must be built to carry more traffic than a system built given less uncertainty.

The following example illustrates the use of the reliability concept. The example is based on these assumptions:

1) Predicted traffic loadings are 10,000,000 ESALs.

2) The designer chooses to construct a rigid pavement using an 85 percent reliability level.

3) Rigid pavement total variance, S_o^2, is 0.1721 as identified above ($S_o = 0.1721^{1/2} = 0.4149$).

Step I:

Identify the standard normal deviate, Z_r, corresponding to an 85 percent reliability level:

Using Table 9 above, $Z_{85} = -1.037$.

Step II:

Substitute S_o and Z_{85} into the formula for F_R:

$$F_R = 10^{-Z_r \, * \, S_o} = 10^{\, 1.037 \, * \, 0.4149}$$

This results in a reliability factor of 2.69.

Step III:

Multiply this reliability factor by the predicted traffic loadings:

10,000,000 ESALs * 2.69 = 26,900,000 ESALs

Step IV:

Design the pavement to carry 26,900,000 ESALs.

This implies that, given rigid pavement total variance, a designer must design all pavements in a system of rigid pavements must be designed to carry 2.69 times their predicted traffic loadings in order to insure that 85 percent of these pavements will survive their design lives.

RELIABILITY AND PAVEMENT LIFE

The difference distribution for the example reliability calculation is shown in Figure 17 below. The distribution is centered at 0.4302 $\log_{10}$ESALs (i.e., $\log_{10}$(26,900,000) $\log_{10}$ESALs - $\log_{10}$(10,000,000) $\log_{10}$ESALs). Because an 85 percent reliability level was used in the analysis, 15 percent of the area under the curve falls below 0.0 $\log_{10}$ESALs on the horizontal axis.
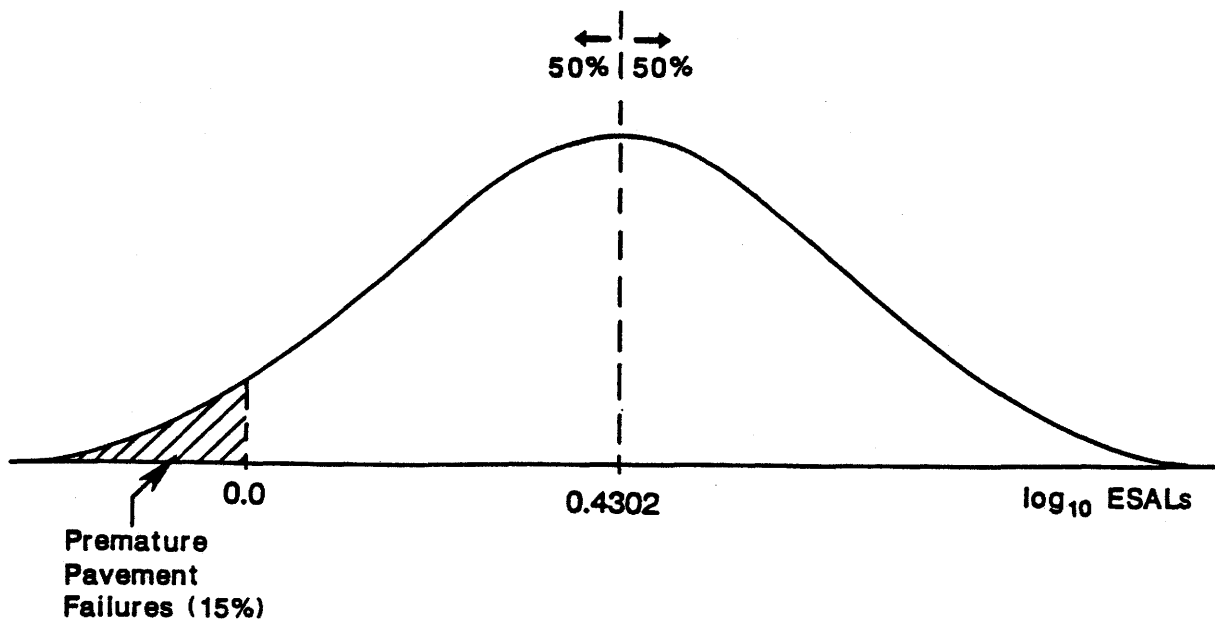
Figure 17. 85 Percent Reliability Level, 2.69 Reliability Factor Distribution

Each point on the horizontal axis of this graph corresponds to:

1) a ratio of actual design period pavement strength to actual design period traffic loadings; and

2) an actual pavement life (assuming a 20-year design life).

Figures 18 and 19 graphically depict these corresponding expressions of the horizontal axis.

Ratio of Actual Pavement Strength to Actual Traffic Loadings

The distribution in Figure 18 is centered at the point 2.69 on the horizontal axis. The ratios which appear on the horizontal axis of Figure 18 were identified by taking the anti-log of the differences in Figure 17. For example, the anti-log of 0.4302 = $10^{0.4302}$ = 2.69; and the anti-log of 0.0 = $10^{0.0}$ = 1.0. By definition, pavements built using a 2.69 reliability factor will have mean actual design period pavement strengths of 2.69 times their actual design period traffic loadings; i.e., the mean of the actual design period pavement strength to actual design period traffic loadings distribution, **PS/TL**$_{bar}$, is 2.69. As a result, half the total area under the curve lies on each side of the point 2.69 on the horizontal axis; i.e., half the

86

pavements designed using a 2.69 reliability factor will have actual design period pavement strengths greater than 2.69 times their actual design period traffic loadings. Likewise, half the pavements designed using a 2.69 reliability factor will have actual design period pavement strengths less than 2.69 times their actual design period traffic loadings.
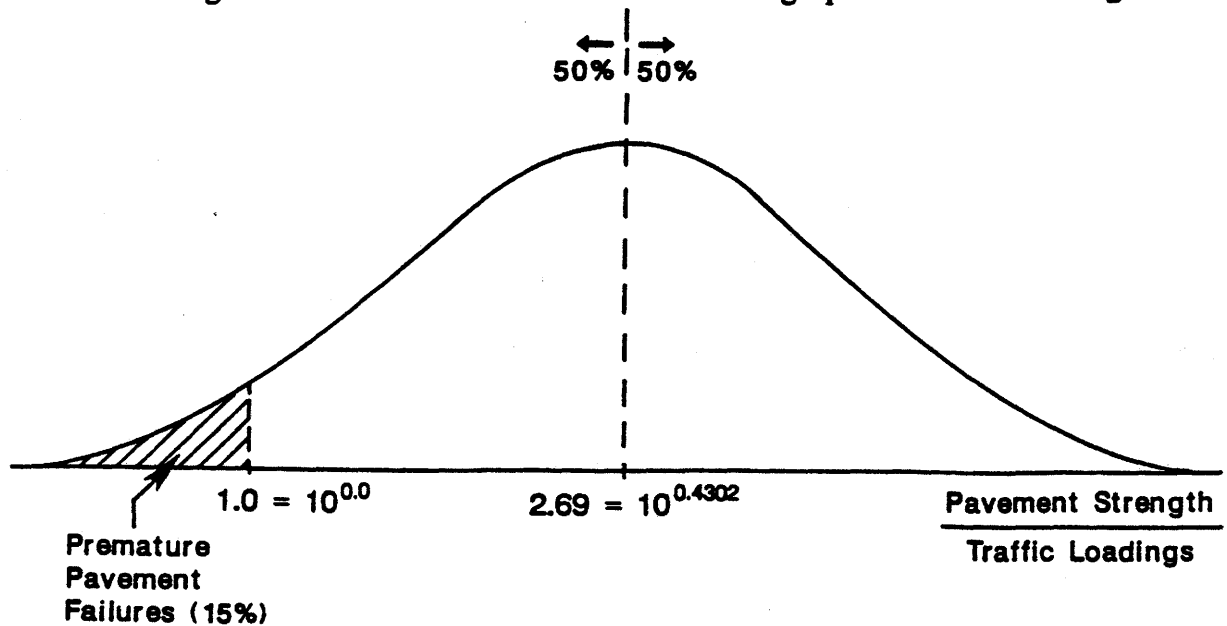
Figure 18. Horizontal Axis - Pavement Strength/Traffic Loadings

Of the total area under the curve, 15 percent lies below the point 1.0 on the horizontal axis. These are the 15 percent of pavements for which actual design period traffic loadings are greater than actual design period pavement strength; for these pavements, the ratio of actual design period pavement strength to actual design period traffic loadings, PS/TL, is less than 1.0. These pavements fail prematurely.

Actual Pavement Life

It is possible to identify the pavement life corresponding to some ratio of actual design period pavement strength to actual design period traffic loadings, given a cumulative traffic growth model. For example, if through some combination of deviations from design pavement strength and predicted traffic loadings, a pavement has an actual design period pavement strength to actual design period traffic loadings ratio of 0.5, that pavement will, by definition, fail when 0.5 times its actual design period traffic loadings have accumulated;

87

the time when 0.5 times a pavement's actual design period traffic loadings will have accumulated depends on the cumulative traffic growth pattern at the site.

Given the cumulative traffic growth model used in this research (i.e., Equation 3.10) and assuming a 20-year design period, the time, T, when PS/TL times a pavement's actual design period traffic loadings will have accumulated can be identified using Equation 5.4.

$$B * T * [(2 + T*GF_{ADT})/2] = (PS/TL) * B * 20 * [(2 + 20*GF_{ADT})/2] \qquad (5.4)$$

where:

B = the actual base year traffic loadings at the site (in the Equation 3.10 formulation, $B = 365 * ADT_o * PCT * EF * D * L$)

T = the time when PS/TL times the pavement's actual design period traffic loadings will accumulate

GF_{ADT} = the actual ADT growth rate at the site

PS/TL = the ratio of actual design period pavement strength to actual design period traffic loadings at the site

Each side of Equation 5.4 is simply the cumulative traffic growth model first shown in Equation 3.10 with the variable B used to represent all the base year traffic terms. The left side of the equation is the traffic loading that will have actually accumulated by T years from construction; the right side is PS/TL times the actual 20-year traffic loading at the site. By solving the equation for T, one finds the time after construction when PS/TL times the pavement's actual design period traffic loadings will have accumulated and, by definition, the pavement life corresponding to the ratio of actual design period pavement strength to actual traffic loadings, PS/TL.

Equation 5.4 may be solved for T using the following steps:

1) Divide both sides by B, yielding:

$$T * [(2 + T*GF_{ADT})/2] = (PS/TL) * 20 * [(2 + 20*GF_{ADT})/2] \qquad (5.5)$$

2) Multiply both sides by 2, yielding:

$$T * (2 + T*GF_{ADT}) = (PS/TL) * 20 * (2 + 20*GF_{ADT}) \qquad (5.6)$$

3) Combine terms on the left, yielding:

$$GF_{ADT}*T^2 + 2*T = (PS/TL) * 20 * (2 + 20*GF_{ADT}) \qquad (5.7)$$

4) Bring the right side of the Equation to the left, yielding:

$$GF_{ADT}*T^2 + 2*T - [(PS/TL) * 20 * (2 + 20*GF_{ADT})] = 0 \qquad (5.8)$$

5) Enter a value for GF_{ADT} (3.3 percent, the median GF_{ADT} at the 56 rural Texas ATR sites studied in Chapter IV will be used here), yielding:

$$0.033*T^2 + 2*T - [(PS/TL) * 20 * (2 + 20*0.033)] = 0 \qquad (5.9)$$

6) Enter the desired value for PS/TL, for example, PS/TL = 0.5, (i.e., actual design period pavement strength equals 50 percent of actual design period traffic loadings), yielding:

$$0.033*T^2 + 2*T - [(0.5) * 20 * (2 + 20*0.033)] = 0$$

7) Combine constants, yielding:

$$0.033*T^2 + 2*T - 26.6 = 0$$

8) Solve for T using the Quadratic Equation.

This procedure yields possible values for T of 11.22 years and -71.83 years. Since a negative pavement life is impossible, it is unnecessary to consider the latter value. This result indicates that, given a 20-year design period and a 3.3 percent linear annual traffic growth rate, 50 percent of a pavement's actual design period traffic loadings will accumulate during the first 11.22 years following construction; and by implication, if through some combination of deviations from design pavement strength and predicted traffic loadings, a pavement's actual design period strength is only half its actual design period traffic loadings, the pavement will fail within approximately 11.22 years following construction.

This procedure was used to express the ratios of actual design period pavement strength over actual design period traffic loadings, on the horizontal axis of Figure 18, in terms of actual pavement life; Figure 19 shows the resulting distribution. The distribution shown in Figure 19 is centered at 42.22 years on the horizontal axis; i.e., the mean of the pavement life distribution, PL_{bar}, is 42.22 years. (Note that while a pavement structure may be capable of carrying 42.22 years of traffic loadings, a 42.22 year pavement life may not be realized due to non-structural factors such as geometric obsolescence [6,40].) Because the distribution is based on an 85 percent reliability level and a 20-year design period, 15 percent of the distribution falls below 20 years on the horizontal axis.
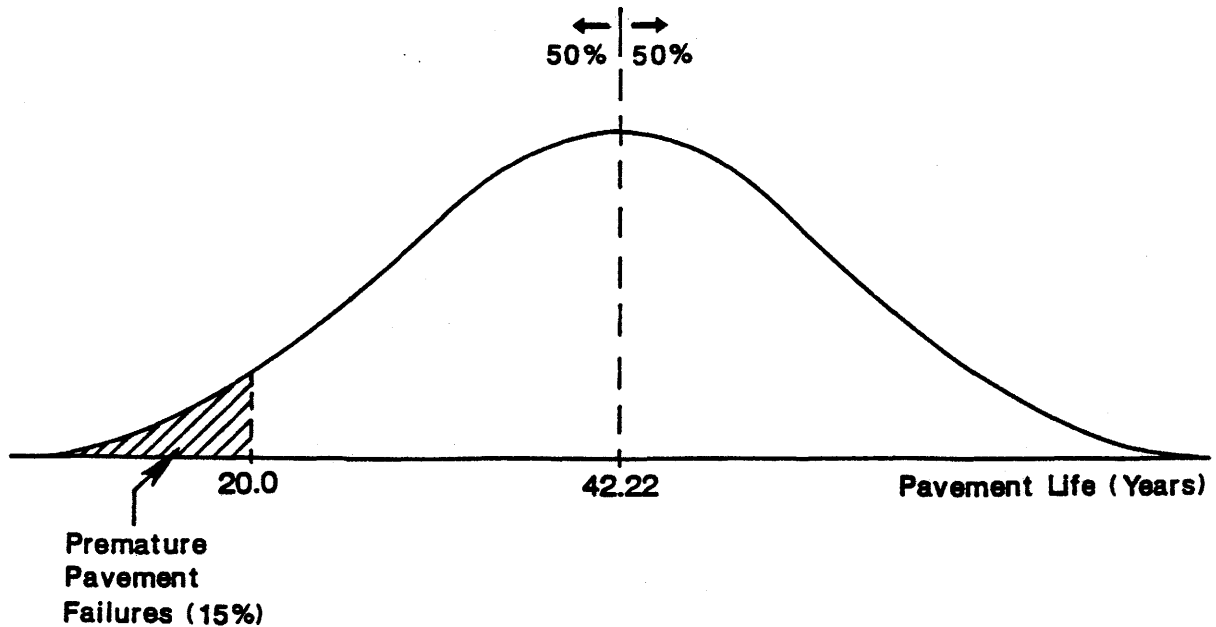
Figure 19. Horizontal Axis - Pavement Life

To summarize the steps taken thus far, the mean of the difference distribution, D_{bar} was identified to be $0.4302 \log_{10}$ESALs. This value was found by subtracting $\log_{10}$(predicted traffic loadings) from $\log_{10}$(design pavement strength). D_{bar} is the average amount by which $\log_{10}$(actual design period pavement strength) exceeds $\log_{10}$(actual design period traffic loadings). The variance of the difference distribution, S_o^2, was found to be 0.1721. This value was identified by adding traffic variance, 0.0593, and rigid-pavement pavement variance, 0.1128. The horizontal axis of the difference distribution was expressed as the "ratio of actual design period pavement strength to actual design period traffic loadings" by taking the anti-log of points on the original axis. For example, the mean ratio of actual design period pavement strength to actual design period traffic loadings, PS/TL_{bar}, was found to be 2.69 by taking the anti-log of D_{bar} (i.e., $10^{0.4302} = 2.69$). The horizontal axis of the distribution was expressed as "pavement life" using a cumulative traffic growth pattern and the Quadratic Equation. For example, the mean pavement life, PL_{bar}, was found to be 42.22 years by substituting PS/TL_{bar}, 2.69, into Equation 5.9 and solving for T using the Quadratic Equation.

Using the relationship between D, PS/TL, and PL, it is possible to identify the timing of cumulative percent pavement failures in a pavement system. To find, for example, the

time before 5 percent of pavements in the Figure 19 system (distribution) will have failed, the following procedure may be used:

Step I: Identify $D_{1-\alpha}$

where:

α = the percentage of pavements in question (5 percent in this case)

$D_{1-\alpha}$ = the difference between pavement strength and traffic loadings corresponding to α percent failures

a) A point $D_{1-\alpha}$ can be identified using the mean and variance of the difference distribution [9]. In this example, the mean, D_{bar}, equals $0.4302 \log_{10}\text{ESALs}$; the variance, S_o^2, is the rigid pavement total variance, 0.1721 (i.e., traffic variance + rigid-pavement pavement variance = $0.0593 + 0.1128$).

b) Given the mean and variance, $D_{1-\alpha}$ can be found using Equation 5.9 [9].

$$D_{1-\alpha} = D_{bar} + Z_{1-\alpha} * S_o \qquad (5.9)$$

where:

$Z_{1-\alpha}$ = the value of the standard normal deviate corresponding to 100 percent - α * 100 percent; in this case, 1-α = 1 - 0.05 = 0.95 or 95 percent (values of the standard normal deviate corresponding to different reliability levels were shown in Table 9 above)

S_o = the square root of total variance (i.e., $0.1721^{1/2}$ = 0.4149)

Substituting $D_{bar} = 0.4302 \log_{10}\text{ESALs}$, $Z_{95} = -1.645$, and $S_o = 0.4149$ into Equation 5.9:

$$D_{1-\alpha} = 0.4302 + -1.645 * 0.4149$$
$$= -0.2523$$

Step II: Find $PS/TL_{1-\alpha}$

where:

$PS/TL_{1-\alpha}$ = the ratio of actual 20-year pavement strength to actual 20-year traffic loadings which corresponds to $D_{1-\alpha}$ on the difference distribution.

The ratio $PS/TL_{1-\alpha}$ is found by taking the anti-log of $D_{1-\alpha}$. In this case, PS/TL_{95} = $10^{-0.2523}$ = 0.5594.

Step III: Find $PL_{1-\alpha}$

where:

$PL_{1-\alpha}$ = the time by which α percent of pavements in the system will have failed (i.e., the time by 5 percent of pavements will have failed in this case)

a) $PL_{1-\alpha}$ may be found using the cumulative traffic growth model and the Quadratic Equation.

b) Step II above found PS/TL_{95}, the ratio of actual 20-year pavement strength to actual 20-year traffic loadings which corresponds to 5 percent failures, to equal 0.5594.

c) Substituting this value into Equation 5.9 for PS/TL and solving using the Quadratic Equation yields possible values for T of 12.36 years and -72.97 years. It is unnecessary to consider the negative value.

d) Hence, PL_{95} = 12.36 years. This is interpreted to mean that 5 percent of rigid pavements designed to be 85 percent reliable, without site-specific classification data, will have failed within 12.36 years after construction.

The portion of the pavement life distribution (Figure 19) which falls below 20 years on the horizontal axis has been enlarged in Figure 20 below. Figure 20 shows that without site-specific classification data, 1 percent of these pavements will fail within 6.96 years, 5 percent within 12.36 years, 10 percent within 16.54 years, and 15 percent within 20 years.
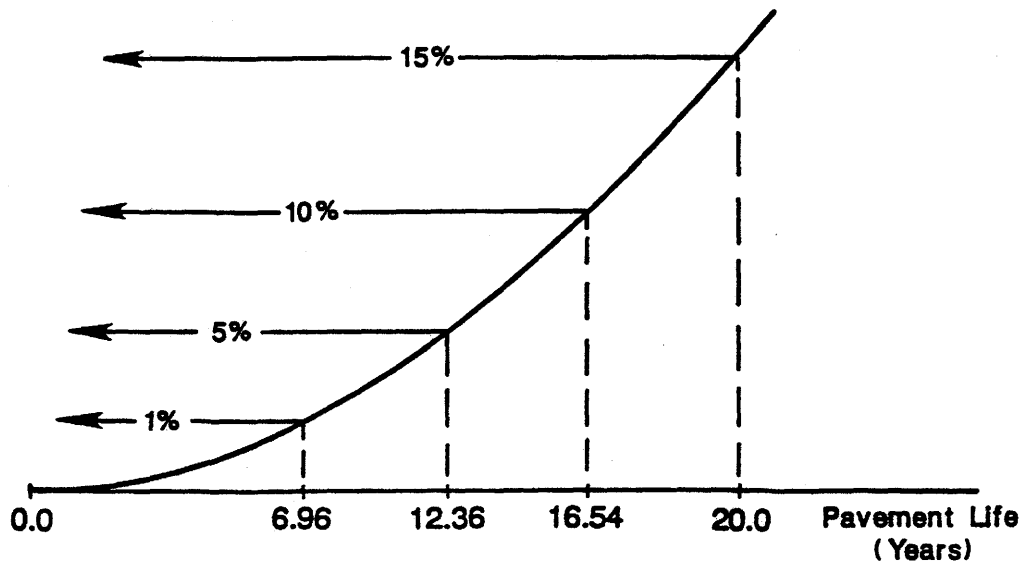
Figure 20. Timing of Pavement Failures without Site-Specific Classification Data

IMPACT OF SITE-SPECIFIC CLASSIFCATION DATA ON PAVEMENT LIFE

It was demonstrated graphically in the "Strategies to Increase Reliability" section that reducing traffic variance would increase a pavement system's reliability, all other things being equal. Figure 21 shows this increase in reliability by superimposing the difference distribution associated with Set 5 traffic variance (i.e., site-specific classification data) on the distribution associated with Set 6a traffic variance (i.e., classification data from another point on the same highway) for the 2.69 reliability factor situation.

Because both distributions in Figure 21 are based on a 2.69 reliability factor, both distributions are centered at 42.22 years on the horizontal axis. However, because total variance with site-specific classification data is 0.1529 as opposed to 0.1721 without, only 13.5 percent of the Set 5 distribution lies below 20 years on the horizontal axis versus 15 percent for the Set 6 distribution. This implies that rigid pavements designed using a 2.69 reliability factor in conjunction with site-specific vehicle classification data are 86.5 percent reliable versus 85 percent reliable without site-specific classification data.

