A METHODOLOGY FOR OBTAINING TRAFFIC DATA INPUT TO THE NCHRP 1-37A PDG

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TO THE NCHRP 1-37A PDG

Abstract

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Traffic loading is an essential input to the pavement analysis and design process because it significantly affects pavement performance. Therefore, it is important to predict it accurately over the life of pavements. This is specially challenging, given the limited information available at design time. The NCHRP 1-37A Pavement Design Guide (PDG) uses mechanistic-empirical relationships to predict pavement performance. Traffic input is in terms of axle loading, axle configuration, and number of axle passes. Traffic loading induced pavement damage accumulation depends on the mechanical properties of the layers, which are affected by environmental conditions (e.g. temperature, humidity), which vary with time. Therefore, the temporal variation in traffic loading parameters needs to be specified.

This thesis addresses two objectives, which are addressed by extracting and analyzing data from Long Term Pavement Performance database (LTPP). The first objective is to develop a methodology for computing the traffic data input necessary to the new PDG. User-friendly software *TI-PG* is developed to generate traffic input to the PDG. *TI-PG* uses daily traffic volume or axle passes as data sources to compute the traffic input elements. The daily data can be continuous over extended periods of time or discontinuous for short time spans. Site-specific

or Regional data sets are combined for these computations. The general data storage file in *Microsoft Access*^{TM} Table format is used as input. Site-specific or Regional traffic information can be computed for different purposes.

The second objective is to document the extent of variation in traffic input as a function of the traffic data collection scenario. Seventeen traffic data collection scenarios are simulated using daily WIM (Weigh In Motion) data from the LTPP database. For each scenario, 30 sites are used for the simulation. Statistical analyses are performed for the main traffic input elements for the PDG. Results show that for traffic volume estimation, one month per season and one week per season of site-specific truck class data show similar accuracy in predicting AADTT (Annual Average Daily Truck Traffic) and MAF (Monthly Adjustment Factors). Site-specific truck class data collected periodically (monthly or seasonally) is very important for AADTT estimation. For axle loading information, one month per season site-specific data has much better accuracy than one week per season site-specific data. It is concluded that the length of data coverage can improve the quality of the axle load distribution estimation.

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CHAPTER ONE

INTRODUCTION

1.1 Background-Objectives

Traffic loading is the most direct factor affecting pavement performance. As the future traffic information is not available at the time pavement is being constructed, the accurate prediction of traffic loading will be very important for the design of pavement. The main attributes of traffic loading affecting pavement performance are the number of axles passing and their axle loading by axle configuration.

The traditional pavement design method uses an equivalent number of standard single axle loads (ESAL) to index traffic-associated pavement damage to a reference load of 18,000 lbs (80 kN) [1]. ESALs were subsequently used in empirical performance equations for design purposes. The new Pavement Design Guide (PDG) [13] uses mechanistic-empirical relationships for predicting performance. This requires computing the pavement structural responses to loading (i.e., stresses and strains), translating them into damage, and accumulating the damage into distress and reduced pavement performance over time. Traffic input is in terms of axle loading, axle configuration, and number of axle passing. The traffic input elements for PDG include the annual average daily truck traffic (AADTT), the vehicle classification (VC), the number of axles per truck type by configuration, the monthly adjustment factors (MAF) and the axle load distribution. Pavement damage accumulation depends on the mechanical properties of the layers, which are affected by environmental conditions (e.g., temperature, humidity), which vary with time. Therefore, the temporal variation of traffic load parameters needs to be specified. The new PDG allows specifying monthly truck traffic volumes by vehicle class. In addition, it allows specifying an hourly distribution of vehicles within the typical day of the month, which is the same for all months.

The Federal Highway Administration (FHWA) distinguishes 13 vehicles classes as a function of their body type and axle configuration (i.e., singles, tandems, tridems and quads) [12]. Pavement design is concerned with truck axles only (i.e., FHWA vehicle classes 4 to 13), since lighter axles cause negligible damage.

Traffic data for pavement design purposes is collected via 3 types of equipment. They are continuous weigh-in-motion (WIM), automated vehicle classification (AVC) and automated traffic recorder (ATR) system. WIM can collect continuous data about truck type, each axle weight, and number of axles for each vehicle passing. WIM equipments are permanent but are costly to acquire and maintain. AVC equipment can collect traffic volume and vehicle class, while ATR equipment can only collect traffic volume (i.e., count) data. If the road being constructed has no WIM data, the axle load distribution data from similar types of road or regional average or national average is used to estimate the axle loads. Another use of continuous WIM data is to simulate and check the accuracy of traffic data predictions from short time data counts. This is particularly useful in some regions, where only short time traffic data information is available.

The data coverage of traffic data acquisition systems can vary widely from continuously operating to simple 48-hour data coverage. Even for continuously operating data acquisition systems however, data coverage may be limited by system malfunctions. These are detected by performing a number of data quality control (QC) checks. They are based on the consistency in traffic patterns (e.g., the distribution of the gross vehicle weight of 5-axle semi-trailer trucks) [12]. Hence, there is a wide variation in traffic data availability and time coverage between pavement design sites. This variation in traffic data coverage affects the traffic data input to the pavement design process, which involves temporal accumulation of damage. As a result, it significantly influences pavement life predictions.

This thesis has two objectives. The first objective is to develop a methodology for computing the traffic data input necessary to the new PDG. This is possible by utilizing traffic data from various data acquisition technologies (i.e., WIM, AVC and ATR) and time coverage. A number of data acquisition scenarios are identified for this purpose, which is compatible with the four levels of traffic data input identified by the PDG. The second objective is to document the extent of variation in traffic input as a function of the traffic data collection scenario. This is possible by analyzing extended-coverage site-specific WIM data from the LTPP database and by considering all possible time coverage combinations. This information could be used by designers to evaluate the possible errors in obtaining these data elements by traffic data collection scenario.

The work documented in this thesis is part of a broader study dealing with traffic data collection requirements for specific pavement design applications [11]. The traffic data used for the statistical analysis is from the Long Term Pavement Performance (LTPP) database [8]. The LTPP program, initiated in 1987, has created the largest pavement performance database. With more than 2000 test sections on in-service highways at over 900 locations throughout North America, it provides an extensive database, including pavement structural information, materials information, environmental information, traffic data and so on. Data are collected through cooperative efforts of the agencies that own the pavements and the LTPP program organization. The data is housed in an information management system (IMS) that provides a unique tool for pavement related research and product development. The data are subject to an extensive series of quality control checks before being made available to the public. The data analyzed in this thesis is extracted from this database. Subsequent statistical analysis is based on these sample traffic data. The LTPP database provides comprehensive information on historical and current pavement performance data. This huge database stores traffic, environmental and materials data related to pavement design, construction, or material testing. In the traffic data module, five different levels of data are provided. The levels represent different detailed information about traffic data. Level 3 data source is what is used for this study. The level 3 data in CTDB (Central Traffic Database) contains daily summaries of traffic loading information, which includes daily volume totals, daily volume totals by vehicle class and daily axle load distributions by vehicle class.

1.2 Thesis Organization

Chapter 2 provides the literature review. Chapter 3 describes the traffic data collection scenarios simulated. Chapter 4 provides a detailed description of the data source used to create traffic input for PDG. Chapter 5 is a manual for the software that implements the methodology. Chapters 6 and 7 introduce the analysis results and final conclusions, respectively.

CHAPTER TWO

LITERATURE REVIEW

2.1 NCHRP 1-37A Study

NCHRP 1-37A [13] is the study that led to the development of the new PDG. Its documentation gives a detailed description of the traffic data needed for pavement design. The mechanistic pavement damage computations in the PDG require detailed traffic loading data in the form of axle load spectra, which is defined as the number of axle passes by load level and axle configuration. In practice, this axle load spectra information is obtained by combining data from WIM, AVC and ATR systems, from either the specific pavement site or from other regional/representative traffic data collection sites. The source of data used in compiling the load spectra defines the traffic level input to the PDG (Table 1).

Table 1: Traffic Input Levels in the PDG [11]

Data Element/Input Variables	Traffic Input Levels			
	1	2	3	4
WIM Data – Site/Segment Specific	x			
WIM Data – Regional Representative Weight Data		x	x	
AVC Data – Site/Segment Specific	x	x		
AVC Data – Regional Representative Truck Volume Data			x	
ATR– Site Specific			x	x

The time accumulation damage models in the PDG require time dependent traffic loading information. The mechanical behavior of pavements changes in response to the temperature variations within the day and the season. At the same time, traffic loading changes within the day due to the hourly distribution of traffic. Traffic loading is also changing from season to season due to different traffic characteristics. The combination of the environmental changes and traffic loading changes leads to the temporal accumulation of damage. For the traffic loading, the PDG uses the following factors to express the time dependent nature of traffic loading: Monthly distribution factors (MAF), Hourly distribution factors and Annual growth rate. The axle load spectra information in the PDG is input using four main modules:

1. Traffic Volume:
    - Annual average two-directional, multi-lane daily truck traffic (AADTT, i.e., FHWA classes 4 to 13)
    - Percent trucks in the design direction
    - Percent trucks in the design lane
    - Truck class distribution, defined in terms of the percentage of the traffic volume by vehicle class (4 to 13).
2. Traffic Volume Adjustment Factors:
    - Monthly adjustments factors (MAF) for each month per truck class (i.e., FHWA classes 4 to 13) with a default of 1.00.
    - Hourly frequency distribution.
    - Annual traffic growth rate by vehicle class.
3. Axle Load Distribution Factors:

- Load frequency distribution (i.e., percent of axles by load level), by axle configuration, by month and by truck class.