93
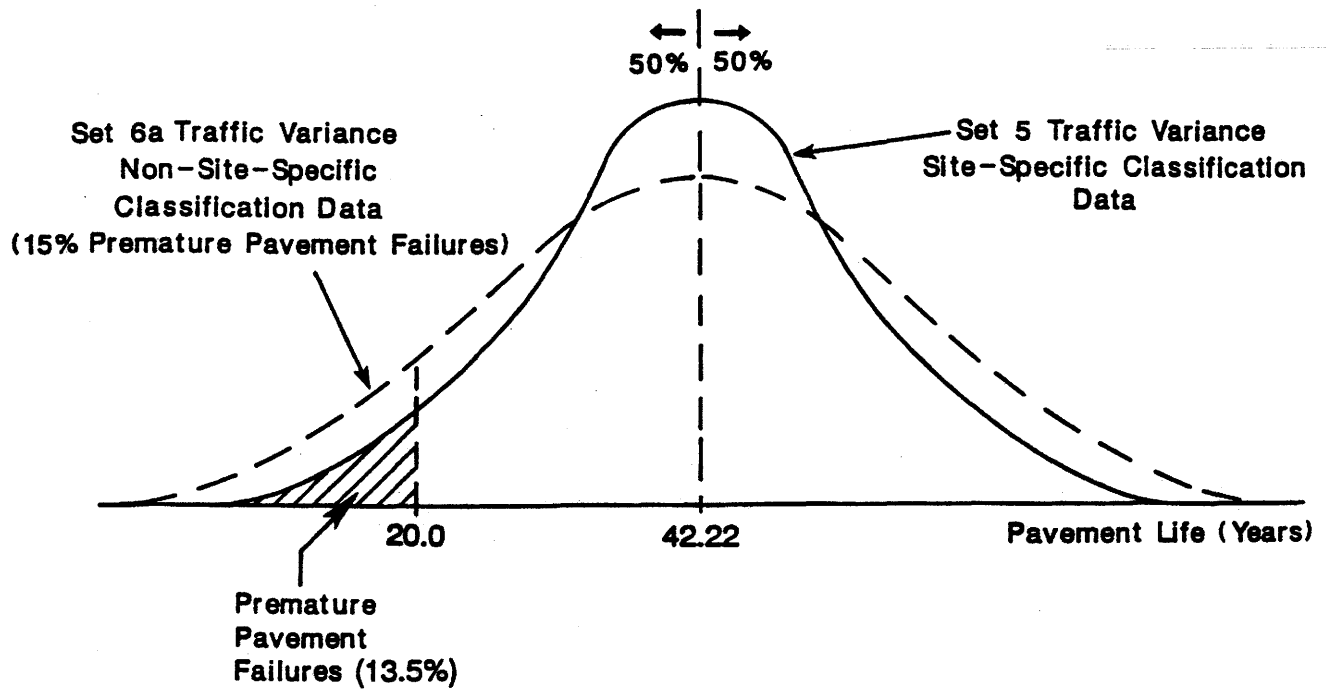
Figure 21. Increase in Reliability Due to Site-Specific Classification Data

The portion of each distribution falling below 20 years in Figure 21 has been enlarged in Figure 22. Figure 22 shows that 1 percent of pavements designed with site-specific classification data will not have failed until 7.81 years (versus 6.96 years without site-specific classification data); 5 percent designed with site-specification classification will not have failed until 13.35 years (versus 12.36 years without); 10 percent designed with site-specific classification will not have failed until 17.52 years (versus 16.54 years without); and only 13.5 percent total designed with site-specific classification data will have failed within 20 years of construction (versus 15 percent without).
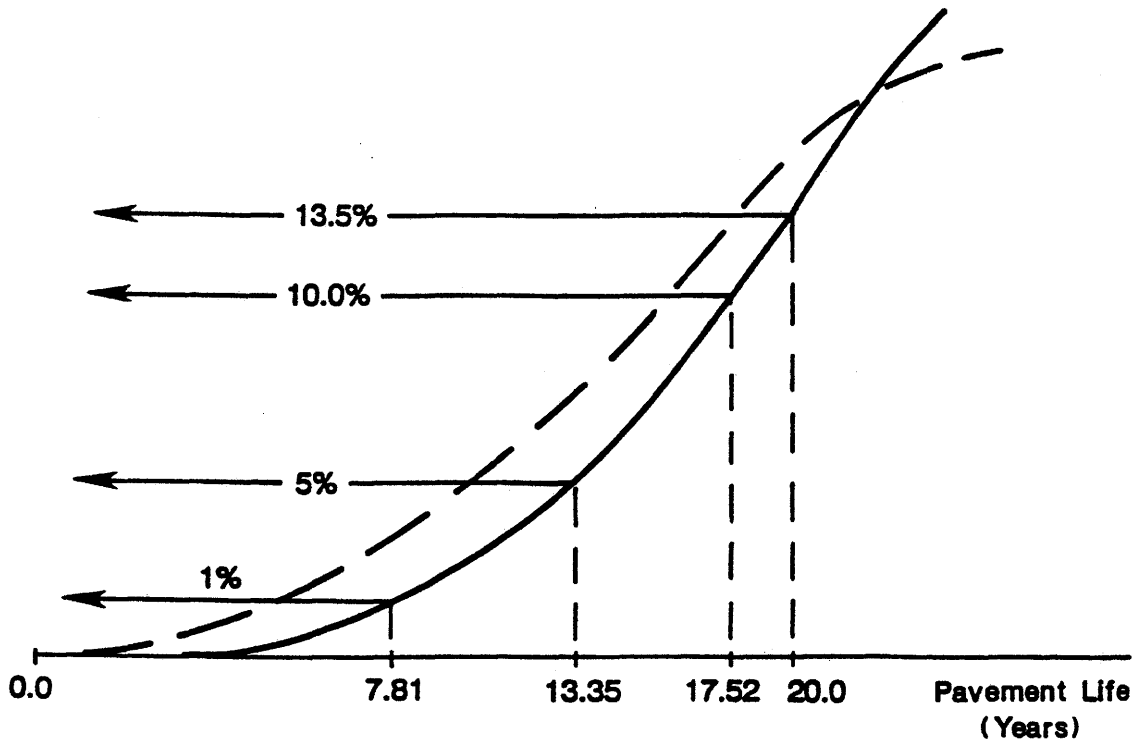
Figure 22. Timing of Pavement Failures with Site-Specific Classification Data

Generally, it can be concluded that obtaining site-specific classification data: 1) reduced the overall percentage of premature failures (from 15 to 13 percent in this case); and 2) extended the lives of pavements which still fail prematurely (i.e., 13.5 percent of pavements still failed prematurely given site-specific classification data; however, these 13.5 percent had not failed until 20 years with these data versus 19.05 years without).

95

CHAPTER VI
THE MONETARY BENEFITS AND COSTS
OF SITE-SPECIFIC CLASSIFCATION DATA

INTRODUCTION

The purpose of this chapter is to assess the monetary benefits and costs of obtaining site-specific classification data for use in pavement design. The first section of the chapter describes the economic principles used to assess the benefits of reducing traffic variance, in general, the present value and equivalent annual cost concepts. The second section uses an example to illustrate these concepts in the context of a premature pavement failure. The third section uses the methodology shown in the example to assess the economic benefits of obtaining site-specific classification data. The fourth section analyzes the sensitivity of the resulting benefits to assumptions made in the analysis. The fifth section assesses the cost to obtain site-specific classification data then uses the cost and benefit information to determine how large a pavement project must be before obtaining these data becomes cost-effective.

PRESENT VALUE AND EQUIVALENT ANNUAL COST

The present value of a future expenditure is the amount which must be invested today at a given compound interest rate for the original investment plus interest to equal to the amount of the future expenditure, at the time the future expenditure is made [41]. The present value concept implies that money has **time value**; i.e., that a sum of money is worth more today than the same absolute sum of money would be worth at a future time [41]. This is because money, in hand in the present, can be invested and earn a return over time [41]. The **discount rate** is the mechanism used in economic analyses to account for the time value of money, i.e., to adjust benefits and costs which occur at different points in time to their respective values at a single point in time, usually the present, so that the benefits and costs may be properly compared [1].

The cost to reconstruct a pavement is incurred when the pavement is reconstructed; however, the lump sum reconstruction expenditure, made at the time of reconstruction, may be thought of in terms of an **equivalent annual cost**. A reconstruction expenditure's

equivalent annual cost is the amount which, if paid annually over the service life of the pavement, would have the same present value as the expenditure. The equivalent annual cost of a reconstruction expenditure may be thought of as the cost, per year of service life purchased by the expenditure, to provide the pavement facility to users.

The longer a pavement's actual service life following its reconstruction, the greater the number of service years over which the lump sum expenditure can be apportioned and the lower the resulting equivalent annual cost of the pavement, all other things being equal. This is because an expenditure made on a pavement with a longer service life, though equal in absolute terms to an expenditure made on a pavement with a shorter service life, actually purchases more years of service life than the expenditure on the shorter-life pavement. To provide the same total years of service life for the pavement with the shorter initial service life would require an additional expenditure when the initial pavement fails. The pavement with the shorter initial service life may be said to have a higher **life-cycle cost** than the other pavement, all other things being equal. This difference in life-cycle cost may also be referred to as the **opportunity cost** associated with building a shorter-, rather than longer-, initial-service-life pavement. As used here, the term "opportunity cost" reflects the fact that the additional money paid into the shorter-initial service life pavement, over its life-cycle, relative to that paid into the longer-initial service life pavement, could have been applied to other projects; however, because it must be spent to make up the difference in initial service life between the two original pavements, the opportunity to use the money on other projects is lost. The example below illustrates these concepts in the context of a premature pavement failure.

THE COSTS OF PREMATURE PAVEMENT FAILURE

The three assumptions below are made for use in the example:

1) A pavement section designed to last 20 years fails eight years prematurely.

2) The cost to reconstruct this pavement section (including only actual pavement construction costs) is $5,000,000 whether reconstruction is undertaken today, in 12 years, or in 20 years.

3) The **long-term real rate of return** is approximately 4 percent.

97

The second and third assumptions warrant explanation. Assumption 2 implies an inflation-free environment. Inflation refers to the general increase in prices and income levels throughout the economy over time [1,41]. In an inflation-free environment, an environment in which overall price levels do not increase over time, the absolute cost to reconstruct a pavement today is the same as the absolute cost to reconstruct it at some time in the future. It is recommended practice in highway economic analyses to assume an inflation-free environment [1,41,42,43,44,45,46].

The long-term real rate of return is the discount rate used to account for the time value of money in an inflation-free environment [1,41,45,46]. The interest rates quoted in investment or debt markets (e.g., on certificates of deposit or home mortgages) are made up of two components: a real rate of return and an inflation premium [1,45]. The inflation premium accounts for the expected increase in the price of goods and services over the time period covered by the investment [1,41]. The real rate of return is the actual increase in the value of the initial investment after the effect of inflation has been factored out [1,41]. For example, if an investor earns seven percent nominal interest (i.e., if the quoted interest rate is seven percent) on a one year certificate of deposit, but inflation runs at seven percent during the year, the investor will have actually earned nothing on the investment. This is because the purchasing power of money fell during the course of the year by the precise amount that the investor nominally earned. The real rate of return to this investor was zero percent. The assumption of 4 percent long-term real rate of return is recommended practice in highway economic analysis [41,44,45,46].

To find the difference in life-cycle cost between a 12-year and 20-year pavement, it is first necessary to convert each pavement's initial cost to an equivalent annual cost. The relationship between a present value and its equivalent annual cost is [47]:

$$A = P * \{ [i*(1+i)^t] / [(1+i)^t - 1] \} \tag{6.1}$$

where:

P = present value

A = equivalent annual cost

i = long-term real rate of return

t = years over which the initial expenditure is to be apportioned

Using Equation 6.1, the equivalent annual cost of $5,000,000, paid over a 12-year period, discounted at a 4 percent annual rate, is $532,761 per year. This is interpreted to mean that a $5,000,000 lump sum payment made today is worth 12 annual payments of $532,761, discounted at a 4 percent annual rate. The equivalent annual of cost of $5,000,000 to be paid over a 20-year period is $367,909 per year.

Given equivalent annual costs, the difference in life-cycle cost between the 12-year and 20-year pavements may be found by discounting the two equivalent annual costs over the 12-year period during which both projects operate. This procedure assumes that every pavement built after each of the current pavements (i.e., after the 12-and 20-year pavements) will be a 20-year pavement. In an inflation free environment, this assumption implies that all the pavements built after the current pavements will have the same equivalent annual cost as the current 20-year pavement. As a result, the equivalent annual costs, over the life-cycles of the two pavements, will be equal beginning in year 13, the first year that a 20-year pavement is in place at both, rather than just one, site. Because the equivalent annual costs are equal beginning in year 13, only the differences in equivalent annual costs during years one through 12 must be considered to find the difference in life-cycle cost associated with the two pavements.

The alternative is to assume that the 12-year pavement is repeated, rather than followed immediately by a series of 20-year pavements. This approach however, assumes that constructing one 12-year pavement dooms the agency to constructing a series of 12-year pavements rather than 20-year pavements; for this reason, assuming that the 12-year project is repeated would unrealistically magnify the negative economic consequences associated with constructing a single 12-year pavement versus a single 20-year pavement.

The difference life-cycle costs, then, between the 12- and 20-year pavements, is the difference in the present values of the 12-year and 20-year equivalent annual costs when these equivalent annual costs are discounted over a 12-year period. The present value of a series of equal annual payments may be found in terms of the payment amount (i.e., the equivalent annual cost), the payment period (i.e., 12 years), and the interest rate (i.e., 4 percent), as shown in Equation 6.2 [47]:

$$P = A * \{ [(1+i)^t - 1] / [i*(1+i)^t] \} \tag{6.2}$$

where:

A = the annual payment amount

P = the present value

t = the payment period

i = the interest rate

Using Equation 6.2, the present value of 12 annual payments of $532,761 is $5,000,000; the present value of 12 annual payments of $367,909 is $3,452,852. The difference in present value between the 12-year project and the 20-year project is approximately $1,547,148. This increase in present value, $1,547,148, is the opportunity cost to the constructing agency associated with this premature pavement failure.

BENEFITS OF OBTAINING SITE-SPECIFIC CLASSIFCATION DATA

Chapter V showed that obtaining site-specific classification data: 1) reduced the incidence of premature pavement failures in a pavement system; and 2) extended the lives of pavements which fail prematurely despite these data. In addition, Chapter V showed that the reliability concept can be used to explicitly identify the time following construction by which percentages of pavements in a pavement system designed given certain traffic and pavement variances will have failed.

This pavement life information may be used in conjunction with the economic analysis framework presented above to assess the economic benefits to TxDOT of obtaining site-specific classification data for use in pavement design. The following analysis demonstrates the benefit calculation for the Set 6a versus Set 5 traffic variance example used throughout Chapter V. Tables 10 and 11 show the time after construction by which certain percentages of pavements in the Set 6a and Set 5 distributions will have failed; these tables are referenced in the calculations below.

Step I: Find the Opportunity Cost of the 15 Percent Set 6a Premature Failures

The opportunity cost calculation is based on the following assumptions:

1) The reconstruction expenditure will be $1,000,000 no matter when it is made. (This expenditure includes only actual pavement construction costs.)

2) The long-term real rate of return is 4 percent per year.

3) Pavements are designed to last 20 years.

Table 10
Timing of Cumulative Percent Failures for
Pavements Designed without Site-Specific Classification Data

Failures (Percent)	Time (Years)
0.01	2.43
0.1	3.54
1	6.96
2	8.79
3	10.17
4	11.33
5	12.36
6	13.30
7	14.17
8	15.06
9	15.80
10	16.54
11	17.28
12	17.98
13	18.69
14	19.35
15	20.00

The opportunity cost to TxDOT of the 0.01 percent of pavements which fail between 0 and 2.43 years is found as follows:

1) Convert to equivalent annual costs using Equation 6.1:

The equivalent annual cost of $1,000,000 over 20 years = $73,582.

The equivalent annual cost of $1,000,000 over 2.43 years = $439,680.

3) Discount both payment streams over the life of the shorter project, 2.43 years, using Equation 6.2:

   a) The present value of a $73,582 equivalent annual cost paid over 2.43 years is $167,353.

   b) The present value of a $439,680 equivalent annual cost paid over 2.43 years is $1,000,000.

The difference in present value is $832,647. However, only 0.01 percent of pavements designed using a 2.69 reliability factor fail within 2.43 years of construction (i.e., there is only a 0.0001 chance that a pavement constructed to an 85 percent reliability level given Set 6a traffic variance will fail within 2.43 years after construction). As a result, the expected opportunity cost to TxDOT per $1,000,000 of reconstruction expenditure is 0.0001 * $832,647 = $83.

The opportunity cost to TxDOT of the 0.09 percent of pavements which fail between 2.43 and 3.54 years is found as follows:

1) Convert to equivalent annual costs:

   The equivalent annual cost of $1,000,000 over 20 years = $73,582.

   The equivalent annual cost of $1,000,000 over 3.54 years = $308,886.

2) Discount both payment streams over the life of the shorter project, 3.54 years:

   a) The present value of a $73,582 equivalent annual cost paid over 3.54 years is $238,217.

   b) The present value of a $308,886 equivalent annual cost paid over 3.54 years is $1,000,000.

The difference in present value is $761,783. Since only 0.09 percent of pavements in this distribution fail between 2.43 and 3.54 years, the expected opportunity cost to TxDOT per $1,000,000 of reconstruction expenditure is 0.0009 * $761,783 = $686.

The opportunity cost to TxDOT of the 0.9 percent of pavements which fail between 3.54 and 6.96 years is found as follows:

1) Convert to equivalent annual costs:

102

The equivalent annual cost of $1,000,000 over 20 years = $73,582.

The equivalent annual cost of $1,000,000 over 6.96 years = $167,482.

2) Discount both payment streams over the life of the shorter project, 6.96 years:

   a) The present value of a $73,582 equivalent annual cost paid over 6.96 years is $439,342.

   b) The present value of a $167,482 equivalent annual cost paid over 6.96 years is $1,000,000.

The difference in present value is $560,658. Since only 0.9 percent of pavements in this distribution fail between 3.54 and 6.96 years, the expected opportunity cost to TxDOT per $1,000,000 of reconstruction expenditure is 0.009 * $560,658 = $5,046.

This process must be repeated for each line of the table up to 20 years (i.e, 15 percent total failures). The total expected opportunity cost to TxDOT per $1,000,000 of reconstruction expenditure is found by summing the incremental expected cost for each line of the table. The total expected opportunity cost per $1,000,000 for pavements designed using an 85 percent reliability level in conjunction with Set 6a traffic variance is $32,227 or approximately 3.22 percent of reconstruction expenditures.

Step II: Find the Opportunity Cost of the 13.5 Percent Set 5 Premature Failures

The same cost assessment procedure used above must be repeated for each line of Table 11, the site-specific classification data distribution. Using this procedure the total expected opportunity cost to TxDOT per $1,000,000 of reconstruction cost is $24,988 or approximately 2.5 percent of reconstruction expenditures.

Table 11
Timing of Cumulative Percent Failures for
Pavements Designed with Site-Specific Classification Data

Failures (Percent)	Time (Years)
0.01	2.92
0.1	4.15
1	7.81
2	9.71
3	11.13
4	12.31
5	13.35
6	14.29
7	15.17
8	16.05
9	16.78
10	17.52
11	18.25
12	18.94
13	19.64
13.5	20.00

Step III: Subtract Set 5 Cost from Set 6 Cost

TxDOT's total opportunity cost per $1,000,000 of reconstruction expenditure without site-specific classification data is $32,227 or approximately 3.22 percent of reconstruction expenditures. TxDOT's total opportunity cost per $1,000,000 of reconstruction expenditure with site-specific classification data is $24,988 or approximately 2.5 percent of reconstruction expenditures. The difference between these two opportunity costs is $7,239 per $1,000,000

or approximately 0.72 percent of reconstruction expenditures. This is the economic benefit associated with having site-specific vehicle classification data for use in pavement design.

The cost to reconstruct a rural U.S. or State Highway is approximately $950,000 per lane-mile in the coastal area of Texas and $600,000 per lane-mile in western Texas [4]. These costs include only actual pavement construction costs (e.g., no user costs, right-of-way costs, traffic control costs, or signing and illumination costs are included). Table 12 shows the expected dollar benefit per U.S./State Highway reconstruction project as a function of number of lane-miles and geographic region.

Table 12
Dollar Benefit per Reconstruction Project
Rural U.S./State Highways

Project Length	Dollar Benefit for Coastal Texas Projects	Dollar Benefit for West Texas Projects
8-lane miles	$54,720	$34,560
12-lane miles	$82,080	$51,840
16-lane miles	$109,440	$69,120
20-lane miles	$136,800	$86,400

While the economic benefits of obtaining site-specific classification data have been expressed as present values, these benefits will not be realized in the design stage a projects; they will be realized over time as projects designed using site-specific classification data outlast projects designed without these data. For example, each time TxDOT collects site-specific vehicle classification data for a 16-lane-mile, coastal area, rigid pavement U.S./State Highway project, TxDOT will have effectively created for itself an investment of $109,440 which will accumulate interest over time and be available to TxDOT for use on other projects in the future.

105

BENEFIT SENSITIVITY ANALYSIS

The monetary benefit of obtaining site-specific classification data for use in pavement design, 0.72 percent of reconstruction expenditures, is based on the following assumptions:

1) the designer uses an 85 percent desired reliability level;

2) the designer chooses to construct a rigid pavement;

3) the long term real rate of return is 4 percent; and

4) the classification data which would otherwise be used in the forecast come from another point on the same highway as the project site.

The sensitivity of the site-specific classification data benefit to each of these assumptions is assessed below.

Sensitivity to Desired Reliability Level

The benefit due to site-specific classification data varies depending on the pavement's desired reliability level. The preceding analysis was based on an 85 percent desired reliability level/2.69 reliability factor. Reducing traffic variance lowered premature failure opportunity costs in this example in two ways:

1) by increasing pavement reliability — obtaining site-specific classification data decreased the total percentage of pavements in the system which fail prematurely from 15.0 percent to 13.5 percent (i.e., pavements constructed using a 2.69 reliability factor are 86.5 percent reliable given Set 5 traffic variance and 85.0 percent reliable given Set 6a traffic variance); and

2) by extending the lives of the pavements which fail prematurely whether or not the data are collected — 13.5 percent of pavements failed prematurely in both the Set 5 and Set 6a distributions. But the 13.5 percent of pavements which failed given site-specific classification data did not fail until 20 years versus 19.05 years without these data.

This combination of reduced incidence of premature failure and longer service lives for pavements which still fail prematurely created the total site-specific classification data benefit. The impact of varying the desired reliability level on the benefit created by each of these elements can be illustrated by considering a pavement designed using a 50 percent

106

reliability level. By definition, 50 percent of highways designed using a 50 percent reliability level (i.e., using a 1.0 reliability factor) will fail prematurely; this will occur independently of total variance. This means that obtaining site-specific classification data will not improve the reliability level of pavements designed using a 50 percent desired reliability level without site-specific classification data. As a result, there will be no benefit due to reduced incidence of premature failure.

Nevertheless, the 50 percent of pavements which fail prematurely given site-specific classification data will fail later, on average, than the 50 percent which fail without these data. The benefit resulting from this increased pavement life is $15,500 per $1,000,000 of reconstruction cost or approximately 1.55 percent of reconstruction cost.

Table 13 below shows, for pavements designed using different desired reliability levels without site-specific classification data:

1) the resulting reliability level, given site-specific classification data;

2) the benefit due to site-specific classification data, as a percentage of reconstruction expenditures, resulting from the increase in reliability;

3) the benefit due to site-specific classification data, as a percentage of reconstruction expenditures, resulting from extended pavement life; and

4) the total benefit, as a percentage of reconstruction expenditures, due to site-specific classification data.

Table 13
Sensitivity of Benefit to Desired Reliability Level
Rigid Pavements, Real Rate of Return = 4 Percent

Desired Reliability Level	Reliability Level with Better Traffic Data	Benefit Due to Increased Reliability	Benefit Due to Extended Pavement Life	Total Benefit
50	50.0	0.00%	1.55%	1.55%
70	71.0	0.01%	1.20%	1.21%
85	86.5	0.02%	0.70%	0.72%
90	91.3	0.03%	0.48%	0.51%
95	95.8	0.00%	0.26%	0.26%

Table 13 shows that total percentage benefit due to site-specific classification data decreases as the desired reliability level increases. It would be incorrect, however, to infer from this table that obtaining these data is necessarily more beneficial, in an absolute sense, on low reliability level (i.e., less important, lower volume) routes.

The benefits in Table 13 have been expressed as percentages of reconstruction expenditures. The table shows that the percentage benefit resulting from reducing traffic variance on a 50 percent reliability route is approximately six times the percentage benefit on a 95 percent reliability route. However, the absolute magnitude of the traffic control and construction costs to reconstruct a highway designed using a 95 percent reliability level (i.e., a very important, high volume route) may be much larger than the absolute magnitude of the cost to reconstruct a 50 percent reliability route (i.e., a less important, lower volume route).

If user costs were included in the calculation, shutting down an urban freeway, for example, to perform reconstruction could be hundreds of times more expensive than shutting down a local road. Hence, the absolute, as opposed to percentage, benefit due to site-specific classification data may still be significantly greater on higher reliability routes than lower reliability routes.

Sensitivity to Pavement Type

The benefit due to site-specific classification data varies depending on the magnitude of pavement variance; and, as discussed in Chapter V, AASHTO's flexible-pavement pavement variance, 0.1938, is significantly larger than its rigid-pavement pavement variance, 0.1128. Table 14 shows the total percentage benefit resulting from reducing traffic variance for different reliability levels and pavement types.

Table 14
Sensitivity of Benefit to Pavement Type

Desired Reliability Level	Rigid Pavement Expected Benefit per Project	Flexible Pavement Expected Benefit per Project
50	1.55%	1.33%
70	1.21%	1.04%
85	0.72%	0.62%
90	0.51%	0.44%
95	0.26%	0.22%

Table 14 shows that the benefit is slightly smaller for flexible pavements than for rigid pavements. This is because the flexible-pavement pavement variance is larger than the rigid-pavement pavement variance. As a result, reducing traffic variance (by obtaining site-specific classification data) has a smaller effect on flexible pavement total variance than rigid pavement total variance. To illustrate, reducing traffic variance from 0.0593 to 0.0401 reduces rigid pavement total variance from 0.1721 to 0.1529, a 11.2 percent reduction; but the same reduction in traffic variance reduces flexible-pavement pavement variance from 0.2531 to 0.2339, only a 7.6 percent reduction. Hence, given AASHTO's pavement variances, site-specific classification data creates greater benefits for rigid than flexible pavements.

Sensitivity to Long Term Real Rate of Return

The benefit due to site-specific classification data depends on the real rate of return used in the benefit calculation. The analysis presented above was based on a 4 percent real rate of return. The Portland Cement Association found that the real rate of return during the last 40 years has ranged "between 0 to 4.5 percent with typical values between 1 and 2.5 percent [48]."

Table 15 shows the rigid pavement total percentage benefit due to site-specific classification data for different long-term real rates of return.

Table 15
Sensitivity of Rigid Pavement Total Benefit
to Real Rate of Return

Desired Reliability Level	Real Rate of Return 2 Percent	Real Rate of Return 3 Percent	Real Rate of Return 4 Percent
50	1.68%	1.61%	1.55%
70	1.36%	1.28%	1.21%
85	0.83%	0.77%	0.72%
90	0.59%	0.55%	0.51%
95	0.30%	0.28%	0.26%

Table 15 shows that the benefit increases as the long-term real rate of return decreases.

Table 16 shows the flexible pavement total percentage benefit for different long-term real rates of return.

Table 16
Sensitivity of Flexible Pavement Total Benefit
to Real Rate of Return

Desired Reliability Level	Real Rate of Return 2 Percent	Real Rate of Return 3 Percent	Real Rate of Return 4 Percent
50	1.42%	1.37%	1.33%
70	1.15%	1.09%	1.04%
85	0.71%	0.66%	0.62%
90	0.50%	0.47%	0.44%
95	0.25%	0.24%	0.22%

Again, as the long-term real rate of return increases, the percentage benefit due to site-specific classification data decreases.

Sensitivity to Vehicle Classification Data Source

The benefit due to site-specific classification data depends on the source of the vehicle classification data which would be used in the forecast if site-specific classification data were not available. Set 6b traffic variance (0.0793), associated with forecasts made using data from the same geographic region and highway system as the project site, is substantially larger than the set 6a traffic variance (0.0593) used in the calculations thus far. Table 17 shows the rigid pavement percentage benefits due to site-specific classification data for different alternative sources of classification data.

Table 17 shows that the percentage benefits associated with site-specific classification data are larger when the classification data which would otherwise be used in the forecast come from another highway in the same geographic region on the same highway system as the project site versus another point on the same highway as the project site.

111

Table 17
Sensitivity of Rigid Pavement Benefit to Source of Classification Data

Desired Reliability Level	Data from Same Highway	Data from Same Region
50	1.55%	3.01%
70	1.21%	2.33%
85	0.72%	1.35%
90	0.51%	0.93%
95	0.26%	0.45%

Table 18 shows the flexible pavement percentage benefit due to site-specific classification data for different alternative sources of classification data.

Table 18
Sensitivity of Flexible Pavement Benefit to Source of Classification Data

Desired Reliability Level	Data from Same Highway	Data from Same Region
50	1.33%	2.61%
70	1.04%	2.02%
85	0.62%	1.19%
90	0.44%	0.83%
95	0.22%	0.41%

Again, the percentage benefits associated with obtaining site-specific classification data are larger when the classification data which would otherwise be used in the forecast come from another highway in the same geographic region on the same highway system as the project site.

112

COSTS OF OBTAINING SITE-SPECIFIC CLASSIFICATION DATA

The reduction in traffic variance, which created the benefits found above, was made possible by the availability of site-specific vehicle classification data for Set 5 traffic load forecasts. These classification data came in the form of a 24-hour manual classification count. As a result, the cost to achieve the reduction in traffic variance is the cost of a 24-hour manual count. This cost is [35]:

1) Labor - 3 data collectors x 8 hour shift per day

   per collector x $8 per hour base salary

   + 28 percent benefits $246

2) Meals and lodging - $75 per person per day $225

3) Mileage - $25 per person per day $ 75

                                         Total $546

At some high volume, urban locations, two teams of data collectors may be required to effectively classify vehicles [35]. In this situation, the cost per session would simply be double that identified.

Given the manual count cost and the percentage benefits identified in the previous section, it is possible to identify how expensive a pavement project must be to warrant a site-specific 24-hour manual count. For example, if site-specific classification data reduce opportunity costs by 1.0 percent of reconstruction expenditures, the project must be worth more than $54,600 (i.e., $546/0.01) before collecting the classification data will be economically beneficial. If the project is worth less than $54,600, the 1.0 percent benefit created by collecting classification data will not outweigh the $546 that it costs to collect the data (i.e., $54,600 is the **break-even project size**).

The break-even project sizes for rigid and flexible pavements designed to varying reliability levels and given a 4 percent long-term real rate of return are shown in Table 19. Table 19 assumes that the classification data which would be used in the forecast if site-specific classification data were not available would come from another point on the same highway as the project site.

Table 19
Break-Even Project Sizes for Site-Specific 24-Hour Manual Count

Desired Reliability Level	Rigid Pavement Break-even Project Sizes	Flexible Pavement Break-even Project Sizes
50	$35,239	$41,101
70	$44,989	$52,609
85	$75,427	$87,474
90	$107,494	$124,237
95	$209,729	$247,248

The break-even project sizes would have been smaller if the Set 6b traffic variance (classification data from another highway in the same region and highway system) had been used in the benefit calculation. This is because the benefits for Set 6b traffic variance are greater than for Set 6a.

Given the lane-mile costs of reconstruction, $950,000 and $600,000 per lane-mile, identified previously for coastal and western Texas U.S./State Highway projects, respectively, the sensitivity analysis indicates that a policy of conducting 24-hour manual counts at specific reconstruction project locations would be cost-effective 1) independent of desired reliability level, 2) independent of pavement type, 3) using even a 4 percent long-term real rate of return, and 4) independent of whether the classification data which would otherwise be used in the forecast come from a another point on the same highway or another highway in the same geographic region on the same highway system as the project site.

In addition, while the discussion thus far has focused on pavement reconstruction projects, per se, many major rehabilitation projects exceed in cost even the approximately $248,000 per project 95 percent reliability level, flexible-pavement break-even project size [4]. The break-even project sizes shown above may be applied to any pavement project designed based on a traffic load forecast, not only reconstruction projects.

114

CHAPTER VII
THE IMPACT OF A SITE-SPECIFIC WEIGH-IN-MOTION PROGRAM

INTRODUCTION

The analyses presented in Chapters V and VI were based on the reduction in traffic variance achieved by taking 24-hour manual classification counts at specific pavement project sites. This reduction in traffic variance required no change in TxDOT's data analysis and forecasting procedures, per se, only the implementation of a policy of collecting site-specific classification data for pavement projects.

The directional distribution of traffic loadings and the average load equivalency factor per truck, the two most significant contributors to traffic variance behind the percent trucks component, are based on truck weight data. As noted in Chapter IV, the literature indicates that the directional distribution of traffic loadings and the average load equivalency factor per truck are site-specific phenomena.

The purpose of this chapter is to evaluate the reduction in traffic variance associated with a site-specific WIM data collection program. The first section of the chapter describes the site-specific WIM program. The second section assesses the accuracy of the individual ESAL forecast components, given the site-specific WIM program, and shows how the program enables the adoption of a simplified Design Lane ESAL formula. The third section assesses overall ESAL forecast accuracy, given the site-specific WIM program. Finally, the fourth section evaluates the economic benefits and costs of implementing the site-specific WIM program.

SITE-SPECIFIC WIM PROGRAM DESCRIBED

The site-specific WIM program would involve collecting truck volume and axle weight data using a portable WIM system during one week-long period at the pavement project site. The week-long data collection period is based on findings [21,26,27,49,50] that there may be substantial differences between weekday and weekend truck volumes and axle weights. Truck volume and axle weight data would be collected in the design lane of each travel direction at the project site.

COMPONENT ACCURACIES AND SIMPLIFIED DESIGN LANE ESAL FORMULA

Base Year ADT, ADT Growth Rate, and Percent Trucks

Under current practice, ADT_o and percent trucks are multiplied together to determine average daily truck traffic ($ADTT_o$). $ADTT_o$ is the critical input for pavement design purposes. If $ADTT_o$ could be identified directly, it would not be necessary to know either ADT_o or percent trucks to calculate design lane ESALs. The unimportance of non-truck traffic for ESAL forecasting purposes was illustrated in the example Design Lane ESAL calculation in Chapter III.

The 1989 SHRP study, referenced previously, evaluated the coefficients of variation associated with average daily 3-S2 volume estimates based on different sampling periods. The median coefficient of variation for estimates based on seasonally-adjusted 48-hour samples was 7.95 percent. The range of coefficients of variation was from 3.7 percent to 11.6 percent. As was noted previously, the SHRP study's variabilities may tend to underestimate the variabilities associated with 3-S2 volume estimates based on 48-hour truck counting sessions. To be conservative, the highest value for an average daily 3-S2 estimate, based on a seasonally-adjusted 48-hour counting session, 11.6 percent, will be used to approximate the precision of a current year average daily truck traffic estimate, $ADTT_{current}$, based on a non-seasonally-adjusted week-long truck counting session.

In the same way that $ADT_{current}$ must be projected to the base year using the ADT growth rate (GF_{ADT}), $ADTT_{current}$ must be projected to the base year using the ADTT growth rate GF_{ADTT}. Chapter II pointed out that under current practice, truck traffic is assumed to grow at the same rate as overall traffic. The evaluation of this assumption in Chapter IV found some evidence which supported it and some which contradicted it. If truck volume and axle weight data are collected at specific pavement project sites, the assumption that truck traffic grows at the same rate as overall traffic could be continued. In the alternative, truck volume data from automatic vehicle classification sites could be used to develop an actual truck volume growth rate [24]. For purposes of this analysis, the assumption that truck traffic grows at the same rate as overall traffic will be continued. As a result, the same GF_{ADT} (3.3 percent) and $CV(GF_{ADT})$ (29.3 percent) that were used in

116

analyzing current practice will be used here.

A modified version of Equation 4.2 is repeated below as Equation 7.1; $CV(ADT_o)$ and $CV(ADT_{current})$ in Equation 4.2 have been replaced in Equation 7.1 with $CV(ADTT_o)$ and $CV(ADTT_{current})$, respectively.

$$CV(ADTT_o) = \{ CV(ADTT_{current})^2 + [T^2 * CV(GF_{ADT})^2 / (1/GF_{ADT} + T)^2] \}^{1/2} \qquad (7.1)$$

where:

$CV(ADTT_o)$	=	base year ADTT coefficient of variation
$CV(ADTT_{current})$	=	current year ADTT coefficient of variation
T	=	time from the current year to the base year
$CV(GF_{ADT})$	=	ADT growth rate coefficient of variation, and
GF_{ADT}	=	ADT growth rate

Substituting, $CV(ADTT_{current}) = 11.6$, $GF_{ADT} = 3.3$ percent, $CV(GF_{ADT}) = 29.3$ percent, and $T = 2$:

$$CV(ADTT_o) = \{ 0.116^2 + [2^2 * 0.293^2 / (1/0.033 + 2)^2] \}^{1/2}$$
$$= 0.117$$

Hence, given site-specific WIM data, $CV(ADTT_o) = 11.7$ percent.

Average Load Equivalency Factor Per Truck, Directional Distribution Factor, and Lane Distribution Factor

Under current practice, the average load equivalency factor per truck, directional distribution factor, and lane distribution factor are used to obtain a Design Lane ESAL. A highway's design lane is generally the right-hand lane, but on some highways it may be the second lane from the right. For pavement design purposes, only design lane ESALs are relevant. If the Design Lane ESAL for each direction of travel could be identified directly, there would be no need for lane and directional factors.

The 1989 SHRP study evaluated the coefficients of variation associated with estimates of the average ESAL per 3-S2 based on different sampling periods. The median coefficient of variation for estimates based on seasonally-adjusted 48-hour samples was 8.15 percent. The range of coefficients of variation was from 3.2 percent to 16.45 percent. As

117

was noted above, these variabilities may tend to underestimate the variabilities associated with average ESAL per 3-S2 estimates based on 48-hour WIM sessions. To be conservative, the highest value for an average ESAL per 3-S2 estimate, based on a seasonally-adjusted 48-hour WIM session, 16.45 percent, will be used to approximate the precision of an average load equivalency per truck estimate based on a non-seasonally-adjusted week-long WIM session.

It was pointed out in Chapter II that under current practice, the average load equivalency factor per truck is assumed to remain constant over the design period. The evaluation of this assumption in Chapter IV found some evidence which supported it and some which contradicted it. If truck volume and axle weight data are collected at specific pavement project sites, the assumption that the average load equivalency factor per truck remains constant over the design period could be continued. In the alternative, a growth rate based on average load equivalency factor data collected at permanent WIM stations could be applied to the average load equivalency factor per truck [24]. For purposes of this analysis, the assumption that the average load equivalency factor per truck remains constant will be continued.

Hence, given site-specific WIM data, CV(EF) = 16.5 percent.

Simplified Design Lane ESAL Formula

Equation 3.10, the original cumulative Design Lane ESAL equation, may now be reduced to Equation 7.2:

$$w_T = 365 * T * ADTT_o * [(2 + GF_{ADT}*T)/2] * EF_o * [(2 + GF_{EF}*T)/2] \qquad (7.2)$$

where:

w_T	= cumulative ESALs
T	= design period
$ADTT_o$	= base year average daily truck traffic
GF_{ADT}	= ADT growth rate
EF_o	= base year average load equivalency factor per truck
GF_{EF}	= the average load equivalency factor per truck growth rate; the average load equivalency factor growth rate term in Equation 7.2 is

of the form used by Cunagin [7].

Because design lane truck volume data are identified directly in the site-specific WIM program, $ADTT_o$ replaces both ADT_o and PCT in the Equation 3.10 formulation. Because the average load equivalency factor per truck in the design lane is identified directly using site-specific WIM data, EF_o replaces EF, D, and LF. The GF_{EF} term is optional and, as it has been for purposes of this analysis, could be set to 0 as a default.

The equation would be calculated for each direction of travel at a site, using each direction's design lane truck volume and average load equivalency factor per truck. For design purposes, D-8 could use the average forecast, use only the greater, or use each individually.

Sensitivity of Design Lane ESAL to Errors in Individual Components

In the Equation 7.2 formulation, errors in the $ADTT_o$ and EF_o components, viewed in isolation, will have directly proportional impacts on the Design Lane ESAL, just as under current practice. Errors in GF_{ADT} and GF_{EF} will have less than proportional effects, just as under current practice.

TRAFFIC VARIANCE WITH SITE-SPECIFIC WIM DATA

Simplified Traffic Variance Formula

Equation 4.1, the original traffic variance equation, may now be reduced to Equation 7.3 (the derivation of Equation 7.3 is analogous to that for Equation 4.1, shown in Appendix A, Part III):

$$
\begin{aligned}
Var(\log_{10} w_T) \quad =& \quad 0.4343^2 * \{ \; CV(ADTT_o)^2 \; + CV(EF_o)^2 \\
&+ T^2 * CV(GF_{ADT})^2 \; / \; (2/GF_{ADT} \; + T)^2 \\
&+ T^2 * CV(GF_{EF})^2 \; / \; (2/GF_{EF} \; + T)^2
\end{aligned}
\tag{7.3}
$$

where:

$Var(\log_{10} w_T)$	=	traffic variance
$CV(ADTT_o)$	=	base year ADT coefficient of variation
$CV(EF_o)$	=	base year average load equivalency factor per truck coefficient of variation

119

$$CV(GF_{ADT}) \quad = \quad \text{ADT growth rate coefficient of variation}$$

$$GF_{ADT} \quad = \quad \text{ADT growth rate}$$

$$CV(GF_{EF}) \quad = \quad \text{load equivalency factor per truck growth rate coefficient of variation}$$

$$GF_{EF} \quad = \quad \text{load equivalency factor per truck growth rate (when } GF_{EF} \text{ is assumed to be } 0.0, \text{as here, the final term of equation 7.3 is } 0.0)$$

Substituting $ADTT_o$ (11.7 percent), EF_o (16.5 percent), GF_{ADT} (3.3 percent), $CV(GF_{ADT})$ (29.3 percent), and T (20) into Equation 7.3:

$$\begin{aligned} Var(\log_{10} w_T) \quad &= \quad 0.4343^2 * \{ \ 0.117^2 + 0.165^2 \\ &\quad + 20^2 * 0.293^2 / \ (2/0.033 + 20)^2 \\ &= \quad 0.0087 \end{aligned}$$

Hence, for Design Lane ESAL forecasts based on site-specific WIM data, $Var(\log_{10} w_T) = 0.0087$.

Lack-of-Fit Variance

As under current practice, lack-of-fit variance may be introduced by the model's assumptions: 1) that annual traffic growth is linear; 2) that truck traffic grows at the same rate as overall traffic; 3) that the truck traffic stream makeup remains constant over the design period; and 4) that the average load equivalency factor per truck remains constant over the design period. As a result, the most appropriate manner in which to compare the variance just identified with the Set 5, 6a, and 6b traffic variances identified in Chapter IV is to evaluate the differences between them, not their individual, absolute magnitudes.

BENEFITS OF SITE-SPECIFIC WIM PROGRAM

Table 20 compares the total percentage benefit due to a site-specific 24-hour manual count with the benefit due to a site-specific week-long WIM session. These benefits are based on rigid-pavement pavement variance and a 4 percent long-term real rate of return.

Table 20
Benefits for Rigid Pavements
Site-Specific 24-Hour Manual Count versus Week-Long WIM

Desired Reliability Level	Benefits Due to Site-Specific 24-Hour Manual Count	Benefits Due to Site-Specific Week-Long WIM Session
50	1.55%	4.06%
70	1.21%	3.12%
85	0.72%	1.76%
90	0.51%	1.18%
95	0.26%	0.55%

Table 21 also compares the total percentage benefit resulting from a 24-hour manual count with the benefit from a week-long WIM session. These benefits, however, are based on flexible-pavement pavement variance and a 4 percent long-term real rate of return.

Table 21
Benefits for Flexible Pavements
Site-Specific 24-Hour Manual Count Versus Week-Long WIM

Desired Reliability Level	Benefits Due to Site-Specific 24-Hour Manual Count	Benefits Due to Site-Specific Week-Long WIM Session
50	1.33%	3.46%
70	1.04%	2.67%
85	0.62%	1.54%
90	0.44%	1.06%
95	0.22%	0.51%

The tables show that the benefits associated with site-specific week-long WIM sessions are approximately two-and-a-half time those associated with site-specific 24-hour manual counts. For example, on a 16-lane mile, rural, 85 percent reliability level, rigid pavement, U.S./State Highway project in the coastal area of Texas (@ $950,000 per lane-mile), the benefits associated with site-specific 24-hour manual counts are $109,440 while the benefits for site-specific week-long WIM sessions are $267,520; for the same project in western Texas (@ $600,000 per lane-mile), the benefits associated with site-specific manual counts are $69,120 while the benefits for site-specific week-long WIM sessions are $168,960.

COST OF SITE-SPECIFIC WIM PROGRAM

Table 22 shows the worksheet used to develop per-project cost estimates for the site-specific WIM program. All assumptions made are shown on the worksheet. These assumptions were developed through interviews with Dean Barrett of TxDOT [35], Ron White of Aviar Equipment [51], and Said Majdi of the Traffic Monitoring Program at Texas Transportation Institute [52].

Table 22 shows that the initial investment in equipment required to implement the site-specific WIM program ranges from $90,000 to $157,500 with $112,500 as the expected value. The maximum number of WIM systems required to support the program is 7 with an expected value of 5 and a best case of 4. This assumes that TxDOT chooses to conduct sessions at 100 pavement projects beginning in the first year of the program. TxDOT could, however, initially focus attention on only the larger projects and acquire the required equipment gradually.

The highest estimate of the data collection cost is approximately $2,790 per project; the expected cost is approximately $2,570 per project; and, in the best-case scenario, the cost is approximately $2,420 per project.

122

Table 22
Cost Worksheet for Week-Long WIM Sessions

	Best Case		Worst Case
Number of weeks per year available for weighing sessions (excludes holidays and bad weather)	42	34	26
Length of each session (weeks)	1	1	1
Sessions per year per project	1	1	1
Number of projects per year	100	100	100
Percentage of time each system is available (not out of service for repairs/transport)	75%	68%	60%
Number of WIM systems needed to support site-specific data collection program at level of effort specified above	4.00	5.00	7.00
Initial capital cost per system (Truvelo) (2 capacitive mats + electronics + computer)	$22,500	$22,500	$22,500
Total initial capital cost	$90,000	$112,500	$157,500
Number of years each system will be used	5	5	5
Yearly maintenance cost per WIM system	$500	$1,000	$1,500
New Mats Per System/Year	1	2	3
Cost per mat	$7,500	$7,500	$7,500
Total capital investment per project (includes initial investment, yearly maintenance costs, and new mats during the system's useful life)	$275	$425	$645
Variable costs per project:			
Loops (four per session, $50/loop)	$200	$200	$200
Personnel (1 person per session, earning $9.50/hour, plus 28% benefits; that person spends two full days per project, + $75 per day per diem + $100 per project for mileage)	$445	$445	$445
Traffic control costs per project (2 lanes per project, $750 per lane)	$1,500	$1,500	$1,500
Total variable cost per project	$2,145	$2,145	$2,145
Total cost per project over the system's useful life (Tot. cap. costs + variable cost)	$2,420	$2,570	$2,790

Sources: [35,51,52]

Given a per-project data collection cost and the percentage benefits shown in the "Week-Long WIM" columns of Tables 20 and 21, it is possible to identify break-even project sizes for week-long WIM sessions. Table 23 shows these break-even project sizes, as a function of pavement type and desired reliability level, using the most conservative estimate of the per project data collection costs, $2,790 per session.

Table 23
Break-Even Project Sizes for Site-Specific Week-Long WIM Session

Desired Reliability Level	Rigid Pavement Break-even Project Sizes	Flexible Pavement Break-even Project Sizes
50	$68,639	$80,670
70	$89,519	$104,554
85	$158,658	$180,901
90	$235,708	$263,978
95	$504,631	$542,333

Again, given the lane-mile costs of reconstruction, discussed previously, Table 23 indicates that a policy of conducting week-long WIM sessions at specific reconstruction project sites would be cost-effective 1) independent of pavement type, 2) independent of desired reliability level, and 3) using even a 4 percent long-term real rate of return.