4. General Traffic Input:
    - Number of axles by axle configuration and truck class.
    - Axle/tire configuration, spacing and tire inflation pressure.
    - Wheel base data.

The procedure used to generate the traffic loading spectra includes:

1. Multiplying the two way AADTT by the percent truck in the direction.
2. Multiplying the directional AADTT by the percent trucks in the design lane.
3. Multiplying the design lane AADTT by the class distribution.
4. Computing the future design lane AADTT by class by multiplying by the growth rate.
5. Multiplying the AADTT by MAF to compute monthly traffic volumes , AADTTi.
6. Multiplying AATDDi by the Hourly Distribution Factors to obtain the vehicle classification counts for a specific hour and month within one year.
7. For each axle configuration (Single, Tandem, Tridem, Quad), multiplying the vehicle classification counts for a specific time interval described above with the number of axles per truck class to obtain the average number of axle passes for a specific vehicle class and axle configuration at certain time range, such as hourly average, daily average per month or annual average or total number of axle passes.
8. Multiplying the number of axle passes computed above with the normalized axle load distribution factors (axle load distribution frequencies) to finally obtain the number of axle passes for a specific load level, vehicle classification and axle configuration over a certain time interval (i.e., the axle load spectra).

A summary of the traffic input components, the size of the associated data tables and the flow of calculations in the NCHRP 1-37A Design Guide is given in Table 2. It should be noted that no differentiation is made in traffic volumes by the DOW (Day of Week) within each month.

Table 2: NCHRP 1-37A Design Guide Flow of Calculations in Assembling Axle Load Spectra [11]

Traffic Input Component	Main Data Element	Input Array Size	Calculation and Result
1	Average annual daily trucks traffic in the design lane	1	-
2	Distribution of trucks by class (i.e., FHWA 4-13).	1x10	1*2 = annual average daily number of trucks by class
3	Monthly adjustment factors (MAF) by truck class	12x10	1*2*3 = adjusted average daily number of trucks by class, by month
4	Number of axles by axle configuration, (single, tandem, triple, quad) by truck class	4x10	1*2*3*4 = average number of axles by axle configuration, by month
5	Load frequency distribution (%) by axle configuration, by month, by truck class	4x12x10x41	1*2*3*4*5 = number of axles by load range, by axle configuration, by month

2.2 Traffic Monitoring Guide

The Traffic Monitoring Guide (TMG) (2001) [12] is the main reference for computing traffic parameters. It recommends using the following formula for estimating Annual Average Daily Traffic (AADT):

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

Where:

VOL_{ijk} = daily traffic volume for day k in day of week i and month j.

i = day of week(DOW) ranging from 1 to 7 (i.e., Monday to Sunday).

j = month of the year ranging from 1 to 12 (i.e., January to December).

n = total number of data days for a particular day of week i in month j.

This approach limits the bias that will result from simply averaging traffic volumes for the days of the year available. In implementing this approach, holidays and the days that precede and follow them should be excluded. The TMG also recommends an averaging procedure for estimating missing traffic volume data. If the traffic volume for a Wednesday is missing, for example, it can be estimated as being equal to the average of the available traffic volumes for the other Wednesdays in a particular month. Similarly, estimating missing vehicle classification data involves averaging the volume counts by class or groups of similar classes for the same days in the month. Furthermore, missing WIM data can be estimated from the vehicle classification data thus obtained and the frequency distribution of axle loads by axle configuration available for the same day(s) of the month.

For short duration traffic data, the TMG recommends using time dependent factors, such as seasonal factors, day of week factors (DOW) and time of day factors (TOD), to adjust the collected data for computing AADT. These factors are obtained from a similar group of continuous data sites.

Automated vehicle classification (AVC) counts are obtained following principals similar to those used for collecting truck volume (ATR) counts. The main difference is that seasonal traffic volume adjustment factors (i.e., monthly and daily) are developed for 3 or 4 broad vehicle classes (e.g., passenger cars, single unit trucks, single trailer trucks and multi-trailer trucks), rather than for all vehicles collectively. This is one of the major differences of the 2001 version of the TMG compared to earlier TMG versions (i.e., 1992 and 1995) and it was introduced to account for the seasonal variation in traffic volume patterns of various classes. These seasonal factors are developed by analyzing data from continuously operating reference AVC stations representing the traffic conditions of the selected roadway groups. These groups can be established subjectively, (e.g., based on roadway functional class), or through clustering techniques.