In addition, many major rehabilitation projects exceed in cost even the approximately $543,000 per project 95 percent reliability level, flexible-pavement break-even project size [4]. As with the break-even project sizes for 24-hour manual classification sessions, shown in Chapter VI, the break-even project sizes shown here may be applied to any pavement project designed based on a traffic load forecast, not only reconstruction projects.

CHAPTER VIII
FINDINGS AND RECOMMENDATIONS

FINDINGS
Traffic Growth Patterns

TxDOT's linear annual traffic growth model was found to appropriately represent the annual traffic growth pattern, over a 16 year period, at a majority of the 56 rural Texas ATR sites studied. In addition, the linear model performed favorably relative to more complex models, evaluated in the literature.

Role of Growth Rate versus Base Year Components in Determining Forecast Accuracy

When a linear annual traffic growth model and its corresponding parabolic cumulative traffic growth model are used to forecast traffic loadings at a site, the accuracy of estimates of the ADT growth rate, used to project current traffic levels through the pavement design period, typically does not have an appreciable impact on overall traffic load forecast accuracy. As a result, efforts to improve the accuracy of ADT growth rate estimates, even if successful, would not lead to significant improvements in traffic load forecast accuracy. (This research has evaluated the impact of the accuracy of ADT growth rate estimates only on design period traffic load forecasts used in pavement structural design. This research has not evaluated the impact of the accuracy of ADT growth rate estimates on future year ADT forecasts used in pavement geometric design. Findings from this study regarding traffic load forecasting for pavement structural design should not be extended to ADT forecasting for pavement geometric design without further study.)

When a linear annual traffic growth model and parabolic cumulative traffic growth model are used to forecast traffic loadings at a site, the accuracy of estimates of the base year forecast components, ADT, percent trucks, the average load equivalency factor per truck, the directional distribution factor, and the lane distribution factor, typically does have an appreciable impact on forecast accuracy. This finding, combined with the finding that improving the accuracy of ADT growth rate estimates would not significantly improve traffic load forecast accuracy, indicates that efforts to improve traffic load forecast accuracy should

125

focus on improving the accuracy of base year component estimates.

Role of Individual Base Year Components in Determining Forecast Accuracy

The percent trucks component, typically based on classification data collected at another point on the same highway or on another highway in the same geographic region as the pavement project site, was found to account for 38 percent of the variability in a typical traffic load forecast. In addition, the model currently used to predict percent trucks when site-specific classification data are not available for use in a forecast has a tendency to over-predict percent trucks, particularly at relatively low volume and high volume sites. It was determined, however, that this tendency toward over-prediction could be substantially eliminated by varying the model's truck-growth constant in relation to the traffic volume at the prediction site. This constant is currently set to "1/2" for all predictions; the bias was substantially eliminated by increasing the constant to "10/11" when prediction site volume is less than 3,500 vehicles per day and by decreasing the constant to "1/8" when prediction site volume exceeds 45,000 vehicles per day.

The directional distribution factor, typically 50 percent of predicted traffic loadings to each direction of travel, was found to account for 37.6 percent of the variability in a typical forecast. This result is based on a previous study of the directional distribution of pavement distress on Texas Interstate sections. This result is corroborated by two other studies which found large differences in the average load equivalency factor per truck in different directions of travel at truck weight data collection sites.

The average load equivalency factor per truck, typically based on the statewide average axle weight distribution, was found to contribute 17 percent of the variability in a typical forecast. This finding, however, is based on an analysis of weigh-in-motion (WIM) data collected almost exclusively at Interstate sites. The average load equivalency factor per truck may be a greater contributor to forecast variability and may lead to consistent over- or under-predictions of traffic loadings at non-Interstate sites. Because only Interstate WIM data were available for analysis, however, the impact of using the statewide average axle weight distribution at non-Interstate sites could not be quantified.

The base year ADT component, typically based on a 24-hour coverage count taken

at or very near the pavement project site, was found to contribute less than 4 percent of the variability in a typical forecast.

The lane distribution factor, while found to contribute less than 2 percent of the variability in a typical forecast, may consistently over-estimate the percentage of predicted traffic loadings that will actually be applied to a highway's design lane; the magnitude of the average over-estimate, however, could not be quantified using available information.

Site-Specific Traffic Data and Traffic Load Forecast Accuracy

The research found that the percentage of trucks in the traffic stream, the directional distribution of traffic loadings, and the average load equivalency factor per truck - the three primary contributors to forecast variability at present - were site-specific characteristics of the traffic stream. As a result, the improvement in forecast accuracy enabled by sampling the traffic stream at specific pavement project sites was investigated.

The research found that traffic load forecast accuracy could be improved by more than 30 percent from current levels by conducting 24-hour manual classification sessions at specific pavement project sites and that forecast accuracy could be improved by more than 85 percent by conducting week-long weigh-in-motion (WIM) sessions at specific pavement project sites. (Vehicle classification data are automatically collected during portable WIM ysessions).

Traffic Load Forecast Accuracy and Pavement Life

The research found that if traffic load forecast accuracy was improved by the amounts shown above, pavements could be designed and built better. As a result, fewer pavement structures would fail prematurely; and, while some pavements would still fail prematurely despite improved forecasts, these pavements would generally have longer service lives than under current forecasting procedures.

The Monetary Benefits and Costs of Improving Traffic Load Forecast Accuracy

The cost to make improvements in traffic load forecasts would be incurred in the design stage of projects, but the benefits would be realized over time. In order to compare

future benefits with present costs, it is necessary to express future benefits in terms of their present value. For example, the research found that for a typical reconstruction project, the present value of the benefits resulting from conducting a 24-hour manual vehicle classification session at the project site is approximately $109,000. This means that, on average, each time TxDOT conducts a 24-hour manual vehicle classification session at a reconstruction project site, TxDOT will have effectively created for itself a $109,000 investment that will accumulate interest over time; this $109,000 plus interest will be available to TxDOT for use on other projects in the future. The cost to conduct a 24-hour manual vehicle classification session is approximately $550. This $550 is the amount TxDOT must actually spend today to realize the payoff of $109,000 plus interest in the future. This indicates a typical benefit-to-cost ratio for 24-hour manual classification sessions of more than 198 to 1. The break-even project size for 24-hour manual counts is approximately $248,000; any time a pavement project is worth more than this amount, the cost to conduct a 24-hour manual count is justified by the benefits received in return.

The present value of the benefits resulting from conducting a week-long WIM session at a typical reconstruction project site is approximately $267,000. The cost to conduct a week-long WIM session is approximately $2,790. This means that by spending $2,790 per project to conduct week-long WIM sessions today, TxDOT will make available to itself an average of $267,000 per project for use on other projects in the future. This indicates a typical benefit-to-cost ratio for week-long WIM sessions of more than 95 to 1. The break-even project size for week-long WIM sessions is $543,000; conducting site-specific week-long WIM sessions is cost-effective planning practice, for projects worth more than this amount.

RECOMMENDATIONS

The report recommends that TxDOT conduct a site-specific 24-hour manual vehicle classification session for any pavement project worth more than $248,000 and that TxDOT conduct a site-specific 24-hour manual vehicle classification session or, preferably, a site-specific week-long WIM session (which includes vehicle classification) for any pavement project worth more than $543,000. The research found that almost all pavement reconstruction projects and most major pavement rehabilitation projects meet even the

128

$543,000 cutoff.

For projects where TxDOT elects not to collect site-specific traffic data, the report recommends TxDOT implement the modified percent truck prediction model and, otherwise, continue to use current forecasting procedures.

REFERENCES

[1]   AASHTO Guide for Design of Pavement Structures, Washington, D.C., 1986.

[2]   Lytton, Robert, Florence D. Wiley Professor of Civil Engineering, Texas A&M University, TTI; Co-author, AASHTO Guide for Design of Pavement Structures - Volume I, Part I, Chapter 4: Reliability; and Volume 2, Appendix EE: Development of Reliability. Personal interviews to discuss pavement reliability, pavement design, and pavement management, November 1990 through June 1991.

[3]   "The AASHO Road Test," Proceedings of a conference held May 16-18, 1962, St. Louis, Missouri, Special Report 73, Washington, D.C., 1962.

[4]   King, John, Director of Programming and Scheduling, D-8, Texas TDHPT. Telephone interviews to discuss pavement construction expenditures, May 1991.

[5]   Highway Design Division Operations and Procedures Manual, Texas State Department of Highways and Public Transportation, last revised February 1987, Austin, Texas.

[6]   Brown, James L., Engineer of Pavement Design, D-8, Texas State Department of Highways and Public Transportation. Telephone and personal interviews to discuss SDHPT pavement design practice, November 1990 through May 1991.

[7]   Cunagin, W.D., "Improved Prediction of Equivalent Axle Loads," Sponsored by FHWA, accepted for publication by USDOT FHWA; referenced with the author's permission, given August 6, 1991; College Station, Texas.

[8]   Darter, M.I. and Hudson, W.R., "Probabilistic Design Concepts Applied to Flexible Pavement System Design," Sponsored by Texas State Department of Highways and Public Transportation in cooperation with the U.S. DOT FHWA, Report # 123-18, Austin, Texas, May 1973.

[9]   Milton, J. and Arnold, J., "Probability and Statistics in the Engineering and Computing Sciences," McGraw-Hill, New York, 1986.

[10]   Cunagin, W.D. and Nassiri, H.S., "Analysis of Texas Traffic Monitoring Program," Sponsored by Texas State Department of Highways and Public Transportation in cooperation with the USDOT FHWA, Report # TX-90/1142-1f, College Station, TX, January 1989.

[11]   Bodle, R. R., "Estimation of Rural Coverage Count Duration for Estimating Annual Average Daily Traffic," HRB, Highway Research Record 199, pp. 67-77, Washington, D.C., 1966.

[12]   Albright, David, "Development of ASTM Highway Traffic Monitoring Standards,"
        The 1990 H.W. Kummer Lecture, American Society for Testing and Materials,
        presented December 4, 1990, San Antonio, Texas.

[13]   Annual Report 1989, Automatic Traffic Recorders, D-10, Texas State Department
        of Highways and Public Transportation, Austin, Texas, 1989.

[14]   Ezekiel, M. and Fox, K., "Methods of Correlation and Regression Analysis," John
        Wiley and Sons, New York, 1967.

[15]   Neveu, A.J., "Quick Response Procedures to Forecast Rural Traffic," TRB,
        Transportation Research Record 944, pp. 47-53, Washington, D.C., 1983.

[16]   Saha, S.K. and Fricker, J.D., "Traffic Volume Forecasting for Rural State Highways,"
        TRB, Transportation Research Record 1203, pp. 10-26, Washington, D.C., 1987.

[17]   Middleton, D., Mason, J., Chira-Chivala, T., and Nassiri, H.S., "Analysis of Texas
        Truck Traffic Between 1977 and 1983," Sponsored by Texas State Department of
        Highways and Public Transportation in cooperation with the USDOT FHWA, Report
        TX-87/68+420-2, College Station, TX, May 1987.

[18]   Wyman, John, Retired Director of Maine Facility Laboratory, Materials and research
        Division, Maine DOT; author of several FHWA reports on vehicle classification.
        Telephone interviews to discuss automated and manual vehicle classification, January
        through May 1991.

[19]   Hamrick, John, Idaho Transportation Department.   Personal and telephone
        interviews to discuss vehicle classification and the Idaho Transportation Department
        report: "Definition of the Axle Configuration Code," November 1990 through March
        1991.

[20]   1988 Manual Vehicle Classification Data, D-10, Texas State Department of Highways
        and Public Transportation, Austin, Texas, 1989.

[21]   Dahlin, Curt, and Harker, Paul, "An Analysis of Continuously Collected WIM Data
        From Minnesota," for the Strategic Highway Research Program, March 1989.

[22]   Dahlin, Curt, Minnesota DOT. Telephone interviews to discuss "An Analysis of
        Continuously Collected WIM Data From Minnesota," January through March 1991.

[23]   Albright, David, Chief, Research Bureau, New Mexico DOT.   Personal and
        telephone interviews to discuss "Development of ASTM Highway Traffic Monitoring
        Standards," December 1990 through May 1991.

[24] Cervenka, K.J. and Walton, C.M., "Traffic Load Forecasting in Texas," Sponsored by Texas State Department of Highways and Public Transportation in cooperation with the USDOT FHWA, Report # FHWA/TX/-85/36+352-1F, Austin, TX, November 1984.

[25] Cunagin, W.D, "Evaluation of Low Cost WIM Alternatives." Sponsored by Texas State Department of Highways and Public Transportation in cooperation with the U.S. DOT FHWA, Report # FHWA/TX-89/1140-1f, College Station, Texas, January 1989.

[26] Basson, J.E.B., et al, "The Measurement of Traffic Axle Load Distributions for Pavement Design Purposes," Proceedings, 3rd International Conference on Structural Design of Asphalt Pavement, London, England, September 1972.

[27] Neumann, D., and Savage, P., "Truck Weight Case Study for the Highway Performance Monitoring System," USDOT FHWA, Washington, D.C., June, 1982.

[28] 1989 and 1990 Permanent Station Weigh-in-Motion Data, D-10, Texas State Department of Highways and Public Transportation, Austin, Texas, 1989.

[29] Lin, H.J., Lee, C., and Machemehl, R., "Texas Traffic Data Acquisition Program," Center for Transportation Research, Research Report 245-1F, Austin, Texas, February 1980.

[30] Hage, R., "Truck Forecasts and Pavement Design," TRB, Transportation Research Record 889, Washington, D.C., 1982.

[31] Darter, M., et al, "Portland Cement Concrete Pavement Evaluation System - NCHRP 277," TRB, Washington, D.C., September, 1985.

[32] Cunagin, W.D., "Lane Distribution Factors for Design," Sponsored by Texas State Department of Highways and Public Transportation in cooperation with the USDOT FHWA, Report # TX-87/476-2F, College Station, TX, July, 1987.

[33] Alexander, M.M., and Graves, R.A., "Determination of the Lanal Distribution of Truck Traffic on freeway Facilities," Division of Highway Planning, State Highway Department of Georgia, November, 1971.

[34] Hodges, Mark, D-10, Texas State Department of Highways and Public Transportation. Telephone interviews to document current SDHPT ESAL forecasting and data collection practice, January through May 1991.

[35] Barrett Dean, D-10, Texas State Department of Highways and Public Transportation. Telephone interviews to document current SDHPT traffic data collection practice

and costs of alternative traffic data collection programs, May 1991.

[36]   St. John, Brian, D-10, Texas State Department of Highways and Public Transportation. Telephone interviews to document current State Department of Highways and Public Transportation traffic data collection practice, May 1991.

[37]   Underwood, Jon, Director of Research, D-10, State Department of Highways and Public Transportation. Telephone interviews to discuss current and planned State Department of Highways and Public Transportation data collection practice, January through May 1991.

[38]   Kreppon, Ronnie, D-10, Texas State Department of Highways and Public Transportation. Telephone interviews to discuss current SDHPT traffic data collection and ESAL forecasting practice, February through May, 1991.

[39]   Kher, R.K., and Darter, M.I., "Probabilistic Concepts and Their Application to AASHO Interim Guide for Design of Rigid Pavement Structures," HRB, Highway Research Record 466, Washington, D.C., 1973.

[40]   Roger Smith, Professor of Civil Engineering, Texas A&M University, TTI, Personal interviews to discuss highway economic analysis, March through June, 1991.

[41]   Peterson, D., "Life Cycle Cost Analysis of Pavements - NCHRP Synthesis 122," TRB, Washington, D.C., December, 1985.

[42]   Winfrey, Robley, "Economic Analysis for Highways," International Textbook, Company, 1969.

[43]   Oglesby, C.H., and Hicks, R.G., "Highway Engineering," 4th Edition, Wiley, New York, New York, 1982.

[44]   Epps, J.A. and Wootan, C.V., "Economic Analysis of Airport Pavement Rehabilitation Alternatives - An Engineering Manual," Report No. Dot-FAA-RD-81-78, Federal Aviation Administration, Department of Transportation, Washington, D.C., 1981.

[45]   AASHTO Manual on User Benefit Analysis of Highway and Bus-Transit Improvements (a.k.a. the Red Book, the Economic Analysis Manual), Washington, D.C., 1977.

[46]   McFarland, Frank, Program Manager, Transportation Economics Program, TTI; authority on highway economic analysis; Personal interviews to discuss methods of highway economic analysis, March through June, 1991.

[47] Fabrycky, W., and Blanchard, B., Life Cycle Cost and Economic Analysis, Prentice Hall, Englewood Cliffs, New Jersey, 1991.

[48] Roy, R., and Ray, G.K., Discussion of "A Comparative Economic Analysis of Asphalt and Concrete Pavements," Florida Department of Transportation. Portland Cement Association, Skokie, Illinois, 1984.

[49] Mactavish, D., and Neumann, D.L., "Vehicle Classification Case Study for the Highway Performance Monitoring System," USDOT FHWA, Washington, D.C. 1982.

[50] Buffington, J., et al, "Procedures for Estimating the Total Load Experience of a Highway As Contributed by Cargo Vehicles," Sponsored by Texas Highway Department in cooperation with the USDOT FHWA, Research Report #131-2F, College Station, Texas, September, 1970.

[51] White, Ron, Aviar Equipment, Telephone interviews to discuss costs of equipment and maintenance to support traffic data collection programs.

[52] Majdi, Said, TTI, (409) 845-9326, Personal interviews to discuss costs of various traffic data collection technologies and programs.
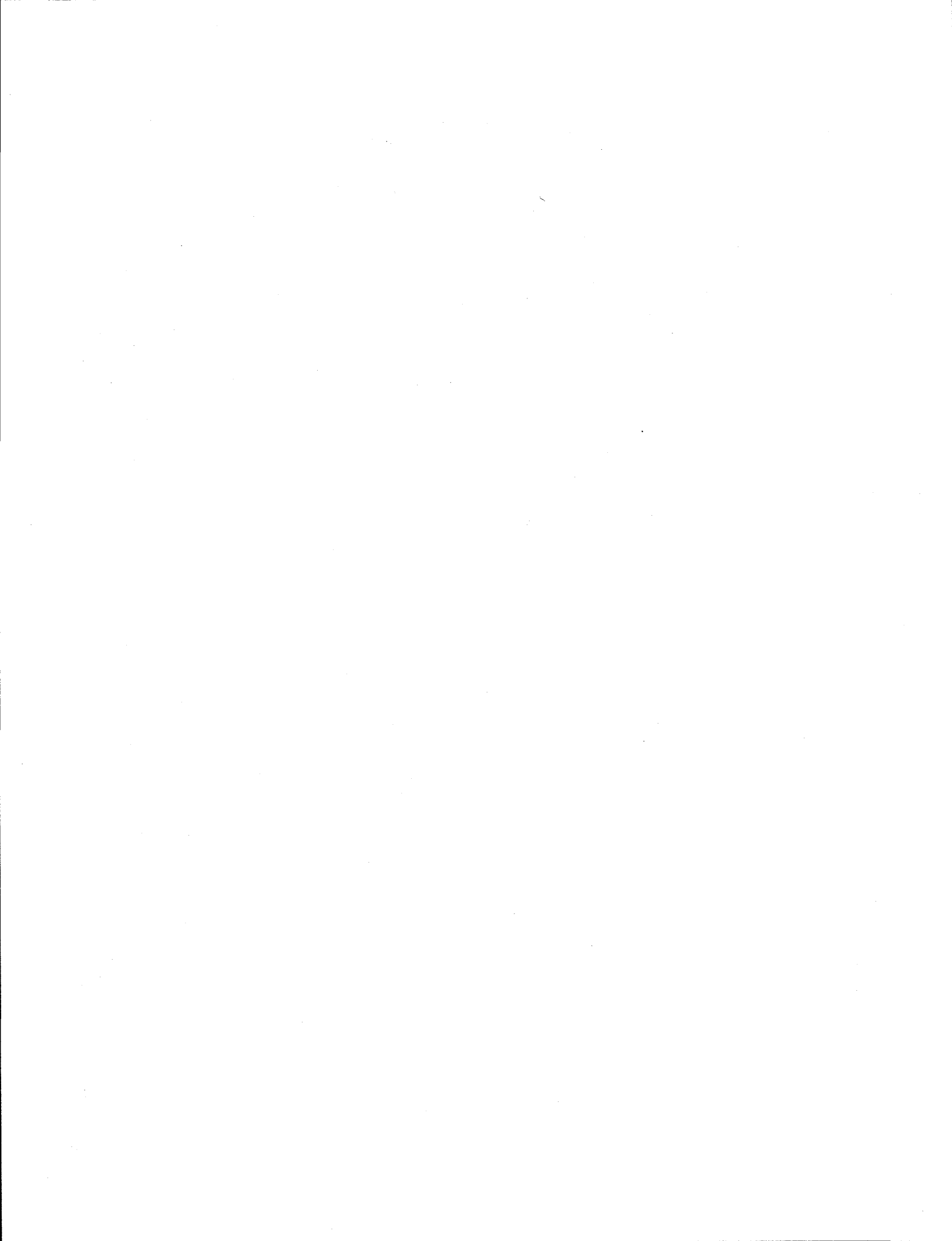
APPENDIX A

DERIVATION OF EQUATIONS USED IN THE ANALYSIS

Derivation of E[f(x)] and VAR[f(x)] [1,2,3,4]

A. Given a random variable **X** with probability density function, *p(x)*, the following are identities:

(1) $\quad \int_{-\infty}^{\infty} p(x)\,dx = 1$

(2) $\quad \int_{-\infty}^{\infty} p(x)\,dx = E[x]$

$\qquad\qquad = \mu_x$

(3) $\quad \int_{-\infty}^{\infty} (x-\mu_x)p(x)\,dx = \int_{-\infty}^{\infty} xp(x)\,dx - \mu_x\int_{-\infty}^{\infty} p(x)\,dx$

$\qquad\qquad = \mu_x - \mu_x$

$\qquad\qquad = 0$

(4) $\quad \int_{-\infty}^{\infty} (x-\mu_x)^2 p(x)\,dx = \int_{-\infty}^{\infty} x^2 p(x)\,dx - 2\mu_x \int_{-\infty}^{\infty} xp(x)\,dx + \mu_x^2 \int_{-\infty}^{\infty} p(x)\,dx$

$\qquad\qquad = E[x^2] - \mu_x^2$

$\qquad\qquad = VAR[x]$

$\qquad\qquad = \sigma_x^2$

B.   Find E[f(x)]

(1) $E[f(x)] = \int_{-\infty}^{\infty} f(x)p(x)\,dx$

Expand **f(x)** as a Taylor Series:

(2) $f(x) = f(x_0) + f'(x_0)(x-x_0) + f''(x_0)\dfrac{(x-x_0)^2}{2!} + \ldots$

where x_0, $f(x_0)$, $f'(x_0)$, and $f''(x_0)$ are all constants.