The Annual Average Daily Truck Traffic (AADTT) for specific vehicle class is computed in the same way as AADT as follows:

$$AADTT_c = \frac{1}{7}\sum_{i=1}^{7}\left[\frac{1}{12}\sum_{j=1}^{12}\left(\frac{1}{n}\sum_{k=1}^{n} AADTT_{ijkc}\right)\right] \tag{2}$$

where:

$AADTT_{ijkc}$ = daily traffic volume for truck class c, for day k of DOW i and month j.

i = DOW ranging from 1 to 7, (i.e., Monday to Sunday).

j = month of the year ranging from 1 to 12, (i.e., January to December).

n = number of times data from a particular DOW is available for computing the average in a given month, (i.e., 1, 2, 3, 4 or 5).

For axle load data, TMG recommends establishing truck weight groups to estimate axle load distribution for those sites that do not have WIM data. The truck weight group can be classified as heavily loaded, medium loaded and lightly loaded.

2.3 Cambridge Systematics Study

A FHWA-funded study conducted by Cambridge Systematics [2] shows the sensitivity of the computed statistics to various simulated sampling schemes and factoring procedures. Seven factoring procedures are described for computing AADT from ATR (i.e., vehicle count) data, which are listed in Table 3 in order of increasing accuracy and complexity.

Table 3: Accuracy of AADT Predictions as a Function of Factoring Procedure [2]

No	Factoring Procedure	Involves	Mean Absolute Error	Average % Error	P(e>0.2)
0	Unfactored	-	12.4%	-0.6%	18.2%
1	Separate month and DOW (MDW)	Set of 12 monthly factors and another set of 7 DOW factors (total of 19)	7.5%	-0.5%	6.2%
2	Combined month and average weekday (CMAWD)	Set of average weekday and average weekend factor for each month (total of 24)	7.6%	+0.4%	5.9%
3	Separate week and DOW (SWDW)	Set of 52 weekly factors and another set of 7 DOW factors (total of 59)	7.5%	-0.9%	6.0%
4	Combined month and DOW (CMDW)	Set of 7 DOW factors for each month (total of 84)	7.4%	-0.2%	5.8%
5	Combined week and average weekday (CWAWD)	Set of average weekday and weekend factors for each week of year (total of 104)	7.3%	+0.5%	5.1%
6	Specific day, (SD)	Set of day factors for each day, (midnight-to-midnight) of the year (total of 365)	7.1%	+0.2%	5.1%
7	Specific day with noon-to-noon factors (SDNN)	Similar to the one above, except counts are noon-to-noon.	7.0%	+0.3%	4.8%

This study recommended that procedure 4, (i.e., the CMDW method highlighted above) is a good compromise between accuracy and complexity, (i.e., this is the same method recommended by the 2001 TMG). Accordingly, the factor for the combined monthly and DOW factor for month i and DOW j at ATR station l, denoted by $CMDWF_{ijl}$, is given by:

$$CMDWF_{ijl} = \frac{AADT_l}{MADW_{ijl}} \tag{3}$$

where, $MADW_{ijl}$ = average traffic volume for month i and DOW j at station l. In applying this procedure, it is recommended to exclude weekdays close to holidays, although these days should be included in computing the AADT.

2.4 NCHRP Study 1-39

NCHRP Study 1-39 [3] developed a methodology for processing the output of a combination of AVC and WIM systems in a jurisdiction to synthesize the axle load spectra input to the PDG for a particular pavement design site. This methodology relies on factoring the available traffic data at that site using the temporal axle load and vehicle classification distribution patterns from similar sites in the jurisdiction (e.g., State), as prescribed by the 2001 TMG (12). The type of technology (i.e., AVC and WIM) and the length of coverage involved at these traffic data collection sites define the level of traffic input. This methodology is implemented in a software package called *TrafLoad.* The input of *TrafLoad* is in terms of the standardized output of AVC and WIM systems (12), namely the hourly summary C Records or 4 Cards and the individual vehicle W Records or 7 Cards, respectively. In addition, the user needs to input:

The vehicle classification scheme in the jurisdiction (i.e., the 13 FHWA classes or other).

- Any aggregation of these vehicle classes.
- Grouping of traffic data sites in the jurisdiction with respect to vehicle classification distributions (e.g., the 17 Truck Traffic Classes (TTC) distinguished in the PDG).
- Grouping of traffic data sites with respect to axle load distributions (e.g., Truck Weight Road Groups (TWRGs) based on actual indicators of roadway loading or functional class).

Seasonal load spectra by either month or by month and DOW is used in factoring incomplete sets of load spectra. It should be noted that some of these inputs, such as the site grouping and the seasonal load spectra computations, might require considerable pre-processing of the available WIM and AVC data, prior to running *TrafLoad.*

TrafLoad distinguishes several levels of traffic input, depending on the load and classification data available at a particular pavement design site/lane. In terms of WIM data availability, these pavement design levels are:

- Level 1: Site-specific high quality WIM data over periods of time "sufficient" to estimate monthly or monthly-DOW load spectra at the site/design lane (i.e., 12 sets or 12x7=84 sets). Where partial sets of WIM data are available (e.g., missing DOW or months), *TrafLoad* estimates them through factoring using index that is related with ESALs.
- Level 2: No site-specific WIM data is available, however the site can be "clearly" assigned to a TWRG for which Level 1 WIM data is available.
- Level 3: No site-specific WIM data is available and the site cannot be clearly assigned to a TWRG. In such cases, jurisdiction-wide averages of load spectra need to be used.

For complete year-long Level 1 WIM data, *TrafLoad* produces all the necessary input to the PDG. For incomplete Level 1 WIM data, *TrafLoad* uses DOW and monthly factor ratios based on complete Level 1 WIM sites belonging to the same TWRG. This is done in terms of the pavement damage impacted by each vehicle class, month and DOW as indexed by the average ESALs per vehicle (*AEPV*).

In terms of AVC data availability, *TrafLoad* distinguishes the following levels:

- Level 1: Continuous AVC data is available for at least 1 week for each of 12 months in a year. This level is further subdivided into 1A and 1B, for site-specific AVC data and adjacent site/same route AVC data, respectively.
- Level 2A: Sites for which continuous AVC counts are available over a period of at least 48 weekday hours.
- Level 2B: Sites where continuous manual vehicle classification counts are available over a period of at least 6 weekday hours.
- Level 3A: Sites where only site-specific vehicle count data is available, (i.e., no vehicle classification data is available).
- Level 3B: Other.

TrafLoad processes the AVC data from Level 1A sites to establish monthly, daily and hourly trends in vehicle classification counts. This is done in the following sequence:

- For each vehicle class i and lane l, the average hourly vehicle count is computed for each month and DOW (i.e., total of 12x7x24=2016 average hourly counts per vehicle class).
- The monthly average DOW volumes ($MADW_{il}$) are computed by summing the hourly volumes within each DOW by vehicle class by month.
- The annual average DOW ($AADW_{il}$) is computed by averaging the $MADW_{il}$ values for 12 consecutive months.
- The annual average daily traffic for vehicle class i and lane l ($AADT_{il}$) is computed by averaging the 7 $AADW_{il}$, values computed above.

This information serves two functions, namely contributes input to the PDG for analyzing the particular pavement site and provides traffic distribution trends for factoring data from similar sites with lesser AVC information (i.e., AVC sites 1B, 2 and 3).

2.5 Optimization of Traffic Data Collection Study

A FHWA funded Study entitled: "Optimization of Traffic Data Collection for Specific Pavement Design Applications" [11], presents a comprehensive approach for establishing the minimum traffic data collection effort required for pavement design applications satisfying a maximum acceptable error under a prescribed confidence level. This approach consists of simulating the traffic data input to the new NCHRP 1-37A Design Guide for 17 distinct traffic data collection scenarios using extended coverage weigh-in-motion (WIM) data from the Long Term Pavement Performance (LTPP) database. This simulation involves data typically collected by other technologies, such as automated vehicle classifiers (AVC) and automated traffic recorders (ATR).

Extended coverage is defined as 299 or more days per year of Level E WIM data, (i.e., data that has passed the quality control checks conducted by State Dept. of Transportation and the LTPP Regional Coordinating Offices). Analysis of DataPave release 16.0 reveals a total of 178 General Pavement Sites (GPS) satisfying this requirement. For all these sites, Central Traffic Database (CTDB) data are extracted in the form of daily summaries, (i.e., level 3). Form these sites, a total of 30, (i.e., 15 flexible and 15 rigid), are selected for NCHRP 1-37A Design Guide simulation. The selection is based on the widest possible distribution of Annual Average Daily Truck Traffic (AADTT) volumes and structural thickness.