(3) $E[f(x)] = \int_{-\infty}^{\infty} f(x_0)p(x)\,dx + \int_{-\infty}^{\infty} f'(x_0)(x-x_0)p(x)\,dx$

$\qquad + \int_{-\infty}^{\infty} f''(x_0)\dfrac{(x-x_0)^2}{2!}p(x)\,dx + \ldots$

$\qquad = f(x_0)\int_{-\infty}^{\infty} p(x)\,dx + f'(x_0)\int_{-\infty}^{\infty} (x-x_0)p(x)\,dx$

$\qquad + \dfrac{f''(x_0)}{2!}\int_{-\infty}^{\infty} (x-x_0)^2 p(x)\,dx + \ldots$

$\qquad = f(x_0)\cdot + f'(x_0)\cdot E[(x-x_0)] + \dfrac{f''(x_0)}{2!}E[(x-x_0)^2] + \ldots$

Let $x_0 = \mu_x$

(4) $\quad = f(\mu_x) + f'(\mu_x) \cdot 0 + \dfrac{f''(\mu_x)}{2} \cdot VAR[x]$

$\quad = f(\mu_x) + \dfrac{f''(\mu_x)}{2} \cdot VAR[x] = E[f(x)]$

C. Find: **VAR[f(x)]**

(1) $\quad VAR[f(x)] = \displaystyle\int_{-\infty}^{\infty} \{f(x) - E[f(x)]\}^2 p(x)\,dx$

$\quad = \displaystyle\int_{-\infty}^{\infty} f(x)^2 p(x)\,dx - 2E[f(x)] \displaystyle\int_{-\infty}^{\infty} f(x) p(x)\,dx$

$\quad + E[f(x)]^2 \displaystyle\int_{-\infty}^{\infty} p(x)\,dx$

$\quad = E[f(x)^2] - 2E[f(x)] \cdot E[f(x)] + E[f(x)]^2 \cdot 1$

$\quad = E[f(x)^2] - E[f(x)]^2$

From **B(2)** above:

(2) $\quad f(x) = f(x_0) + f'(x_0)(x - x_0) + f''(x_0)\dfrac{(x - x_0)^2}{2!} + \ldots$

A-4

$$(3) \quad f(x)^2 = f(x_0)^2 + f(x_0)f'(x_0)(x-x_0) + f(x_0)f''(x_0)\frac{(x-x_0)^2}{2!}$$

$$+ f(x_0)f'(x_0)(x-x_0) + f'(x_0)^2(x-x_0)^2 + f'(x_0)f''(x_0)\frac{(x-x_0)^3}{2!}$$

$$+ f(x_0)f''(x_0)\frac{(x-x_0)^2}{2!} + f'(x_0)f''(x_0)\frac{(x-x_0)^3}{2!} + f''(x_0)^2\frac{(x-x_0)^4}{2!2!}$$

$$= f(x_0)^2 + 2f(x_0)f'(x_0)(x-x_0) + f(x_0)f''(x_0)(x-x_0)^2$$

$$+ f'(x_0)^2(x-x_0)^2 + f'(x_0)f''(x_0)(x-x_0)^3 + \frac{f''(x_0)^2}{4}(x-x_0)^4$$

$$(4) \quad E[f(x)] = \int_{-\infty}^{\infty} f(x_0)^2 p(x)\,dx + 2\int_{-\infty}^{\infty} f(x_0)f'(x_0)(x-x_0)p(x)\,dx$$

$$+ \int_{-\infty}^{\infty} f(x_0)f''(x_0)(x-x_0)^2 p(x)\,dx$$

$$+ \int_{-\infty}^{\infty} f'(x_0)^2(x-x_0)^2 p(x)\,dx + \int_{-\infty}^{\infty} f'(x_0)f''(x_0)(x-x_0)^3 p(x)\,dx$$

$$+ \frac{1}{4}\int_{-\infty}^{\infty} f''(x_0)^2(x-x_0)^4 p(x)\,dx$$

$$= f(x_0)^2 \int_{-\infty}^{\infty} p(x)dx + 2f(x_0)f'(x_0) \int_{-\infty}^{\infty} (x-x_0)p(x)dx$$

$$+ f(x_0)f''(x_0) \int_{-\infty}^{\infty} (x-x_0)^2 p(x)dx + f'(x_0)^2 \int_{-\infty}^{\infty} (x-x_0)^2 p(x)dx$$

$$+ f'(x_0)f''(x_0) \int_{-\infty}^{\infty} (x-x_0)^3 p(x)dx + \frac{f''(x_0)^2}{4} \int_{-\infty}^{\infty} (x-x_0)^4 p(x)dx$$

$$= f(x_0)^2 + 2f(x_0)f'(x_0)E[(x-x_0)] + f(x_0)f''(x_0)E[(x-x_0)^2]$$

$$+ f'(x_0)^2 E[(x-x_0)^2] + f'(x_0)f''(x_0)E[(x-x_0)^3] + \frac{f''(x_0)^2}{4}E[(x-x_0)^4]$$

(5)   Let $x_0 = \mu_x$

$$= f(\mu_x)^2 + 2f(\mu_x)f'(\mu_x)E[(x-\mu_x)] + f(\mu_x)f''(\mu_x)E[(x-\mu_x)^2]$$

$$+ f'(\mu_x)^2 E[(x-\mu_x)^2] + f'(\mu_x)f''(\mu_x)E[(x-\mu_x)^3] + \frac{f''(\mu_x)^2}{4}E[(x-\mu_x)^4]$$

Aside:

From A(3) above, $E[(x-\mu_x)] = 0$

From A(4) above, $E[(x-\mu_x)^2] = VAR[x]$

Find: $E[(x-\mu_x)^3]$

From B(4) above,

$$E[q(x)] = q(\mu_x) + \frac{q''(\mu_x)}{2} VAR[x]$$

$$q(x) = (x-\mu_x)^3 \ \rightarrow \ q(\mu_x) = (\mu_x-\mu_x)^3 = 0$$

$$q'(x) = 3(x-\mu_x)^2 \cdot 1$$

$$q''(x) = 6(x-\mu_x) \cdot 1 \cdot 1 \rightarrow q''(\mu_x) = 6(\mu_x-\mu_x) \cdot 1 \cdot 1 = 0$$

$$E[q(x)] = 0 + \frac{0}{2} \cdot VAR[x] = 0$$

Find: $E[(x-\mu_x)^4]$

From **B(4)** above,

$$E[r(x)] = r(\mu_x) + \frac{r''(\mu_x)}{2} VAR[x]$$

$$r(x) = (x-\mu_x)^4 \ \rightarrow \ r(\mu_x) = (\mu_x-\mu_x)^4 = 0$$

$$r'(x) = 4(x-\mu_x)^3 \cdot 1$$

$$r''(x) = 12(x-\mu_x)^2 \cdot 1 \cdot 1 \rightarrow r''(\mu_x) = 12(\mu_x-\mu_x)^2 \cdot 1 \cdot 1 = 0$$

$$E[r(x)] = 0 + \frac{0}{2} \cdot VAR[x] = 0$$

By substitution from the aside:

(6) $E[f(x)^2] = f(\mu_x)^2 + 0 + f(\mu_x)f''(\mu_x)VAR[x]$

$$+ f'(\mu_x)^2 VAR[x] + 0 + 0$$

$$= f(\mu_x)^2 + f(\mu_x)f''(\mu_x)VAR[x] + f'(\mu_x)^2 VAR[x]$$

From **B(4)** above:

$$E[f(x)] = f(\mu_x) + \frac{f''(\mu_x)}{2}VAR[x]$$

(7) $E[f(x)]^2 = f(\mu_x)^2 + f(\mu_x)f''(\mu_x)VAR[x] + \frac{f''(\mu_x)^2}{4}VAR[x]^2$

From **C(1)** above:

(8) $VAR[f(x)] = E[f(x)^2] - E[f(x)]^2$

From C(6) and C(7) above:

(9) $VAR[f(x)] = f(\mu_x)^2 + f(\mu_x)f''(\mu_x)VAR[x] + f'(\mu_x)^2 VAR[x] - f(\mu_x)^2$

$$- f(\mu_x)f''(\mu_x)VAR[x] - \frac{f''(\mu_x)^2}{4}VAR[x]^2$$

$$= f'(\mu_x)^2 VAR[x] - \frac{f''(\mu_x)^2}{4}VAR[x]^2$$

The second term may be ignored without significant loss of accuracy [1,2].

PART II

Derivation of $\mathrm{Var}[\log_{10}(x)]$ and $\mathrm{Var}[\log_{10}(c + ax)]$ [2,3]

A.   Given $\mathrm{VAR}[f(x)] = f'(\mu_x)^2\,\mathrm{VAR}[x]$ from Part I:

Find

$$VAR[\log_{10}(x)] :$$

$$f(x) = \log_{10}x$$

$$= \frac{\ln(x)}{\ln(10)} = .4343\ln(x)$$

$$f'(x) = \frac{.4343}{x} \;\rightarrow\; f'(\mu_x) = \frac{.4343}{\mu_x}$$

By substitution:

$$VAR[\log_{10}(x)] = \frac{.4343^2}{\mu_x^2}VAR[x] = .4343^2 \cdot CV(x)^2$$

B.   Given $\mathrm{VAR}[f(x)] = f'(\mu_x)^2\,\mathrm{VAR}[x]$ from Part I:

Find

$$VAR[\log_{10}(c + a \cdot x)] :$$

$$f(x) = \log_{10}(c + ax)$$

A-10

to find **f ' (x)**:

$$f(x) = \log_{10}(g(x)) \text{ where } g(x) = c + a \cdot x$$

$$= \frac{\ln(g(x))}{\ln(10)} = .4343 \ln(g(x))$$

$$f'(x) = \frac{df}{dx} = .4343 \cdot \frac{1}{g(x)} \cdot \frac{dg}{dx} = .4343 \frac{1}{(c + ax)} \cdot a$$

By substitution:

$$VAR[\log_{10}(c + a \cdot x)] = \frac{.4343^2 a^2}{(c + a \cdot \mu_x)^2} VAR[x]$$

$$= \frac{.4343^2 a^2}{(c + a \mu_x)^2} \cdot VAR[x] \cdot \frac{\mu_x^2}{\mu_x^2}$$

$$= \frac{.4343^2 a^2}{(c + a \mu_x^2)} CV(x)^2 \cdot \mu_x^2$$

$$= \frac{.4343^2 a^2 CV(x)^2}{(c + a \cdot \mu_x)^2} \cdot \frac{1}{\frac{1}{\mu_x^2}}$$

$$= \frac{.4343^2 a^2 CV(x)^2}{\dfrac{(c^2 + 2ca\mu_x + a^2\mu_x^2)}{\mu_x^2}}$$

$$= \frac{.4343^2 a^2 CV(x)^2}{(\dfrac{c^2}{\mu_x^2} + \dfrac{2ca}{\mu_x} + a^2)}$$

$$= \frac{.4343^2 a^2 CV(x)^2}{(\dfrac{c}{\mu_x} + a)^2}$$

if $c = 2$; $a = T$; and $\mu_x = GF_{ADT} \implies$

$$= \frac{.4343^2 T^2 CV(GF_{AADT})^2}{(\dfrac{2}{GF_{AADT}} + T)^2}$$

PART III

Derivation of Var $(\log_{10} w_T)$ [2,3]

A.   Given Equation 3.10

$$w_T = T \cdot 365 \cdot ADT_0 \frac{[(2 + GF_{ADT} \cdot T)]}{2} \cdot PCT \cdot EF \cdot D \cdot LF$$

B.

$$\log_{10} w_T = \log_{10}(T) + \log_{10}(365) + \log_{10}(ADT_0)$$

$$+ \log_{10}(2 + GF_{ADT} \cdot T) - \log_{10}(2)$$

$$+ \log_{10}(PCT) + \log_{10}(EF)$$

$$+ \log_{10}(D) + \log_{10}(LF)$$

C.   Assuming independence between component pairs:

$$VAR(\log_{10} w_T) = VAR[\log_{10}(T)] + VAR[\log_{10}(ADT_0)]$$

$$+ VAR[\log_{10}(2 + GF_{ADT} \cdot T)]$$

$$+ VAR[\log_{10}(2)] + VAR[\log_{10}(PCT)]$$

$$+ VAR[\log_{10}(EF)] + VAR[\log_{10}(D)] + VAR[\log_{10}(LF)]$$

D.   T, 365, and 2 are constants.

$$VAR[\log_{10}(T)] = VAR[\log_{10}(365)] = VAR[\log_{10}(2)] = 0$$

E. From Part II:

$$VAR[\log_{10}x] = 0.4343^2 CV(x)^2$$

$$VAR[\log_{10}(c+ax)] = \frac{0.4343^2 a^2 CV(x)^2}{(\frac{c}{x} + a)^2}$$

F. Using **C.**, **D.**, and **E.** :

$$VAR(\log_{10}w_T) = 0.4343^2 CV(ADT_0)^2 + 0.4343^2 CV(PCT)^2 + 0.4343^2 CV(EF)^2$$

$$+ 0.4343^2 CV(D)^2 + 0.4343^2 CV(LF)^2 + \frac{0.4343^2 T^2 CV(GF_{ADT})^2}{(\frac{2}{GF_{ADT}} + T)^2}$$

Derivation of CV(GF$_{ADT}$)

A. Given:

$$GF_{ADT} = \frac{GR}{ADT(0)}$$

where: GF$_{ADT}$ =   ADT growth rate (percent per year)
GR   =   ADT growth rate (vehicles per year)
ADT(0) =   year 0 ADT identified by the regression

B. Find CV(GF$_{ADT}$):

C.

$$GF_{ADT} = \frac{GR}{ADT(0)}$$

D.

$$\log_{10}(GF_{ADT}) = \log_{10}(GR) - \log_{10}(ADT(0))$$

E. Using the partial derivative method [1] to find the variance of a function of two correlated variables [4]:

$$VARG[x_1, x_2] = (\frac{\partial G}{\partial x_1})^2 VAR[x_1] + (\frac{\partial G}{\partial x_2})^2 VAR[x_2]$$

$$+ 2r_{GR,ADT(0)} \frac{\partial G}{\partial x_1} \cdot \frac{\partial G}{\partial x_2} STD[x_1] \cdot STD[x_2]$$

F.

$$VAR[\log_{10}(GF_{ADT})] = 0.4343^2 \cdot \frac{STD[GR]^2}{GR^2} + 0.4343^2 \frac{STD[ADT(0)]^2}{ADT(0)^2}$$

$$- 0.4343^2 \cdot 2r_{GR,ADT(0)} \frac{STD[GR]}{GR} \cdot \frac{STD[ADT(0)]}{ADT(0)}$$

G.

$$0.4343^2 CV(GF_{ADT})^2 = 0.4343^2 CV(GR) + 0.4343^2 CV(ADT(0))^2$$

$$- 0.4343^2 \cdot 2r_{GR,ADT(0)} CV(GR) \cdot CV(ADT(0))$$

H.

$$CV(GF_{ADT}) = [CV(GR)^2 + CV(ADT(0))^2 - 2r_{GR,ADT(0)} CV(GR)CV(ADT(0))]^{1/2}$$

PART V

Derivation of CV(ADT$_0$)

A. Given:

$$ADT_0 = ADT_{current} \cdot [1 + T \cdot GF_{ADT}]$$

where:

ADT$_0$	= base year ADT
ADT$_{current}$	= current year ADT
T	= years from current year to base year
GF$_{ADT}$	= ADT growth rate

B. Find CV(ADT$_0$):

C.

$$ADT_0 = ADT_{current} \cdot (1 + T \cdot GF_{ADT})$$

D.

$$\log_{10}(ADT_0) = \log_{10}(ADT_{current}) + \log_{10}(1 + T \cdot GF_{ADT})$$

E. Assuming independence between ADT$_{current}$ and GF$_{ADT}$:

$$VAR[\log_{10}(ADT_0)] = VAR[\log_{10}(ADT_{current})] + VAR[\log_{10}(1 + T \cdot GF_{ADT})]$$

From Part II:

F.

$$VAR[\log_{10}(x)] = 0.4343^2 CV(x)^2$$

and

$$VAR[\log_{10}(c + ax)] = \frac{0.4343^2 a^2 CV(x)^2}{(\frac{c}{\mu_x} + a)^2}$$

G.   Using **E.** and **F.**:

$$0.4343^2 CV(ADT_0)^2 = 0.4343^2 CV(ADT_{current})^2 + \frac{0.4343^2 T^2 CV(GF_{ADT})^2}{(\frac{1}{GF_{ADT}} + T)^2}$$

H.

$$CV(ADT_0) = [CV(ADT_{current})^2 + \frac{T^2 CV(GF_{ADT})^2}{(\frac{1}{GF_{ADT}} + T)^2}]^{\frac{1}{2}}$$

Derivation of CV(ADT$_{current}$)

A. Given:

$$ADT_{current} = CC \cdot MF$$

where: | ADT$_{current}$ | = | current year ADT |
|---|---|---|
| CC | = | coverage count volume |
| MF | = | monthly adjustment factor |

B. Find CV(ADT$_{current}$):

C.

$$ADT_{current} = CC \cdot MF$$

D.

$$\log_{10}(ADT_{current}) = \log_{10}(CC) + \log_{10}(MF)$$

E. Assuming independence between CC and MF:

$$VAR[\log_{10}(ADT_{current})] = VAR[\log_{10}(CC)] + VAR[\log_{10}(MF)]$$

F. From Part II :

$$VAR[\log_{10}(x)] = 0.4343^2 CV(x)^2$$

G. Using E. and F. :

$$0.4343^2 CV(ADT_{current})^2 = 0.4343^2 CV(CC)^2 + 0.4343^2 CV(MF)^2$$

H.

$$CV(ADT_{current}) = [CV(CC)^2 + CV(MF)^2]^{1/2}$$

This equation is used by Bodle [5].

PART VII

Derivation of CV(PCT)

A. Given:

$$PCT = \frac{TK}{ADT}$$

Where: PCT = percent trucks
TK = truck volume
ADT = total volume

B. Find CV(PCT) :
C.

$$PCT = \frac{TK}{ADT}$$

D.

$$\log_{10} PCT = \log_{10} TK - \log_{10} ADT$$

E. Using the partial derivative method [1] to find the variance of a function of two correlated variables [4], as shown in Part IV E., above:

$$VAR[\log_{10}(PCT)] = 0.4343^2 \frac{STD[TK]^2}{TK^2} + 0.4343^2 \frac{STD[ADT]^2}{ADT^2}$$

$$- 0.4343^2 \cdot 2r_{TK,ADT} \frac{STD[(TK)]}{TK} \cdot \frac{STD[(ADT)]}{ADT}$$

F.

$$0.4343^2 CV(PCT)^2 = 0.4343^2 CV(TK)^2 + 0.4343^2 CV(ADT)^2$$

$$- 0.4343^2 2r_{TK,ADT} CV(TK) CV(ADT)$$

G.

$$CV(PCT) = [CV(TK)^2 + CV(ADT)^2 - 2r_{TK,ADT}CV(TK) \cdot CV(ADT)]^{\frac{1}{2}}$$

Part VIII
Derivation of CV(EF)

A. Given:

$$EF = AF \cdot [PSA \cdot SA + (1 - PSA) \cdot TA]$$

Where:

EF =	average load equivalency factor per truck
AF =	axle factor
PSA =	percent single axles
SA =	average load equivalency factor per single axle
TA =	average load equivalency factor per tandem axle

B. Find CV(EF)

C. Assuming independence between component pairs, then using the partial derivative method [1,4]:

$$VAR\ G(x_1, x_2, x_3, x_4) = \sum_{i=1}^{4} (\frac{\partial G}{\partial x_i})^2 VAR[x_i]$$

D.

$$VAR(EF) = [PSA \cdot SA + (1 - PSA) \cdot TA]^2 \cdot VAR[AF]$$

$$+ [AF \cdot (SA - TA)]^2 \cdot VAR[PSA]$$

$$+ [AF \cdot PSA]^2 \cdot VAR[SA]$$

$$+ [AF \cdot PSA]^2 \cdot VAR[TA]$$

E.

$$VAR[AF] = \{E[AF] \cdot CV[AF]\}^2 \ ;\ VAR[PSA] = \{E[PSA] \cdot CV[PSA]\}^2$$

$$VAR[SA] = \{E[SA] \cdot CV[SA]\}^2 \ ;\ VAR[TA] = \{E[TA] \cdot CV[TA]\}^2$$

F.

$$STD[EF] = VAR[EF]^{1/2}$$

G. The expected value of $G(x_1, x_2, x_3, x_4)$ may be approximated as [4]:

$$G(\overline{x_1}, \overline{x_2}, \overline{x_3}, \overline{x_4})$$

H.

$$E[EF] = \overline{AF} \, [\, \overline{PSA} \cdot \overline{SA} + (1 - \overline{PSA}) \cdot \overline{TA} \,]$$

for an individual forecast:

$$\overline{AF} = AF$$

$$\overline{PSA} = PSA$$

$$\overline{SA} = SA$$

$$\overline{TA} = TA$$

I.

$$CV[EF] = \frac{STD[EF]}{E[F]}$$

J.

$$CV[EV] = \{ \ [PSA \cdot SA + (1 - PSA) \cdot TA]^2 \cdot AF^2 \cdot CV[PSA]^2$$

$$+ \ [AF \cdot (SA - TA)]^2 \cdot PSA^2 \cdot CV[PSA]^2$$

$$+ \ [AF \cdot PSA]^2 \cdot SA^2 \cdot CV[SA]^2$$

$$+ \ [AF \cdot PSA]^2 \cdot TA^2 \cdot CV[TA]^2 \ \}^{1/2}$$

$$\overline{\quad AF \cdot [PSA \cdot SA + (1 - PSA) \cdot TA] \quad}$$

REFERENCES

[1]   Darter, M.I. and Hudson, W.R., "Probabilistic Design Concepts Applied to Flexible Pavement System Design," Sponsored by Texas SDHPT in cooperation with the U.S. DOT FHWA, Report # 123-18, Austin, Texas, May 1973.

[2]   Lytton, Robert, Florence D. Wiley Professor of Civil Engineering, Texas A&M University, TTI; Co-author, AASHTO Guide for the Design of Pavement Structures - Volume I, Part I, Chapter IV: Reliability; and Volume 2, Appendix EE: Development of Reliability. Personal interviews to discuss pavement reliabililty, pavement design, and pavement management, November 1990 through May 1991.

[3]   Cunagin, W.D., "Improved Prediction of Equivalent Axle Loads," Sponsored by USDOT FHWA, accepted for publication by USDOT FHWA; referenced with the author's permission, given August 6, 1991; College Station, Texas.

[4]   Harr, Milton H., "Reliability-Based Design in Civil Engineering," McGraw Hill, Inc., New York, New York, 1987.

[5]   Bodle, R.R., "Estimation of Rural Coverage Count Duration for Estimating Annual Average Daily Traffic," HRB, Highway Research Record 199, pp. 67-77, Washington, D.C., 1966.

APPENDIX B

ANNOTATED LITERATURE REVIEW

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

FIGURE

INTRODUCTION

The purpose of this appendix is to present the findings of past research concerning 1) the variability of truck volumes, classifications, and weights from location to location; 2) the variability of these parameters at the same location over time; and 3) the performance of various ESAL estimation procedures.

In presenting the findings of these reports, the original authors' words have been used to the extent possible. The original author's comments and conclusions are noted in the text by quotation marks. The figures and tables presented with some of the summaries have also been drawn from the original text.

SUMMARY OF FINDINGS

The previous research supports the following conclusions:

Truck Volumes and Classifications

1) The vehicle mix varies significantly from one location to another [STUDIES VII, XVI, XVIII, XIX, and XXI; see especially XVIII for an analysis of seven years of Texas data].

2) The vehicle mix is not correlated with ADT or geographic region [Study XVIII] and is dependent on factors specific to the site in question [STUDIES XVIII and XXI].

3) The truck traffic stream makeup varies significantly from one location to another [STUDIES XVIII and XXI].

4) The truck traffic stream makeup is not correlated with ADT, geographic region, or highway system [Study XVIII] and is dependent on factors specific to the site in question [STUDIES XVIII and XXI].

5) There may be significant seasonal variations in the vehicle mix at a site [STUDIES XIV, XV].

6) There may be significant seasonal variations in the truck traffic stream makeup at a site [STUDY XIV].

7) It is difficult to appraise the magnitude of seasonal variation in the vehicle mix using seasonal classification sessions lasting 24 hours or less [STUDIES VI, XV].

Truck Weights and Load Equivalency Factors

1) Truck load equivalency factors/axle weight distributions vary significantly from site to site [STUDIES III, V, VI, VII, VIII, XV, XXI].

2) Truck loading characteristics may vary significantly from season to season at a site [STUDIES VI, XIX, XX].

3) Truck load equivalency factors and the overall pavement distress attributable to traffic loadings may vary significantly from one direction of travel to the other at the same site [STUDIES VIII, XIII, XV].