A number of the traffic data collection scenarios simulated involve continuous site-specific data coverage for axle loads, classification or counts, while others involve discontinuous site specific data coverage, (e.g., 1 month per season, 1 week per season and so on). Data elements, which are assumed to be unavailable at a site for simulation purposes, are estimated from regional data. Regional vehicle classification and load data are obtained from the remaining LTPP sites identified using clustering techniques. Scenarios involving national data utilize the default traffic input in the NCHRP 1-37A Design Guide. For each of the traffic data collection scenarios involving discontinuous coverage of site-specific data, statistics for each traffic data element are computed, by considering all possible time coverage combinations. This allows establishing low percentiles for each of these inputs to simulate underestimation of the actual traffic volumes/loads at a site. This is considered as critical, since it will result in thinner pavement designs that fail prematurely. Three confidence levels are selected, namely 75%, 85% and 95%. Traffic input for the continuous coverage traffic data collection scenarios involve no variation due to the sampling scheme used.

The NCHRP 1-37A Design Guide pavement life predictions for each scenario are analyzed to compute percent errors in pavement life predictions with respect to the life predictions obtained under continuous site-specific WIM data. Results provide reliability information in predicting pavement design life using different traffic data resources. (Table 4)

Table 4: Range in Combined Life Prediction Errors From Low Percentile Traffic Input [11]

	Overall Range in Errors by Probability of Exceeding Them:		
Scenario	**25%**	**15%**	**5%**
1-1	20.89%	27.45%	41.57%
1-2	28.59%	35.91%	55.81%
2-0	10.74%	16.65%	27.08%
2-1	34.70%	42.65%	58.96%
2-2	23.79%	36.55%	44.31%
2-3	37.24%	51.79%	89.88%
3-0	25.29%	39.22%	63.78%
3-1	30.07%	45.78%	74.02%
4-0	27.08%	41.99%	68.29%
4-1	32.14%	47.47%	76.75%
4-2	47.22%	72.55%	105.66%
4-3	63.66%	92.44%	151.79%
4-4	30.17%	46.78%	76.08%
4-5	35.36%	54.36%	86.77%
4-6	70.17%	112.32%	174.65%
4-7	83.84%	139.25%	206.75%

CHAPTER THREE

TRAFFIC DATA COLLECTION SCENARIO DESCRIPTION

3.1 Introduction

A number of traffic data collection scenarios are identified in terms of the combination of traffic data acquisition technology involved and the length of data coverage, (Table 5). It should be noted that these scenarios are extensions of the four traffic input levels identified by the PDG (Table 1). They are defined by the combination of traffic data collection technologies involved and the length of data coverage of the site-specific data.

Table 5: Selected Traffic Data Collection Scenarios [11]

PDG Traffic Input Level	Traffic Data Source	Time Coverage of SS Data over one Year Period	Scenario ID
1	**WIM Data = SS**	Continuous	1-0
	AVC Data = R	1 month/4 seasons	1-1
		1 week/4 seasons	1-2
2	WIM Data = R	Continuous	2-0
	AVC Data = SS	1 month/4 seasons	2-1
		1 week/4 seasons	2-2
		1 week	2-3
3	WIM Data = R	Continuous	3-0
	AVC Data = R	1 month/4 seasons	3-1
	ATR Data = SS		-
4	WIM Data = N	Continuous	4-0
	AVC Data = R	1 week/4 seasons	4-1
	ATR Data = SS	1 week	4-2
		1 weekday+1 weekend day	4-3
	WIM Data = N	Continuous	4-4
	AVC Data = N	1 week/4 seasons	4-5
	ATR Data = SS	1 week	4-6
		1 weekday+1 weekend day	4-7

SS=Site Specific, R=Regional, N=National (PDG defaults)

The traffic data collection scenarios identified are simulated using extended coverage WIM data from the LTPP database. WIM data includes all the information that AVC and ATR systems collect. As a result, WIM data tables can be used to simulate data collection scenarios involving AVC and ATR data. Thirty sites with more than 299 days of WIM data per year are obtained from the LTPP database to conduct this simulation. In addition, another 148 extended coverage WIM sites from the LTPP database are used to obtain regional traffic data groups for simulation purposes. Sets of regional factor groups are developed for truck class distributions and axle load distributions. For the latter, only tandem axles are considered. Each of the 30 simulated sites is assigned to one of these regional groups. This grouping is established using clustering techniques [11].

There is a special problem involved in simulating ATR data, due to the lack of light vehicle data in the WIM databases extracted, (i.e., vehicle classes 1 to 3 are not recorded). To circumvent this problem, the percentage of trucks is assumed equal to the average percentage of trucks from the regional AVC dataset for each site.