Estimation Procedures, Site-Specific Traffic Data, and Pavement Design Impacts

1) An early Kentucky study [Study IV - 1969] attempted to predict vehicle mix percentages based on local conditions including traffic volume, maximum allowable gross weight, and road type. The coefficient of variation of predictions of heavy truck type percentages ranged from 45.8 percent for two-axle six-tire single unit trucks to 261 percent for 5-axle combination trucks. The authors stated: "Despite the relative inaccuracy of the technique, it was found superior to others investigated on the basis of the criteria of accuracy, simplicity, reasonableness, and predictability."

2) A recent Texas study [STUDY XVIII - 1987] by Middleton, et al., of TTI, found "a need for classification data at or very near the site being considered for redesign. A low cost, portable, vehicle classifier is needed to accomplish this goal."

3) One early study [STUDY VIII - 1972] found that obtaining site-specific truck weight data greatly improved the precision of base year ESAL estimates. The authors stated: ". . . there is no estimation procedure which does not result in significant inaccuracies in the design thickness of a pavement. By contrast, the direct measurement of axle load distributions, using one of several dynamic weighing techniques, reduces the errors in the evaluation of present traffic to negligible proportions, and is considered to be the approach most suitable for pavement design purposes." "Even for a route only a few kilometers in length, [the] savings [in pavement materials costs] will far outweigh the costs of collecting the traffic data."

4) More recently, Cunagin [STUDY XXI - accepted for publication by USDOT FHWA; quoted with the author's permission, given August 6, 1991] found that "for pavement design purposes it is essential [emphasis added by original authors] that site-specific weight data be collected." "This service will be cost effective, as errors of the magnitude [realized using non-site-specific data] can lead to grossly over-designed or under-designed pavements."

B-7

GENERAL COMMENTS

For the reader with limited time, STUDIES XV and XVIII address the truck volume and vehicle classification issues. STUDIES VIII and XXI address the truck weight and average load equivalency factor per truck issues.

STUDY I

Title: A New Method of Traffic Evaluation for Pavement Design

Author: Conrad J. Derdeyn, Texas Highway Department.

Publication: Highway Research Record #46, Washington, D.C., 1964.

Study Objective: To present a new method for taking into account the effects of mixed traffic on pavement life.

Data Used: 1960 data from 21 Texas loadometer stations and 1959-61 manual classification data from throughout Texas.

Findings: The author recommends the following method of traffic evaluation for pavement design:

Given a site-specific ADT on a highway, select a percent trucks level from a figure depicting the maximum and minimum percent trucks on Texas highways as a function of ADT. Use the given ADT and percent trucks to estimate the number of single and tandem axles expected over the design period. To obtain design period ESALs, apply loadometer axle-weight distributions and AASHO load equivalency factors to the number of axles in each category (single and tandem).

Comments: The author stresses the need for "additional study on a recurring basis of: (a) the reliability of loadometer sampling, (b) the statistical analysis of the number and location of sampling stations, and (c) the size and time of sample." A number of later studies address these questions.

STUDY II

Title: Estimating the Distribution of Axle Weights for Selected Parameters

Authors: Kenneth W. Heathington and Paul R. Tutt, Texas Highway Department.

Publication: Highway Research Record #189, Washington D.C., 1967, pages 44-78.

Study Objective: To determine which of three estimation methods would provide the best axle weight distribution table prediction at a specific site.

Data Used: 1960-63 data from 21 Texas loadometer stations. Nineteen sites were rural, two were urban. At each site, data was collected for during one 8-hour period each month for 12 months. The 8-hour period rotated from month to month so that every three months, each of the 24 hours of the day were covered. During a session, weights were collected in each direction of travel for 4 of the 8 total hours. In this manner, one 48-hour sample per year of weights for trucks moving in each direction at a site was obtained.

Methodology: Group loadometer station axle-weight distributions according to 1) station percent trucks, 2) station highway system classification*, and 3) overall statewide area. Use grouped axle weight distributions to predict the ESAL's at a specific loadometer station within the grouping. Determine the error associated with using the estimated distribution instead of the actual distribution at the station.

Findings: The authors show the results from only one station in each grouping. The prediction errors ranged from +50.5 percent to -7.3 percent. The prediction errors averaged 32.8 percent. The highest errors were associated with the statewide area method - average error, 35.4 percent. Next was facility type - average error, 33.0 percent. The best was the percent trucks method, - average error, 29.9 percent. The authors found that the grouped interstate distribution predicted the results at the single interstate site to within -7 percent.

Comments: Kenneth Cervenka and C. Michael Walton, in their 1984 report, "Traffic Load Forecasting in Texas," say about the principal study: "Since only three stations were selected for evaluation of the three methods of grouping axle-weight data, the results of this study are inconclusive."

* The three highway system classifications employed were Type A - interstate or approaching interstate design standards, primarily through truck movements; Type B - primary highway with two or more lanes, more local truck movements than Type A but still predominantly through truck movements; and Type C - primarily local truck movements.

STUDY III

Title: A Method for Comparing Alternate Pavement Designs

Author: E.P. Ulbricht, University of Minnesota, Department of Civil Engineering.

Publication: Report 28, Joint Highway Research Project, Purdue University, November 1967. (This study was also Ulbricht's master's thesis at the University of Minnesota, completed in August 1967.)

Study Objective: (Among other objectives) To develop a traffic load prediction method not based on site-specific weight and classification data.

Data Used: Data gathered at 22 loadometer stations each year for three years. The duration and frequency of the weighing sessions is not stated.

Methodology: Develop an "Equivalence Coefficient" (later referred to as a Weighted Equivalence Factor or WEF) which can be applied to an estimate of the average daily traffic at a site to estimate design traffic. Group WEF's by functional class (Interstate and US, all other primary, and secondary) and pavement type (flexible or rigid) to provide six average WEF's.

Findings:

"There is a large variation in the WEF's among loadometer stations."

"For a given station, the amount of variation is slight among the WEF's for the three years."

STUDY IV

Title: "Equivalent Axle Loads for Pavement Design,"

Authors: John A. Deacon, Assistant Professor of Civil Engineering, University of Kentucky; and Robert C. Deen, Assistant Director of Research, Kentucky Department of Highways. This article is a condensed version of work completed and published as part of "Determination of Traffic Parameters for the Prediction, Projection, and Computation of EWL's." Kentucky Department of Highways, August 1969; R.L. Lynch co-authored the full-length study.

Publication: Highway Research Record #291, Washington, D.C., 1969.

Study Objective: To identify and evaluate alternative ESAL prediction methods.

Data Used: Weight data obtained from permanent loadometer stations operating from 1942 to 1969. Data were taken once per year for 8 hours in each direction during the summer months. Further data were obtained from two special truck weight surveys, one in 1957 and the other in 1964. These surveys covered 51 rural sites, including a number of low volume roads. Vehicle classification data were obtained from the loadometer stations (using four 24-hour seasonal counts per year), automatic traffic-recording stations, special classification surveys, and origin-destination surveys.

Methodology: Use local conditions such as site-specific ADT, road type, maximum allowable gross weight, direction of travel, season, presence of alternative routes, service provided, and geographical area to predict vehicle mix and average ESAL per vehicle type at specific sites. Use predictions to generate pavement design thicknesses at specific sites.

Findings:

Vehicle Mix Predictions

The "most significant" relationships for vehicle mix percentages were obtained using the local conditions: traffic volume, maximum allowable gross weight, and road type. The coefficients of variation for heavy truck type percentage predictions were as follows: SU-SA-6T (2-axle six-tire single unit) -- 45.8 percent; SU-3A (3-axle single unit) -- 238 percent; C-3A (3-axle combination) -- 105 percent; C-4A (4-axle combination) -- 106 percent; C-5A (5-axle combination) -- 263 percent. The authors stated: "Despite the relative inaccuracy of the technique, it was found superior to others investigated on the basis of the criteria of accuracy, simplicity, reasonableness, and predictability."

Pavement Thickness Impacts of Overall EAL Predictions

Figure 1 shows the predicted versus actually required combined pavement thicknesses at the sites studied. (Combined thickness includes "base and pavement"). The solid diagonal line represents correct predictions. Points below the solid line are over-designs. Points above the solid line are under-designs. The numerals next to each point represent the number of stations for which that combination of predicted versus actually required thickness was observed. Note the general bias toward over-design and, in particular, the single 10-inch over-design, the two 6-inch over-designs, and the six 4-inch over-designs.

FIGURE 1. Combined flexible pavement thickness based on actual and predicted 20-year EAL accumulations

STUDY V

Title: Development of Traffic Parameter for Structural Design of Flexible Pavements in Minnesota

Author: Eugene L. Skok, Jr., Civil Engineering Department, University of Minnesota.

Publication: Highway Research Record #291, Washington, D.C., 1969. This article is a condensed version of work completed and published as part of Minnesota Highway Department Investigation 183 Interim Report, 1968; M.S. Kersten co-authored the full-length study.

Study Objective: To assess the accuracy of ESAL prediction procedures.

Data Used: 1964-1969 count, classification, and weight data obtained on 41 Minnesota highway sections. Data was obtained as part of a comprehensive study of flexible pavement design and performance. Weighing operations were conducted by weighing all trucks passing a site during three 16-hour periods each year, one period in each of three seasons. Classification sessions were conducted for nine 16-hour periods a year: a weekday, a Saturday, and a Sunday during each of three seasons a year. Counting sessions were conducted for seven consecutive days, four times a year, one week during each season.

Methodology: Identify average load equivalence factors for each vehicle type during each season in each study year. Correlate site-specific values for 1) ADT, 2) heavy-commercial ADT, and 3) average daily number of type 4 (4-axle combination) and type 5 (5-axle combination) trucks with the site-specific number of ESAL's. Develop an ESAL prediction model, based on the parameters 1), 2), and 3).

Findings: Average load equivalency factors per truck vary significantly across seasons, highway type, and vehicle type:

(See table on next page)

Table 1
Summary of Seasonal Truck Factors* by Road Classes

Road Class**	Season	TRUCK TYPE				
		1	2	3	4	5
A	Spring	0.210	0.273	0.947	1.249	1.682
	Summer	0.277	0.492	0.745	1.362	1.640
	Fall	0.291	0.701	1.410	1.750	1.948
B	Spring	0.144	0.213	0.544	1.428	1.850
	Summer	0.215	0.273	0.811	1.408	1.893
	Fall	0.216	0.304	0.837	2.062	2.199
C	Spring	0.113	0.232	0.126	0.659	0.411
	Summer	0.184	0.311	0.186	1.097	1.827
	Fall	0.278	0.424	0.665	1.077	1.988
All	Spring	0.150	0.240	0.687	1.253	1.678
	Summer	0.219	0.352	0.619	1.329	1.737
	Fall	0.256	0.454	1.028	1.761	2.034

* The authors use the term "truck factor" to mean load equivalency factor per truck.

** The three road classes were:

    Class A) - Highways carrying interstate trucks and very few local trucks
    Class B) - Medium-high traffic roads with some interstate trucks and some local trucks
    Class C) - Low traffic roads with almost all local trucks

The best correlation between traffic parameters and ESAL's was achieved using the summation of type 4 and 5 trucks; the second best, with HCADT; and the poorest, with ADT only. The errors associated with these estimates are shown below. Each inch of gravel equivalent thickness corresponds to approximately 0.5 inches of asphalt thickness.

Table 2
Error in Thickness of Granular Base Owing
to Standard Error of Correlations
Used to Estimate N18

Traffic Parameter	HCADT Category	Error Factor	Gravel Equivalent Thickness Error (in.)
ADT	Light (<150)	2.126	1.8
	Heavy (>150)	1.691	1.3
	All	2.328	2.0
HCADT	Light	1.695	1.3
	Heavy	1.240	0.6
	All	1.649	1.2
(4 + 5)	Light	1.475	0.9
	Heavy	1.124	0.3
	All	1.455	0.9

The authors assumed: 1) the weight samples used were large enough to give accurate site-specific estimates; and 2) the planner has access to a site-specific estimate of the number of 4-axle and 5-axle trucks in the traffic stream.

The full-length report contains a table showing the equivalency factor for each truck type at each site studied. The average, standard deviation, and coefficient of variation of the truck type load equivalencies are summarized below.

Table 3
Load Equivalencies by Truck Type

	Type 1	Type 2	Type 3	Type 4	Type 5
Average Load Equivalency Factor	0.2137	0.3126	0.5640	1.2057	1.6554
Standard Deviation	0.0858	0.1591	0.4320	0.5386	0.6422
Coefficient of Variation	40.13%	50.91%	76.58%	44.67%	38.79%

Variation in Average Load Equivalency per Truck Type
over 44 Different Pavement Sections in Minnesota

The high coefficients of variation indicate high site-to-site variability in truck-type load equivalency factors.

Comments: The authors recommend that a future study be conducted in which week-long and month-long periods of classification and weight data are obtained, to test the assumption of validity of 16-hour weight samples. Such a study would make it possible to determine the accuracy levels associated with predictions based on different data collection periods.

STUDY VI

Title: Procedures for Estimating the Total Load Experience of a Highway as Contributed by Cargo Vehicles

Authors: Jesse L. Buffington, Dale L. Schafer, and William G. Adkins.

Publication: Texas Transportation Institute, Research Report #131-2F, Sponsored by Texas Highway Department, September 1970.

Study Objectives: (Among other objectives) To develop a an ESAL prediction procedure not based on site-specific weight data. To statistically evaluate differences in axle weight distributions segregated by vehicle type and highway system. To test the adequacy of SDHPT's truck volume and truck weight sampling program.

Data Used: 1964-68 weight and classification data obtained at 21 conventional loadometer stations and one weigh-in-motion station. Classification data from 167 other manual classification stations. (About 55 percent of these stations were at intersections where it was possible to count two roads at once. As a result, there were about 300 separate road counts; of these 300 counts, about 37 percent are bi-directional counts.)

Methodology: Group axle-weight frequency distributions 1) by vehicle type, 2) by axle location (on the vehicle - i.e., rear vs. front, etc.) overall and within vehicle types, 3) by load characteristic (empty or loaded) overall and within vehicle types, 4) by year of weighing; by summer of weighing; and 5) by location (urban or rural).

Findings:

"Combining stations by highway system produces unlike groups, but the vehicle type axle-weight distributions are also heterogeneous within each group. Stations grouped geographically yield essentially the same results."

"It is evident that individual loadometer stations have varying frequency distributions of log-axle kip equivalents depending on the proportion of loaded or partially loaded to empty vehicles weighed. This loaded to empty vehicle proportion varied widely from station to station, even within vehicle types, and is the source of much of the variation in log-kip axle equivalents between vehicles."

"Even when the 3-S2 vehicles were separated into loaded and empty groups, the tests still revealed statistically significant between[-]station variation."

"There is enough difference between the weekday and weekend [weight] data for a major vehicle type to suggest the necessity of collecting [weight] data seven days of the week. The

[previous analysis] has already indicated that there is a significant difference in the weight data between seasons."

"It is difficult to reflect actual seasonal changes with only one 24-hour count per season."

For purposes of obtaining reliable average axle- and vehicle-weight distributions for each vehicle type at the highway system-level (Interstate, F-M, etc), "continuous seven-day weighing periods during each season of the year are recommended to be conducted at several stations. Perhaps two or three for each highway system would be enough. Then it could be determined whether true station to station differences in vehicle or axle weights actually exist."

STUDY VII

Title: Use of Traffic Data for Calculating Equivalent 18,000-LB Single-Axle Loads

Authors: Eugene L. Skok, Jr., University of Minnesota, and Richard E. Root, The Asphalt Institute.

Publication: Highway Research Record #407, Washington, D.C., 1972.

Study Objectives: To determine whether or not 1) site-to-site variation and 2) within-site variation over time, in truck volumes and average load equivalency factors, have appreciable pavement thickness impacts. To develop an ESAL prediction procedure.

Data Used: Axle weight distributions and classification count data from 40 Minnesota test sections.

Methodology: Examine the impact on pavement thickness of varying vehicle classification percentages and average load equivalency factors.

Findings:

1) The vehicle mix should be varied on a site-by-site basis for pavement design purposes. This conclusion is reached by showing that when the type 8 truck (5 axle-semi) percentage is varied from low to average values, 4.4" asphalt thickness differences result (i.e., a 10" granular equivalent thickness times an asphalt layer coefficient of 0.44); and when the type 8 truck percentage is varied from average to high values, 2.2" asphalt thickness differences result.

2) The vehicle-type axle weight distributions should be varied on a site-by-site basis for pavement design purposes. This conclusion is reached by showing that when the load equivalency factors per truck type are varied from low to average values, 2.64" asphalt thickness differences result; and when the load equivalency factors per truck are varied from average to high values, 3.96" asphalt thickness differences result.

3) It is appropriate to vary the vehicle mix and axle-weight distributions with time. The asphalt pavement thickness changes were approximately 0.88" due to vehicle mix changes over time and 1.41" for axle-weight distribution changes over time.

Comments: These authors found that the base year differences in the vehicle mix and axle weight distributions (i.e., site-to-site variations) account for substantially higher thickness differences than within-site variations over time.

STUDY VIII

Title: The Measurement of Traffic Axle Load Distributions for Pavement Design Purposes

Authors: J.E.B. Basson and G.L. Dehlen, National Institute for Road Research, C.S.I.R., South Africa; R.G. Phillips, Ministry of Roads and Road Traffic, Rhodesia; and P.J. Wyatt, formerly of National Institute for Road Research, C.S.I.R., South Africa.

Publication: Proceedings of 3rd International Conference on Structural Design of Asphalt Pavements, London, England, 1972.

Study Objective: To evaluate the precision of various ESAL estimation procedures. To relate forecast precision differences to pavement thickness differences. To use pavement thickness differences to evaluate the monetary benefits and costs of improving forecast precision.

Data Used: Week-long measurements of axle loads obtained using Axle Weight Analyzers (capacitive mats) on 56 roads in southern Africa between 1969 and 1971; also seasonal 8-hour single session loadometer surveys of truck and bus traffic at 13 sites, from 1967-1970. The AASHO load equivalence factors were used to convert axle weights to ESALs.

Methodology: Document five ESAL estimation methods:

Method 1, Great Britain's procedure: Uses one of three non-site-specific average load equivalence factors per heavy commercial vehicle. The choice of average equivalency factor depends roadway being designed. An ESAL estimate is obtained by combining the load equivalence factor with the average daily number of heavy-commercial vehicles at the site.

Method 2, Illinois Division of Highways' procedure: Uses average load equivalence factors stratified by vehicle type (cars, single unit trucks, and multiple unit trucks), highway classification (four types), and pavement type (flexible or rigid). These non-site-specific equivalence factors are applied to a classified traffic count from the site (count duration is not stated) to yield an ESAL estimate.

Method 3, California Department of Highway's procedure: Uses site-specific average daily truck traffic, classified by axle configuration, combined with non-site-specific equivalent wheel-load per axle configuration factors, to generate ESALs. One set of factors is provided for each of two highway categories.

Method 4, New Zealand's procedure: Uses site-specific number of vehicles classified by commodity hauled and axle configuration; combines number of vehicles with a load equivalence factor based on commodity and sometimes axle configuration.

B-21

Method 5, Deacon and Dean's Kentucky procedure (reviewed above as STUDY IV): Uses site-specific ADT, road type, maximum allowable gross weight, direction of travel, season, presence of alternative routes, service provided, and geographical area to predict vehicle-type percentages and average load equivalencies per vehicle type.

Identify the estimation uncertainty associated with some methods relative to the uncertainty associated with estimates based on site-specific WIM data. Using the reliability concept, design a pavement based on each method's level of uncertainty. Determine the asphalt thickness differences introduced by the various uncertainties.

Findings:

Directional Distribution of Loadings

"Directional effects [in the average load equivalency factor per truck] were noted at certain sites and at one particular site, the average factor for trucks travelling in one direction was 17 times that for the trucks travelling in the opposite direction."

Site-Specific Nature of Truck Load Equivalency Factors

"The data however showed that the [load equivalency factors by truck type] varied significantly from site-to-site."

A "site-effect was evident" when trucks where grouped by commodity hauled; "the mean factors for trucks carrying raw agricultural products for example [varied] between 0.23 and 1.17."

Precision of Estimation Procedures

The asphalt thickness differences resulting from some of the methods are shown in Table 4 below. (Note that 25.4 millimeters = 1 inch; Method 1 corresponds to "average for all trucks" in Table 4; Method 3 corresponds to "averages for 5 truck configurations"; Method 4 corresponds to "averages using 17 commodities"; the authors evaluated Method 5 using data presented in Deacon and Deen's Highway Research Record article [Study IV]. This evaluation indicated that Method 5 required a 37mm thickness increase over site-specific WIM.)

The authors note that the average week-long traffic data collection session using a capacitive mat cost approximately $130 in 1970; the cost of adding 53mm (about 2") of asphalt (the thickness difference resulting from using the least and most precise methods in the table) to a 10 kilometer stretch of two-lane road was quoted at $200,000. The authors concluded, "Even for a route only a few kilometers in length, these savings will far outweigh the costs of collecting traffic data. If only for this reason, the use of the most accurate technique shown up by this study, namely that of dynamic weighing, seems a logical step."

Table 4
Additional Asphalt Thickness Necessary Because of Inaccuracies in the Traffic Evaluation

Description of Measurement of Estimation Technique	Nature of Errors	Coefficient of Variation of Traffic Estimate**	Additional Surfacing Thickness in in mm
Static weighing of sample of vehicles during daylight hours of a single day	Inaccurate projection of results to cover a week	0.74	32
Dynamic weighing using Lee scale	Errors in load measured due	0.01	1
Dynamic weighing using RRL weigh-bridge	to dynamic effects and to limitations in response of	0.01	1
Dynamic weighing using BAST counter	the instruments***	0.02	2
Dynamic weighing using AWA [Capacitive Mat]		0.01	1
Estimate using average for all vehicle axles		1.49	53
Estimate using average for all trucks		0.54	25
Estimate using averages for 15 truck configurations	Inability to account for the characteristics of the	0.34	16
Estimate using averages for 5 truck configurations	traffic at specific sites at different times of the	0.35	17
Estimate using average for all truck axles	year****	0.37	18
Estimate using averages for 17 commodities		0.39	18

*This additional thickness requirement relates only to the errors in the measurement of present traffic, and does not take account of the uncertainties that arise because of errors in the prediction of future traffic, the evaluation of the environmental effects, the measurement of material properties, and also to allow for the construction tolerances.

**The coefficients of variation shown are not strictly comparable, since they were derived using different sets of data. Whichever technique is used, an increase in the number of vehicles will result in an increase in accuracy with respect to the random errors, but the inaccuracies stemming from the systematic errors will remain unchanged. The latter will be small in the case of dynamic measurements at a well-selected site, but may be large in the case of estimation techniques.

***In a week-long dynamic weighing survey on a road carrying 100 equivalent 80 kN axles per day, the data presented in the previous section indicate that approximately 7,000 axle loads would have been measured. The coefficients of variation of the measured number of equivalent 80 kN axles was then computed using the approximate relation.

$$C_e = \frac{7 C_a}{n^{1/2}}$$

The assumption was made that no systematic errors were present.

****If the visual traffic counts do not cover at least a week, for 24 hours a day, then these estimation procedures are subject to additional errors introduced by projecting the results to cover a week.

STUDY IX

Title: A Contribution to the Establishment of Design Loads for the Thickness Design of Flexible Pavements

Author: H. Keller.

Publication: Proceedings of 3rd International Conference on Structural Design of Asphalt Pavements, London, England, 1972.

Study Objective: To examine the problem of assessing design loads for flexible pavement design.

Data Used: Weight data drawn from 16 permanent stationary axle weighbridges located in the Federal Republic of Germany.

Methodology: Perform detailed statistical analyses of data designed to illustrate design implications of using short samples or not sampling at all.

Findings:

1) On within-day variation in loadings at a single site: ". . . sampling of axle loads must be carried out both day and night. To restrict them to a few hours when an average axle load distribution might be expected, does not provide the statistical data required on axle loads -- particularly in the heavier classes."

2) On overall variation in truck traffic characteristics between sites: "It has indeed been shown that the traffic on each of the surveyed roads has its own particularities."

3) On day-to-day loading variations at a site: ". . . [Figure 5 - (not presented here)] shows an example of class frequencies [of axle loads] over 46 working days excluding Saturday. The standard deviations in daily class frequencies are up to $\pm 5.3\%$. These deviations would have considerable consequences for pavement design. If the influence of the magnitude of the loads on the life of the pavement is taken into account, e.g., in accordance with the equivalent load factors of the AASHO test, the deviations in the upper load categories become particularly significant. This example shows that standard deviations from the number of design axle loads may be $\pm 25\%$. This is completely unsatisfactory."

STUDY X

Title: Evaluation of AASHO Interim Guides for Design of Pavement Structures, NCHRP Report #128

Authors: C.J. Van Til, B.F. McCullough, B.A. Vallerga, and H.G. Hicks of Materials Research and Development, Inc.

Publication: NCHRP, Highway Research Board, Division of Engineering, National Research Council, national Academy of Sciences - National Academy of Engineering, 1972. (Chapter 3 and Appendix C contain information of interest to this analysis).

Study Objectives: To evaluate the AASHO Interim design guides. To discuss "the implications of short-cut methods for converting mixed traffic to 18-kip equivalent single-axle load applications for design purposes."

Data Used: "Data from three loadometer stations in the U.S. were selected for analysis. Two [were] Interstate highways, one in Ohio, and the other in Iowa. The third loadometer station, an urban location in Montana, shows the effect of highway type as well as geographical area."

Methodology: Compare the estimated design ESAL resulting from each of seven axle weight distribution estimation methods.

The seven methods are:

Method A: Uses the axle-weight distribution from the test sites broken into 24 axle-weight categories. The mean axle weight in each category is converted to a load equivalency for design load estimation purposes. This is the basis against which all other methods are compared.

Method B: Divides traffic into three categories: passenger cars, single-unit vehicles, and multi-unit vehicles. A weighted equivalence factor for each of three vehicle types on each roadway classification (based on statewide averages) is used to convert the mixed traffic to equivalent axle loads. The equivalent axle loads are then distributed to the design lane.

Method C: Same as Method A except this method uses only 10 instead of 24 axle-weight categories. A statewide average axle weight distribution is used to find the equivalence factors for axles in each weight category. The equivalence factors are applied to the number of axles, in each weight category, expected to use the facility.

Method D: Similar to Methods A and C except the user may modify the axle weight distribution to account for expected future changes. A constant load distribution factor is

used for all highway classifications.

Method E: Uses the total amount of heavy commercial traffic by season as a basis for determining the expected number of equivalent axle loads. The seasonal load equivalency factors applied to the HCADTs are statewide average values.

Method F: Uses a statewide average equivalency factor for each truck axle configuration times the number of vehicles expected for each configuration.

Method G: Same as method F but this method sums the equivalencies using a 10-kip instead of an 18-kip axle load as the base load. A formula is then used to convert 10-kip to 18-kip equivalencies.

Findings: The method used to summarize axle-weight data and the use of statewide average equivalency data to generate design ESAL estimates at specific sites can introduce substantial errors into the ESAL estimation process.

Table 5a
Percent Deviation from Method A
by Various Methods of Converting Traffic
(Flexible Pavement)

Method of Conversion	PERCENT DEVIATION BY LOCATION AT LOADOMETER STATIONS		
	Urban Montana	Interstate Ohio	Interstate Iowa
B	+127.6	-33.1	-36.6
C	-14.6	-15.8	+26.0
D	+15.9	-4.1	+10.0
E	+65.5	-51.7	-52.4
F	-50.6	-64.1	-55.9
G	-30.0	-49.2	-37.6

Table 5b
Percent Deviation from Method A
by Various Methods of Converting Traffic
(Rigid Pavement)

Method of Conversion	PERCENT DEVIATION BY LOCATION AT LOADOMETER STATIONS		
	Urban Montana	Interstate Ohio	Interstate Iowa
B	+240.8	+8.4	-18.9
C	+16.4	+8.4	+11.1
E	+183.4	-37.0	-30.5
F	-35.5	-66.5	-53.9
G	-9.0	-52.5	-34.7

STUDY XI

Title: Estimation of 18-kip Equivalent on Primary and Interstate Road Systems in Virginia

Authors: N.K. Vaswani and D.E. Thacker, Virginia Highway Research Council.

Publication: Highway Research Record #466, Washington, D.C., 1973

Study Objective: To identify a procedure to estimate the flexible pavement design ESAL without having to collect site-specific truck weight data.

Data Used: One-day weight samples from 93 different sites (21 suburban and 72 rural areas) taken between 1963 and 1966; W-3 and W-4 tables from truck weight study reports for 1961-1970; average daily traffic volumes on Interstate, arterial, and primary roads for 1960 through 1970; and traffic data on 412 flexible pavement projects for 1960 through 1970.

Methodology: Develop regression models which employ traffic parameters at specific sites, to predict ESAL's. Calibrate these models using site-specific weight data.

Findings: Five regression models were developed and tested. Descriptions of the methods and the findings associated with each are presented below:

Method 1. The percent method: Uses number of vehicles segregated by vehicle classification and weight. Total ESALs are found by summing number of vehicles times average ESAL per vehicle for each type and weight category. This method was rejected because it might require extensive future data collection.

Method 2. The W-4 table method: Uses an average equivalency factor for each vehicle type based on site-specific weight data. This method was rejected because it requires site-specific truck axle weight data.

Method 3. The Asphalt Institute method: Uses a linear regression equation based on the logarithms of the legal single-axle load limit, the average heavy truck gross weight (including 2-axle 6-tire pickups), and the number of heavy trucks at the site. The coefficients of the independent variables are given by the Asphalt Institute.

Method 4) The Modified Asphalt Institute method: Uses the Asphalt Institute Method model with Virginia-specific coefficients calculated by the authors but without the legal single axle load limit as an independent variable. This method was rejected in favor of Method 6, the three equation method, below.

<u>Method 5. The five-equation method</u>: Uses regression models based on a site-specific truck classification count; trucks are grouped into five classes: 2-axle, 3-axle single-unit, 3-axle multi-unit, 4-axle multi-unit, and 5-axle multi-unit. One equation is developed for each truck class. This method was rejected because the Virginia traffic volume maps do not separate multi-unit heavy trucks into 3-axle, 4-axle, and five-axle sub-groups.

<u>Method 6. The three-equation method</u>: Uses only three truck classes: 2-axle, 3-axle single-unit, and all multi-unit vehicles. Uses one equation for each truck class. The independent variables in each equation are the truck class volume and truck class average weight per truck. This method was recommended for use.

A figure in the paper indicates that about two-thirds (i.e., ±one standard deviation) of predictions made using the procedure would lead to approximately 1.1" or less asphalt pavement thickness errors (i.e., ≈ 0.48 or less errors in the unitless "pavement thickness index (or structural number)"; the conversion to asphalt thickness from structural number is approximately $\Delta SN*(1/0.44)$).

STUDY XII

Title: Probabilistic Design Concepts Applied to Flexible Pavement System Design

Authors: Michael I. Darter and W. Ron Hudson

Publication: Research report 123-18, Center for Highway Research, The University of Texas at Austin, May 1973.

Study Objective: To evaluate the many random variables which impact flexible pavement performance. To develop a design procedure which accounts for these variables. These variables include materials properties, environmental conditions, pavement design equation lack-of fit, and traffic loadings.

Data Used: Information published in STUDY II (Texas, Heathington and Tutt), the full-length version of Study IV (Kentucky, Deacon and Lynch), Study VI (Texas, Buffington, et al.) and STUDY X (Van Til, McCullough, et al) above.

Methodology: Use information from the literature and engineering judgement to estimate traffic variance.

Findings: The authors identified a traffic variance of 0.0333 (pg. 137); lane and directional distribution factor variances were expressly ignored. This accounted for approximately 10 percent of total variance (i.e., traffic plus non-traffic or pavement variance). Concerning traffic variance, the authors stated: "In most cases, estimates of variations were based only on engineering judgment as there were no available data. Estimates which are more accurate are certainly needed, so that the overall variation of predicting 18-kip equivalent load applications may be better quantified."

Comments: Cunagin, in Study XXI below, found "results [which] suggest that the contribution of the traffic elements to the total variance may be equal to or greater than the variance of the non-traffic elements."

The traffic variance assessment framework used by Darter and Hudson in the principal study is followed in Chapter IV, above.

STUDY XIII

Title: Texas Traffic Data Acquisition Program

Authors: Han-Jei Lin, Clyde E. Lee, and Randy Machemehl.

Publication: Research Report 245-1F, Center for Transportation Research, University of Texas at Austin, February 1980.

Study Objective: To evaluate Texas' traffic data acquisition program from the standpoint of FHWA requirements and user needs. A specific sub-objective of the WIM program analysis was to determine whether it was necessary to weigh trucks in both directions at a site.

Methodology: Examined accumulated pavement distress by travel direction.

Data Used: Pavement distress data summarized by direction from 12 Texas Interstate sections.

Findings:

"A modified sampling schedule is needed for at least one year to define any significant daily or seasonal variations in truck weight patterns that might exist at each survey site. Truck traffic in both directions must be surveyed at each site. . . . In the first year, each of the six selected weigh stations should be occupied four times, once in each season, for a 7-day period each time . . . weighing should be in both directions simultaneously."

The authors' recommended bi-directional weighing on the following basis:

"Field surveys of [pavement] distress as evidenced by cracking, spalling, punch-outs, and patching in continuously reinforced concrete pavements in Texas have shown that considerably more distress exists in one direction than the other. This can, in all probability, be attributed almost entirely to heavier traffic loadings as all other conditions at the sites were virtually identical."

The table on next page shows the directional distributions of distress on the 12 sections.

Table 6
Directional Distribution of Observed
Distress on Continuously Reinforced Concrete Pavements, 1979

Location	Length	Direction	Percent of Total Observed Distress	
			NB* or EB	SB or WB
Interstate 10 (from Luling to US Highway 11)	39.9	E-W	30	70
Interstate 10 (From US Highway 77 to US Highway 71)	22.6	E-W	30	70
Interstate 10 (US Highway 71 to end of research sections)	14.7	E-W	31	69
Interstate 10 (Winnie to Port Arthur)	17.4	N-S	31	69
Interstate 10 (Van Horn to Reeves County)	48.2	E-W	34	66
Interstate 20 (Kaufman County to SH 19)	10.0	E-W	55	45
Interstate 20 (SH 19 to SH 69)	33.0	E-W	57	43
Interstate 20 (SH 69 to US 271)	15.2	E-W	61	39
Interstate 20 (US 271 to SH 135)	13.0	E-W	76	24
Interstate 20 (SH 135 to Longview)	12.2	E-W	35	65
Interstate 35 East (CFHR Sections 906, 903)	9.6	N-S	32	68
Interstate 35 (CFHR Sections, 910, 909, 908, 907, 905, 904)	6.9	N-S	43	57

*Northbound direction of traffic, etc.

STUDY XIV

Title: Highway Performance Monitoring System -- Vehicle Classification Case Study

Authors: Douglas Mactavish and Donald L. Neumann, P.E.

Publication: U.S. Department of Transportation, Federal Highway Administration, Washington, D.C., 1982.

Study Objective: To examine the mix of vehicles in the traffic stream using parameters such as functional class, rural vs. urban, weekday vs. weekend, night vs. day, season by season, etc.

Data Used: Hourly, daily, weekly, and seasonal data from at least two sites on each functional class of highway (except local) from the following agencies: Arkansas, Iowa, Minnesota, Washington, and Delaware. The total number of sites covered was 139, and the total number of vehicles classified was 11,709,156.

Methodology: Perform statistical tests to determine relationships between the parameters of interest and the vehicle mix.

Findings: As presented by the original authors:

I. Highlights

The Vehicle Classification Case Study was conducted from late summer to 1980 to early fall of 1981 by five agencies--the Delaware Valley Regional Planning Commissions and the States of Arkansas, Iowa, Minnesota, and Washington. The 11,709,156 vehicles classified by these agencies at 139 sites show the following characteristics:

<u>Rural Versus Urban</u>

● *Seasonal variation in the distribution of most vehicle types in the traffic stream was greater in rural areas than in urban areas.*

● *The distribution of most vehicle types in the traffic stream did not change greatly from season to season in urban areas.*

● *The distribution of each truck category varied less than 1 percent of the total traffic stream from season to season in urban areas.*

● *All truck categories, particularly 3S2's, comprised a larger percentage of the traffic stream in rural areas than in urban areas.*

● *Automobiles comprised a larger percentage of the traffic stream on weekends than on weekdays.*

- *Trucks comprised a larger percentage of the traffic stream on weekdays than on weekends.*

Functional System

- *Standard/compact cars comprised a greater percentage of the traffic stream on urban systems than on rural systems.*

- *The distribution of most vehicle types in the traffic stream varied greatly from season to season for rural systems.*

- *The distribution of most vehicle types in the traffic stream did not vary from season to season for most urban systems.*

- *Motorcycles, buses, and most individual truck categories amounted to less than 2 percent of the traffic stream on each system.*

- *Single-unit trucks and 3S2's comprised the largest part of truck traffic for nearly all functional systems in all seasons.*

- *The rural Interstate System had the greatest percentage of 3S2's while urban minor arterials and urban collectors had the least for each season.*

- *The rural Interstate System had the highest seasonal variation in distribution of 3S2's in the traffic stream.*

- *Vehicle distribution in the traffic stream varied significantly from weekday to weekend.*

- *Distribution of cars, motorcycles, buses, and pickups increased from weekday to weekend.*

- *The percent of most truck types in the traffic stream was lower on the weekends.*

- *The percent of trucks in the traffic stream increased at night.*

Highway Design Type

- *Vehicle type distribution varied significantly among highway design types.*

- *Seasonal variation for most vehicle types was higher for rural design types than urban design types.*

- *Freeways and expressways in both rural and urban areas had the highest percentage of trucks.*

- *Single-unit trucks and 3S2's comprised the largest part of truck traffic for all design types in all seasons.*

STUDY XV

Title: Truck Forecasts and Pavement Design

Author: Robert J. Hage.

Publication: Transportation Research Board, Transportation Research Record #889, Washington, D.C., 1982.

Study Objective: "Discuss the problem of estimating the present or base-year annual-average daily load on an existing route or alignment..."

Methodology: Examine the components of a base year ESAL estimate: truck volumes, equivalency factors, and lane distributions.

Data Used: Data on 3-S2 volumes and weights were collected in Minnesota from 1977 through 1981.

Findings:

Truck Volumes

1) "There is strong evidence that a single 16-hour class count, no matter how recent or well located, may be grossly inadequate for estimating base-year heavy commercial AADT by truck type. There are, of course, the obvious uncertainties associated with filling in the uncounted 8 [hours] ..."

2) "Whereas one might expect truck volumes to vary significantly from season to season, and perhaps even from week to week, it has now been determined that they may also vary markedly from day to day."

3) "Class counts recently taken Monday through Friday from 8:00 a.m. to 5:00 p.m. . . . showed the five-axle tractor-semitrailer volume varying by 30 percent from the low day (Friday) to the high day (Wednesday). At this location the AADT for this vehicle type is roughly estimated at 4000, and it accounts for an estimated 87% of the traffic-associated pavement wear. Obviously, the design load estimate made for the Interstate route to be constructed on this alignment could have a wide range of values that depend simply on the day or days the class count happened to be taken."

4) "Because truck volumes may vary widely from one day to the next, it is inevitable that attempts to identify seasonal variations on the basis of a single 16-hour class count taken at different times of the year will meet with disappointing results."

5) "It appears, then, that even if Minnesota had only two seasons, which is certainly not the case, even two 16-hour class counts would provide an inadequate basis for establishing year-to-year trends."

Directional Distributions and Average Load Equivalency Factors

1) "Average truck [load equivalency] factors . . . vary widely by route, by time of year, and in the case of tractor semitrailers, by trailer type. . . . The variability of [load equivalency factors] is even more pronounced when factors are analyzed by direction. For example, on Trunk Highway 2 . . . the loaded direction [load equivalency] factor [for 3-S2 trucks] averaged 1.95 [while the factor for the unloaded direction] was 0.34."

2) "Unfortunately there appears to be a significant degree of unexplained year-to-year variability. . . . At least part of the year-to-year variation in the five-axle semitrailer truck factor at a given location is probably attributable to the proportion of grain trucks that happen to be in the traffic stream at the time the weighing operations are conducted."

Base Year Lane Distribution

"A critical step in developing a design load estimate is determining the lane distribution of estimated truck volumes. Errors here will have the same impact as inaccurate estimates of truck volumes or damage factors."

Developments in Pavement Design

"Pavement designers are now also asking planners to estimate confidence levels associated with their design load estimates so that designers can weigh the additional costs of providing a 'safety margin' in their designs against the risks and costs of early failure."

General Conclusions

"The dimensions of the uncertainty associated with making 20-year design load estimates are indisputably enormous. But it is also apparent that simply estimating existing loads is highly speculative. With the incremental cost of an inch of flexible and rigid pavement running at about $6500 and $7500/lane-mile, respectively, it is imperative that the planner continue to improve each aspect of the design load estimating process."

Title: Traffic Load Forecasting in Texas

Authors: Kenneth J. Cervenka and C. Michael Walton, Center for Transportation Research.

Publication: Research Report 352-1F, Center for Transportation Research, November 1984.

Study Objective: To document and evaluate Texas' procedure for traffic load forecasting.

Data Used: Texas truck weight and vehicle classification data from 1965-1984.

Methodology: Document current Texas forecasting practices. Perform sensitivity analysis on forecasting process to determine relative importance of various input parameters.

Findings:

". . . sensitivity analysis showed that an improper specification of [RDTEST68's] input parameters (such as 'percent trucks' and selection of a 'representative' WIM station) can have a drastic effect on the total projected traffic load over a 20-year design period."

"Based on vehicle classification data collected at over 700 stations in 1980, the percentage of trucks in the traffic stream ranged from 1.4 percent to 58.2 percent. The average was 16.8 percent, with a standard deviation of 8.6 percent."

Table 7 shows the variation in load equivalency factors by truck type at Texas WIM stations.

Table 7
Variation in Load Equivalency Factors by Truck Type
from Station to Station

| | WIM STATION | | | | | |
	501	502	503	504	505	506
Single-Unit (SU)						
2-Axle	0.45	0.33	0.18	0.31	0.26	0.23
3-Axle+	0.73	0.37	0.36	0.74	0.80	0.80
All	0.50	0.34	0.21	0.40	0.47	0.39
Multiple-Unit (MU)						
3-Axle	0.55	0.43	0.48	0.83	0.58	1.06
4-Axle	0.98	0.62	0.56	1.06	0.86	0.84
5-Axle+	1.33	0.95	1.02	1.26	1.45	1.42
All	1.30	0.92	0.98	1.22	1.40	1.39
All trucks	1.09	0.82	0.86	1.08	1.22	1.20

The authors also recommend making "greater use of lane-wise distribution factors" for design purposes.

Comments: The paper describes the history of the Texas weighing program and analyzes previous Texas studies. Among those analyzed are:

1) the 1972 TTI study (STUDY VI) which documented the need for seasonal week-long data collection sessions; and

2) the 1975 CTR study (STUDY XIII) which directional differences in pavement distress.

STUDY XVII

Title: Evaluation of the Texas Truck Weighing Program

Authors: D.A. Maxwell, T. Chira-Chavala, H. Nassiri, and J.M. Mason.

Publication: Research Report 424-1F, Texas Transportation Institute, June 1986.

Study Objective: (Among other objectives) To evaluate the Texas truck weighing program's ability to provide valid system-level summary data.

Methodology: Evaluate two methods for estimating the necessary number of WIM sites. Distribute the number of sites indicated by the chosen method over the various regions and highway systems of the state.

Data Used: National average data from FHWA reports and mean truck weights from the six existing Texas WIM sites.

Findings:

1) "STANDARD METHOD" - Using the FHWA data, the researchers estimated the variability of truck weights. These variability estimates were then combined with error tolerances administratively set by SDHPT personnel for different types of routes. This enabled the researchers to determine the appropriate number of sites:

Table 8
Number of Sites by Road Class -- Standard Method

	Road Class	% Error	Sites
1.	Interstate	10	18
2.	US Numbered	20	20
3.	Texas Numbered	30	17
4.	Farm-to-Market	40	19
	TOTAL		74

2) "ECONOMIC DESIGN METHOD" - Using mean gross truck weights from the six existing WIM sites and estimating the distribution of trucks using different road classes, the authors found the following number of sites to be necessary:

Table 9
Number of Sites by Road Class -- Economic-Design Method

Road Class		Sites
1.	Interstate	10
2.	US Numbered	6
3.	Texas Numbered	6
4.	Farm-to-Market	4
	TOTAL	26

With respect to the number of sites actually needed, the authors state the following: "Once the twenty-six sites are in place and a year's worth of data gathered, the problem of how many sites are required (remember we estimated the distribution by road class) and their location need to be reworked using the procedure described in this report. This may show that more or less sites are needed, or that they need to be redistributed."

STUDY XVIII

Title: Analysis of Truck Traffic between 1977 and 1983

Authors: D.R. Middleton, J.M. Mason, T. Chira-Chavala, and H.S. Nassiri.

Publication: Texas Transportation Institute, The Texas A&M University System, May 1987.

Study Objective: To examine Texas truck traffic characteristics.

Methodology: Perform statistical analyses of ADT and vehicle classification data stratified by highway system geographic region. "Regional stratifications were devised based on the predominance of 'special-use' industries and the existing highway-district boundaries."

Data Used: Count and classification data from Texas Manual Count Annual Report for years 1977 through 1983.

Findings:

1) Truck classes as a proportion of total traffic:

"Although the proportions [of] SU-1 (3 axle single-unit) and 5-or-more-axle tractor-semitrailers differed by road classes, there was also great variation in these proportions among count locations. This, plus the fact that neither ADT nor regions were found to be correlated with these proportions implied that proportions of 5-or-more-axle tractor-semitrailers and of SU-1 trucks varied significantly from one count location to another. Since there were no easily discernible patterns or trends in the proportions of 5-or-more-axle tractor-semitrailers or SU-1 trucks, their variation was mostly location specific. The proportions of SU-2, 2-S2, and other trucks were so small that any variation among these [by] road classes would not be 'practically' significant." Very little change in these proportions was found over time at the same site.

(See table on next page)

Table 10
Summary of Percent Trucks of Total Traffic

	Percent of Total Traffic		
Truck Type	Interstate Highways	U.S./State Highways	Farm-to-Market
5-or-more-axle semitrailers	6-45	2-25	0-40
SU-1	3-6	3-5	0-15
SU-2	1	1	*
2-S2	2-3	1-2	1-3
Other	≤ 1	≤ 1	≤ 1

*No data continually for a number of years

2) Truck classes as a proportion of total truck traffic:

"Although slight differences existed among the three highway classes, the differences within highway classes were more significant. The differences in these proportions were not attributable to regions (or highway districts). It was likely that the variability in truck proportions was highly attributable to specific locations of the count stations. Highway class, region of the state, and year, therefore, would not necessarily provide sufficient information for an accurate prediction of the mix of trucks at that location (emphasis added by original authors). In order to predict the mix of trucks at a specific location and time, one must know more about other factors such as surrounding industries, economic factors, and seasonal influences upon truck traffic."

(See table on next page)

Table 11
Proportion of Each Truck Type as Percentages of Total Trucks

| Truck Type | Percent of Total Trucks | | |
	Interstate Highways	U.S. Highways	Farm-to-Market
5-or-more-axle semitrailers	50-80	30-75	30-70
SU-1	6-30	10-50	15-50
SU-2	1-8	1-15	1-22
2-S2	5-15	5-20	5-15
Truck & Trailer	< 10	< 10	< 10
Doubles	< 5	< 5	< 5

3) Variation of truck proportions within the truck traffic stream between and among multiple sites on the same highway.