From each WIM site, two data tables are extracted for the analysis:

- The first table involves daily volume data, (i.e., class data). This data table includes the daily traffic volume for each FHWA vehicle class. It is used to compute the annual average daily truck traffic (AADTT), monthly adjustment factors (MAFs), DOW distribution factors and class distribution factors for each site of each year. This data table is used to simulate the site-specific AVC data and the ATR data.
- The second table involves axle counts by type and load, (i.e., weight data). It includes the daily axle passes for each axle group of each vehicle class. It is used to compute the monthly-normalized axle distribution for each site of each year.

Simulation of the data collection scenarios identified above is conducted for each of the selected 30 sites. The regional data sets established from cluster analysis are used to adjust the simulated short term traffic data sampling [14].

3.2 Principle/Assumptions for Processing Daily WIM Data

The data extracted from the LTPP database covers more than 299 days per year. As a result, a number of data days may be missing for a particular site. These missing data days may be the result of temporary equipment malfunction or could have been eliminated during data quality control. Nevertheless, this data is sufficient for obtaining the traffic input to the PDG, following the Traffic Monitoring Guide [12] procedure, which is given by Equation 1.

To explain how this is done, a number of variables are defined:

- Average monthly day-of-week traffic volumes are obtained by averaging the data in the same day of week for each month (e.g., Monday's data in January).
- Monthly average: for each month, all available Monthly day-of-week averages are averaged to get monthly averaged data.
- Annual average (AADTT): for each data year, all available Monthly averages are averaged to get annual averaged data (equation 2).
- MAF is the ratio of monthly average over annual average traffic volume data for each class [13]:

$$MAFi = \frac{AADTTi}{AADTT} \qquad (4)$$

Where:

MAFi = monthly adjustment factor for month i;

AADTTi = AADTT for month i;

The sum of the *MAFi* for all 12 months must equal to 12.

Where entire months or DOW per month are missing, they are computed from the available data using the following assumptions:

- Where one or several months of data are entirely missing, they are assumed equal to the average of the monthly data for the months available.
- Where one or several data from all the same day of week (such as that all Monday's data is missing) in one month is missing, the average of Monthly day-of-week average from other day of week in this month represents the missing day of week's data.

3.3 Scenario 1-0: (SS Continuous WIM data):

This scenario represents the most complete traffic data set for generating input to the PDG and hence, it is defined as the "truth" in traffic data. Obviously Scenario 1-0 has only one time coverage combination since it uses continuous data. For the 30 sites analyzed, WIM data coverage ranges from more than 299 days per year to more than 359 days per year. The 5 traffic data input components to the PDG are computed as follows:

Components 1, 2 and 3 of the PDG Input (AADTT, Truck Class Distribution and MAFs)

- For each month and DOW, sum up the number of trucks by class.
- Divide each sum by the number of days of data computed above, to obtain the average number of daily vehicle passes by truck class, per DOW and month.
- Average the number of trucks by class for the 7 DOWs to obtain the monthly average number of trucks by class per month.
- Average the number of trucks for the 12 months to obtain AADTT by trucks class.

- Translate these average values into frequencies (percent) to get normalized vehicle classification (Truck Class Distribution).
- Add the number of trucks for all classes to obtain AADTT.
- MAFs by truck class are ratios of monthly average number of trucks per month over AADTT by class (Equation 4).

Component 5 of the PDG Input (Axle Load Distributions):

- Browse the daily summary data table to obtain the number of days per DOW (from Sunday to Saturday) for each month that has traffic records.
- For each month and DOW, sum up the axle passes per truck class, for each axle type and each load bin.
- Divide each sum by the number of data days computed above, to obtain the average number of daily axle passes per bin, per axle type, per truck class for each DOW and month.
- Average the number of daily axle passes per bin for the 7 DOWs to obtain the monthly average number of axle passes by axle type, load bin and truck class for each month.
- Translate the number of passes per bin into load distributions (percent) by axle type, truck class and month to get the normalized axle load distribution.

Component 4 of the PDG Input (Number of axles per truck):

- Sum up the annual average daily axle passes for all load bin by axle type and truck class
- Use the annual average daily number of trucks by class (AADTT by class).

Divide the two values computed above to obtain the average number of axles by truck class and axle type.

3.4 Scenario 1-1: (SS WIM Data 1 Month/4 Seasons)

This scenario involves WIM data that covers 1 month in each of 4 seasons. It is simulated from the continuous WIM dataset of the 30 sites selected. It is carried out by computing all the necessary traffic input to the PDG from random combinations of sets of 4 months, each from a different season, (i.e., a maximum of 81 combinations is possible). Only months with more than 25 days of data are considered for this analysis. The challenge in simulating this scenario is that the traffic volume by truck class is not known for all months of the year. All that is known for the site is the volume for four months of the year. According to analysis of the database, two methods can be used to estimate AADTT and MAF.