"There were 2 count locations on U.S. 183 on either side of the intersection with S.H. 29 -- northwest of Austin, yet the proportions [of 5-or-more-axle tractor-semitrailers within the truck traffic stream] on these 2 count locations differed as much as 20 percent. Also, there were 4 count locations on U.S. 77. Three locations showed relatively similar proportions which were up to 25 percent higher than the proportion at the other location."

4) Conclusion:

"The findings also demonstrate a need for classification data at or very near the site being considered for [pavement] redesign. A low cost, portable, vehicle classifier system is needed to accomplish this goal."

STUDY XIX

Title: Traffic Forecasting for Pavement Design

Authors: Desai, Deen, and Noble.

Publication: U.S. Department of Transportation, FHWA Final Report, March 1988, (specifically, Appendix C).

Study Objective: To report the results of research into the problem of traffic forecasting for pavement design. Research was conducted separately by the Florida DOT, Kentucky Transportation Research Program, Oregon DOT, Washington DOT, and Texas Transportation Institute. Appendix C of the report addresses the sensitivity of the Design ESAL to errors in base-year traffic inputs.

Data Used: Vehicle mix data collected on rural principal arterials in Washington state. These data were collected as part of the Vehicle Classification Case Study (Study XIV). Also, historical volume, classification, and weight data on file at participating agencies.

Methodology: Analyze historical traffic data and compare asphalt overlay thicknesses indicated by varying the percentage of 5-axle semi's in the traffic stream.

Findings:

"[Using statewide and regional average data] may cause significant errors in the estimation of design traffic."

"In many locations, truck traffic varies both in number and loading characteristics throughout the year."

Varying the percentage of 3-S2's from the mean percentage on a rural principal arterial in Washington state to the mean plus one standard deviation yielded a change in asphalt overlay thickness, holding volumes and ESAL factors constant, of 0.6". Varying the percentage of 3-S2's from the mean to the mean minus one standard deviation yielded a change of 1.1".

Appendix C of the report illustrates the financial impact of pavement fund misallocation by stating that if each of the 1200 miles of overlay to be constructed in Washington state over the two-year period from 1988 through 1990 was under- or over-designed by 1/4", approximately $6.6 million would be misallocated.

Comments: Note that the costs of misallocation are not necessarily the best measure of the financial impacts of errors in ESAL estimation. While a two inch over- or under-design of a highway could be quite costly, a pavement which is 1/4" too thick or too thin, relative to the actual traffic that passes over it, would not last much longer or shorter than it was designed to last.

In Study VIII above, Basson presents another way to measure the cost of ESAL forecast variability. Basson notes that ESAL errors manifest themselves in the pavement design process as uncertainties. There is uncertainty associated with the base year traffic data and with the growth rates used to generate a 20-year forecast. Using the reliability concept, pavement thicknesses are increased to compensate for these uncertainties. While increases in thickness are appropriate when a designer is given ESAL estimates which are too low, they are inappropriate when the estimates are already too high. In this way, highways which would have been under-designed are brought closer to the correct thickness, but highways which would have been over-designed are further over-designed.

The cost of design ESAL estimation errors using "Basson's formulation" is due to the resulting net over-design of pavements. Basson argues that it is against the net over-design cost created by base year traffic uncertainty that the cost of actually collecting base year traffic data should be weighed.

STUDY XX

Title: An Analysis of Continuously Collected WIM Data from Minnesota

Authors: Curtis Dahlin, Minnesota Department of Transportation, and Paul Harker, Federal Highway Administration.

Publication: Strategic Highway Research Program, March 1989.

Study Objective: To examine the variability of 3-S2 volumes and load equivalency factors.

Methodology: Perform statistical analyses of 3-S2 volumes and load equivalency factors.

Data Used: Continuously collected 3-S2 volume and load equivalency factor data from four permanent WIM sites in Minnesota. Data from one site covered three years and allowed for examination of seasonal patterns over time. Data from another site covered both the right-hand and median lanes at that site allowing comparisons of two lanes in the same direction of travel at that facility. Two of the four sites were interstates with a mix of urban and rural traffic (I-94 and I-494); one was a rural principal arterial (TH 2); and the last was a rural minor arterial (TH 99). By treating data collected in each year, in each direction, and in each lane at a site, as distinct for analysis purposes, the authors generated a total of 10 data sets. These sets are identified in the table below.

Table 12
Data Set Descriptions

Site	Lane #	Description	Year	File Code Name
I-494	1	Right EB	1982	BL182
I-494	1	Right EB	1983	BL183
I-494	1	Right EB	1984	BL184
I-494	2	Left EB	1984	BL284
TH 2	1	Right EB	1984	BM184
TH 2	1	Right EB	1985	BM185
TH 2	3	Right WB	1984	BM384
TH 2	3	Right WB	1985	BM385
TH 99	2	EB	1985	MN285
I-94	1	Right EB	1987	AT187

Findings:

Variability of 3-S2 Volumes: Volume variabilities, for each day of the week, for each data set, as measured by coefficient of variation, are presented in Table 13 below:

Table 13
Coefficient of Variation for Volume by Day of the Week
for Full Years without Holidays

Site Code	Mon	Tue	Wed	Thu	Fri	Sat	Sun
BL184	.13	.12	.13	.12	.13	.18	.12
BL284	.21	.18	.20	.18	.22	.24	.20
BL182	.18	.15	.21	.17	.20	.29	.28
BL183	.17	.16	.14	.18	.17	.19	.16
BM184	.18	.18	.15	.17	.18	.18	.22
BM384	.25	.18	.19	.19	.17	.21	.19
BM185	.19	.23	.23	.22	.17	.20	.28
BM385	.21	.19	.21	.19	.28	.21	.25
MN285	.19	.23	.23	.21	.20	.29	.32
AT187	.09	.10	.10	.08	.12	.12	.11
Average	.180	.172	.179	.171	.184	.211	.213
Range	.09-.25	.10-.23	.10-.23	.08-.22	.12-.28	.12-.29	.11-.32

Variability of 3-S2 Load Equivalency Factors: Load equivalency factor variabilities, for each day of the week, for each data set, as measured by coefficient of variation, are presented in Table 14 below:

(See table on next page)

Table 14
Coefficient of Variation* for ESAL's by Day of the Week
for Full Years without Holidays

Site Code	Mon	Tue	Wed	Thu	Fri	Sat	Sun
BL184	.10	.11	.11	.11	.09	.15	.11
BL284	.16	.20	.17	.18	.20	.21	.16
BL182	.16	.17	.19	.18	.20	.25	.21
BL183	.12	.14	.14	.15	.17	.14	.14
BM184	.12	.13	.15	.14	.13	.18	.10
BM384	.34	.35	.35	.36	.41	.36	.32
BM185	.11	.09	.11	.11	.12	.18	.16
BM385	.27	.25	.25	.28	.25	.25	.21
MN285	.32	.38	.41	.37	.43	.59	.60
AT187	.08	.08	.10	.10	.11	.08	.05
Average	.178	.167	.198	.198	.211	.239	.206
Range	.08-.34	.08-.38	.10-.41	.10-.37	.09-.43	.08-.59	.05-.60

*Coefficient of Variation in average daily ESAL per 3-S2.

Sampling:

1)   The authors found that the range of the 95 percent confidence interval for average daily 3-S2 estimates, at a site, was reduced from ± 20.0 percent to ± 14.9 percent by using 48-hour versus 24-hour counts of that vehicle type.

2)   The authors found that the range of the 95 percent confidence interval for average ESAL per 3-S2 estimates, at a site, was reduced from ± 22.6 percent to ± 15.8 percent by using 48-hour rather than 24-hour weight samples.

Other Findings:

1)   There is significant variation in 3-S2 volumes and average load equivalency factors per vehicle over the seasons at the same site.

2)   These seasonal patterns vary with site location, at the same site from one year to the next, and even from one lane to the next at the same site.

B-48

3) Three-S2 volumes and load equivalency factors were considerably more stable through the year in the right lane than the left, at site BL. This can be seen in Tables 13 and 14 above: data set BL184 is the right lane; BL 284 is the left lane.

4) The average daily weekend 3-S2 volume is considerably lower than the average daily weekday volume. However, the average load equivalency factor per 3-S2 is much higher on the weekend.

STUDY XXI

Title: Improved Prediction of Equivalent Axle Loads

Authors: Wiley D. Cunagin, Texas Transportation Institute.

Publication: Report accepted for publication by U.S. Department of Transportation, Federal Highway Administration, 1991. Permission to quote the report was given by the author, August 6, 1991.

Study Objective: Analyze the ESAL forecasting process including base year volume, classification, and weight data; growth factors; lane and directional distributions; and the pavement design process (the reliability concept, in particular). Examine the sensitivity of pavement design to traffic inputs. Develop an appropriate forecasting procedure.

Methodology and Data Used: Perform statistical analyses on Florida truck volume, classification, and weight data, collected between 1974 and 1984 at 18 permanent WIM stations. Perform statistical analyses on less comprehensive data sets from California, Florida, Iowa, Kentucky, Minnesota, Ohio, Oregon, Pennsylvania, and Washington. Examine the data collection and forecasting procedures of the participating states.

Findings:

"For pavement design purposes it is <u>essential</u> that site-specific weight data be collected" (emphasis added by original author).

"First, the volumes of the heavier truck types are increasing at most sites. Second, the AADT is increasing each year at most sites. Third, the average EAL per vehicle is approximately constant [over time] at most sites. The most important conclusion, however, is that both the absolute values and trends of these variables are very site-specific. There are no apparent trends that can be relied on to provide accurate [estimators] of either trends or absolute values at particular sites based on data from other sites."

"Both AADT and the number of heavy trucks showed clearly increasing trends, although this occurrence varies widely among sites, including those that have apparently similar functional characteristics."

"Specifically, automated vehicle classification and weigh-in-motion WIM technologies offer the opportunity for a quantum jump in the amount of information available about vehicle mix and weight distributions. This will contribute significantly to the accuracy of EAL predictions since greater amounts of more statistically reliable site-specific data can be collected."

"It is clear from the results [of a traffic variance analysis] that the reliability factors are out of the range defined in Appendix EE of the draft AASHTO Guide. Both the means and variances of the traffic factors differ widely. For example, [the results from the Rural Interstate sites are] entirely outside the [range] specified in the AASHTO Guide. These results also suggest that the contribution of the traffic elements to the total variance may be equal to or greater than the variance of the non-traffic elements. The variation in the traffic elements is due principally to the variance of the equivalency values. The proportion attributable to the equivalency factors was greater than 90% at each site. Similar results were found for the Urban Interstate, Primary, and Secondary sites."

"It is clear that this equivalency factor varies significantly even among sites with apparently similar physical and traffic characteristics. It is strongly suggested that site-specific truck weight data be collected for each project under design."

7) "Typically estimating 18 kip equivalents is a function of a 'Traffic Planning' section ... The truck weight data used to make loading estimates are not site-specific. Typically they were collected on similar highways in the same geographic region. However, this assumption can introduce major errors into the 18-kip [ESAL] estimates for a particular pavement section. The data analyzed in this research showed errors in magnitude of 3 or 4 can be introduced with this assumption. It is for this reason it is argued [sic] that site-specific [emphasis added by original author] truck weight data should be collected for pavement design purposes. This service will be cost effective, as errors of the magnitude discussed above can lead to grossly over-designed or under-designed pavements. Furthermore, site-specific design data is routinely collected by several overseas countries. For the past ten years the National Institute of Transportation and Road Research in South Africa has provided WIM services to Highway Departments for major design projects."

Basson's 1972 study in Southern Africa, demonstrating the cost-effectiveness of week-long WIM sessions, is included as Study VIII, above.

APPENDIX C

OTHER STATE PRACTICES

ARIZONA [1,2]

Counting

In addition to operating 35 ATR sites, Arizona conducts semi-annual 24-hour coverage counts at 1,000 sites on the state highway system. In addition, annual 24-hour counts are conducted at 1,000 coverage count sites not on the state system (located in 13 of the 15 different counties in the state). The state now uses Golden River counters, half of which use pneumatic tubes and half, inductive loops.

Classifying

Arizona operates 135 manual classification sites. Vehicles are classified at these sites for three to six hours a day, one day per year. Arizona recently received 30 AVC's to be installed at current ATR sites. The 135 manual sites are distinct from the traffic counting sites.

Weighing

Arizona conducts annual 24-hour weighing sessions at 32 sites using Golden River WIM. Static scales are used by the Department of Public Safety at port-of-entry sites, but the Department of Transportation does not obtain enforcement data from the police.

Data Checks

ATR data are checked by hour and lane against data from the same hour of the year and same lane for the three previous years at the site. The data are checked in an effort to insure that the ATR is operating properly. If a discrepancy (e.g., much higher or lower volume than previously observed[1]) arises, the whole days' data will be checked to see if the hour in question was an anomaly. Maintenance and safety divisions will also be contacted to see if the road was closed for some period of time. If there is still no explanation for the discrepancy, a technician will be dispatched to the site to repair the counter.

WIM equipment is calibrated against a static scale before each session. Trend checks are then performed on the data for Class 9 trucks (these 3-S2's make up 70 percent of the truck traffic) to locate problem equipment.

Forecasting

The traffic group uses a linear regression on AADT to obtain a historical growth

---

[1] No quantitative definition of the term "discrepancy" was available; this is true of the term "discrepancy" throughout this section.

rate. This rate is used to project AADT through the design period; then, forecast AADT is modified using knowledge of the local conditions. The traffic group also generates a D-factor using the 30th highest hourly directional volume. The materials section uses an average of the last five year's truck percentage to get the percent trucks used in the forecast. Currently all lanes are designed to support the load in the heaviest lane, but the state is considering designing the outside lanes of multi-lane facilities for heavier loads and then restricting the trucks to those lanes.

CALIFORNIA [3,4,5,6]

Counting

California operates 7,600 total traffic count stations. These included 100 continuous count stations and 1,500 stations where traffic is counted during quarterly week-long sessions. The remaining stations are counted for either one week every three years or one day every three years. Three out of 12 districts are still using Fisher Porter counters; however, these devices are being phased out. California is now using primarily Saratec counters. The directional distribution of AADT's for count locations is available to data users, but the lane distribution is not available.

Classifying

California classifies vehicles at 3000 sites. Vehicles are classified at each site at least once every three years but sometimes more frequently. Vehicles at urban sites are classified manually for a few hours at a time using a "number of axles" scheme (i.e., 2,3,4,5,>5). Vehicles at rural sites are classified during week-long sessions for 16 to 24 hours each day during the week; these rural sites use road tubes and classify using a 15 vehicle type classification scheme. This is the TMG 13 type scheme but, since class 9 is the most prominent truck type in California, the state divides class 9 into 9 and 14. Class 15 is a default, "none of the above." For FHWA reporting purposes, California combines classes 9 and 14. The state is currently testing several different classifiers at rural sites (the manufacturers represented include IRD, Diamond, Saratec, and PAT).

Weighing

Trucks are weighed at 14 permanent sites and 19 portable sites; 9 of the 19 portable sites are low volume SHRP sites. When a new WIM station is added, trucks are weighed at the site for one week per month during each month of the year. This provides a base measure of the seasonal pattern at the site. After the first year, the site is weighed one week per quarter, 24 hours per day during that week. California uses primarily PAT Bending Plate equipment for high speed weighing; but Saratec low speed (6 to 10 mph) and IRD Hydraulics equipment are used at weigh stations.

Data Checks

Counters and classifiers are checked on site for one hour after being set out to insure that they are functioning properly. Thereafter, hourly count data are plotted and checked against historical data from the site. The data are checked in an effort to insure that the data collection equipment is functioning properly. WIM sites are automatically calibrated once per year but more often when necessary. Calibration is indicated based on trend analyses (typical sample size = 2,000 vehicles) of steering axle weights and/or axle spacings on 3-S2's.

Forecasting

AADT is forecast using a single growth rate for all classes of vehicles. Trucks are required by law to remain in the two outermost lanes of multi-lane facilities; as a result, the two outermost lanes are designed separately from the innermost.

FLORIDA [21,22,23,24]

Counting

Florida operates 100 permanent ATR sites. Vehicles at these sites are counted 365 days per year, 24 hours per day using imbedded loops. Florida takes quarterly 24-hour coverage counts at 7,400 additional locations using junior counters.

Classifying

Florida classifies vehicles at 560 locations; most locations are classified four times per year for 24-continuous hours using portable AVC's (Saratec 241's). Those sites not classified using the AVC's are classified manually four times per year for six hours per session; each session runs from 11 a.m. to 5 p.m. Both the automatic and manual sessions are accomplished using the TMG 13-vehicle type scheme.

Weighing

The Florida WIM program includes seven permanent sites. Trucks at these sites are weighed 365 days per year, 24 hours a day. Florida no longer uses Radian WIM systems because the manufacturer is no longer supporting the equipment. The state now uses PAT permanent equipment which counts, classifies, and weighs. They also have five portable Golden River and five PAT capacitance pads for use at SHRP sites.

Data Checks

Hourly ATR data are checked against the same hour of data from each of the last three years. If discrepancies (e.g., much higher or lower volumes than previously observed)

arise, the whole day's data are examined; if no explanation for the anomalous count is discovered, that data point is thrown out. Seasonal counts are also checked against history at the site and against local ATR results. Portable automatic vehicle classifiers (PAVC's) are checked visually when set out and then afterwards if "unrealistic" trends appear. WIM data (speed, axle spacing, and axle weight) are checked against preset limits to insure "reasonableness."

Forecasting

AADT and percent trucks are forecast using a historical growth rate. This growth rate is based on the stable portion of the past 10 years of traffic history at or near the project site. The projections are made assuming a compound rate of growth for the first 10 years of the forecast period and a linear rate thereafter. The forecast is modified to account for the geometric capacity of the highway and for the predicted impacts of other highway work in the area. The ESAL factor used will generally be a projection of the current factor (one factor for all truck types). This factor is based on engineering judgment. The state does not design different pavement layer thicknesses based on directional split unless the truck traffic at the site runs almost exclusively loaded in one direction and unloaded in the other. The state uses a preset distribution of AADT among the lanes and does not design each lane separately.

OREGON [25,26,27,28]

Counting

Oregon counts traffic at 14,067 total sites; these include 115 ATR's, 6140 primary and secondary sites, 1,652 ramps, and 4,290 county sites. Permanent sites are monitored using Saratec Trafi-COMP III's while non-continuous sites are counted using portable K-Hills. Lane and directional counts are accomplished using loops. Each of five regions in the state takes its own counts and sends these to the planning section for processing. The ATR sites are operated 365 days per year 24 hours per day while all other sites are counted for 24-continuous hours every other year.

Classifying

Oregon classifies vehicles at 418 sites including 115 ATR sites, 120 project stations, and 183 other sites. All classifying is done manually (using tally boards) except for sites where WIM equipment with classifying capability (Saratec Trafi-COMP III) is in place. The classification scheme distinguishes vehicles based on number of axles, log truck or not, and in or out of state. The ATR sites are classified during one weekday every three years. The manual classifying sessions run for 16 to 24 hours per day.

Weighing

The current weighing program consists of 95 sites including 62 scale houses, 5 semi-portable scales, 25 pits, and 3 WIM systems; 4 new WIM sites are being added. Equipment used includes weigh stations, portable static scales, and WIM equipment from CMI-IRD Hydraulics and PAT Equipment. Scale houses run 190 days per year on a random schedule; port-of-entry sites operate 363 days per year; WIM sites run 365 days per year.

Data Checks

Hourly count data are checked against historical data. If discrepancies (e.g., much higher or lower volumes than previously observed) occur, the central processing office will contact the local office from which the data came to determine whether there were any special circumstances which would account for the anomaly. If no explanation is plausible, an equipment check is indicated. Classification equipment is checked using periodic one-hour sampling during which the machine is checked against a manual count (tolerance = ±5 percent). WIM data are checked against data from nearby static scales.

Forecasting

AADT is projected using one historical growth rate for all vehicle classes at a given site and then is modified using professional judgment. Lane and directional distributions are not used in forecasting. Designers are currently using ESAL factors from the 1979 truck weight study but are conducting a new study using the WIM equipment and will be going to the updated factors soon.

WISCONSIN [11,35,36,37]

Counting

The Wisconsin counting program includes 20,000 total sites; however, vehicles are counted at only 6,700 of these sites per year. The state currently operates 66 ATR sites and 3,260 HPMS sample sections. Coverage counts are 48 hours long; possible count days are limited to Monday, Tuesday, Wednesday, and Thursday. The equipment used includes aging Saratec counters and miscellaneous other brands; these are being replaced by Saratec Trafi-COMP III's. SHRP sites have been integrated into the regular traffic counting program and are counted during semi-annual week-long sessions.

Classifying

Wisconsin is overhauling its classification program. The new program involves classifying vehicles at a site for seven consecutive days every four to ten times the site is counted in order to obtain a database to use in designing a classification program. The state uses the FHWA 13 vehicle type scheme. The state is using Saratec Trafi-COMP III's.

Weighing

Trucks are weighed at a total of 69 sites but at only 23 sites each year. Two of the 23 sites per year are control sites; these operate for three week-long sessions during the year. Trucks at the other 21 sites are weighed during one 48-hour session per year. Possible weighing days at the 48-hour sites are limited to Monday, Tuesday, Wednesday, and Thursday. The traffic data collection group uses portable WIM systems from Saratec and PAT.

Data Checks

Count and classification data are checked against historical records from the site and against data from other points on the same facility. If discrepancies (e.g., much higher or lower volumes than previously observed) arise, the equipment is checked, and a recount is taken. The first and last partial hours of WIM data from each session are generally thrown out so that what remains are complete hourly measurements.

Forecasting

AADT is forecast using one growth rate for all classes. The state currently uses a either a 60/40 or 50/50 directional split; the distribution of traffic across lanes is based on AADT and number of lanes at the site.

REFERENCES

[1]   Gastelum, Al, Arizona DOT, (602) 255-7835, Telephone interview to discuss pavement and materials.

[2]   Green, Ed, Arizona DOT, (602) 255-7893, Telephone interview to discuss traffic data collection and forecasting.

[3]   Archuleta, Koney, California DOT (916) 323-4361, Telephone interview to discuss weigh-in-motion.

[4]   Copeland, Craig, California DOT (916) 327-2916, Telephone interview to discuss weigh-in-motion.

[5]   Stoker, Emory, California DOT (916) 445-5163, Telephone interview to discuss traffic counting and classifying.

[6]   Van Berkel, John, California DOT (916) 445-5851, Telephone interview to discuss weigh-in-motion and forecasting.

[7]   Brown, Molder, Florida DOT, (904) 488-4111, Telephone interview to discuss weigh-in-motion.

[8]   Florida DOT, "DESIGN TRAFFIC (TRAFFIC FORECASTING AND 18 KIP EQUIVALENT SINGLE AXLE LOAD)," Tallahassee, Florida, October 1989.

[9]   Reel, Rick, Florida DOT, (904) 488-4111, Telephone interview to discuss traffic counting and classifying.

[10] Smith, Jim, Florida DOT, (904) 488-4640, Telephone interview to discuss design traffic.

[11] Apple, Linda, Oregon DOT (503) 378-4083, Telephone interview to discuss weigh-in-motion.

[12] San, Ken, Oregon DOT (503) 373-7099, Telephone interview to discuss traffic data collection and analysis.

[13] Tabery, Vernon, Oregon DOT (503) 373-7098, Telephone interview to discuss traffic data collection and analysis.

[14] Tabery, Vernon, Oregon DOT, written response to questions regarding Oregon practice in forecasting heavy truck volumes.

[15]   Aunet, B.A., "A Statewide Traffic Counting Program for the Wisconsin Department of Transportation," for Wisconsin DOT, Madison, Wisconsin, January 1989.

[16]   Novenski, George, Wisconsin DOT (608) 266-0169, Telephone interview to discuss traffic counting, classifying, and weighing.

[17]   Stein, Paul, Wisconsin DOT (608) 266-1010, Personal interview to discuss all aspects of traffic data collection and forecasting.