The first method is combining regional MAF with the 4 months' site-specific volume data to obtain AADTT and MAFs. Specifically, The sum of additional 8 months' data is projected according to the ratio of the sum of the 8 months' MAFs and sum of the 4 months' MAFs. Then the 8 month's data can be allocated according to the weight of their MAFs.

The second method is using the available month's data to represent each month's data within the season. If the regional MAFs have a very similar trend with the actual MAFs of given site, the first method will be better than the second, vice versa. This thesis uses the first method since the regional data sets obtained from cluster analysis are similar to the site-specific data.

3.4.1 Components 1, 2, and 5 of the PDG Input, (AADTT, Truck Class, and MAFs):

Having established the volumes by truck class for the missing months, the algorithm used for obtaining traffic data input components 1, 2 and 3 is identical to that for Scenario 1-0.

The group of sites is used for obtaining the regional MAF data if it is identified as the State specific cluster that exhibits a similar truck classification pattern as the site at hand. This is considered as a reasonable compromise between using statewide average MAF data for all truck classes and MAF cluster data for individual truck classes.

3.4.2 Component 4 of the PDG Input (Number of axles per truck):

The number of axles by axle configuration and truck class are assumed to be constant and equal to each state-wide average for the sites analyzed (Table 6). The standard deviation for the state-wide average number of axles per truck for class 5 and class 9 are below 12% (Table 7).

Table 6: State Average Number of Axles per Truck

State	Axle group	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13
50	1	1.71	1.50	0.96	1.54	1.61	1.07	1.97	2.29	1.49	1.25
	2	0.29	0.50	0.92	0.84	1.41	1.71	1.17	1.15	1.47	1.52
	3	0.00	0.00	0.46	0.46	0.01	0.39	0.70	0.67	0.92	1.12
	4	0.00	0.00	0.01	0.01	0.00	0.07	0.08	0.08	0.32	0.52
27	1	1.54	1.99	1.00	1.00	2.29	1.16	1.02	4.11	2.80	1.24
	2	0.53	0.02	1.00	0.73	0.72	1.92	1.00	0.67	1.07	1.30
	3	0.00	0.00	0.00	0.81	0.00	0.01	0.98	0.53	0.74	1.55
	4	0.00	0.00	0.00	0.46	0.00	0.00	0.14	0.01	0.31	0.81
9	1	1.27	2.00	1.00	0.96	2.24	1.12	1.97	4.59	2.39	1.07
	2	0.86	0.00	1.00	0.26	0.81	1.93	0.99	0.07	0.78	1.10
	3	0.00	0.00	0.00	0.97	0.01	0.06	0.66	0.24	0.46	1.06
	4	0.00	0.00	0.00	0.04	0.00	0.00	0.05	0.00	0.00	0.77
53	1	1.48	1.99	1.03	0.98	2.34	1.18	1.10	4.35	3.58	2.16
	2	0.68	0.02	0.98	1.07	0.69	1.90	1.03	0.50	1.12	2.25
	3	0.00	0.00	0.00	0.87	0.04	0.01	0.93	0.22	0.19	0.28
	4	0.00	0.00	0.00	0.07	0.00	0.00	0.12	0.00	0.00	0.05
28	1	1.43	1.99	1.00	0.87	2.38	1.10	1.07	4.86	3.80	2.07
	2	0.67	0.01	1.00	0.35	0.67	1.95	1.05	0.15	1.04	1.60
	3	0.00	0.00	0.01	0.85	0.02	0.00	0.95	0.01	0.23	0.74
	4	0.00	0.00	0.00	0.04	0.00	0.00	0.10	0.00	0.02	0.65
18	1	1.67	1.95	1.00	0.92	2.28	1.21	1.13	4.76	3.47	1.30
	2	0.41	0.03	1.00	0.43	0.75	1.89	1.04	0.23	1.16	1.76
	3	0.00	0.00	0.01	0.84	0.02	0.01	0.88	0.15	0.41	1.00
	4	0.00	0.00	0.00	0.21	0.00	0.00	0.17	0.00	0.06	0.73
26	1	1.59	2.00	1.00	1.04	2.43	1.28	1.19	4.38	3.80	1.86
	2	0.52	0.01	0.99	0.31	0.62	1.84	1.19	0.34	1.01	1.24
	3	0.00	0.00	0.01	0.97	0.05	0.02	0.81	0.01	0.15	0.34
	4	0.00	0.00	0.00	0.06	0.01	0.02	0.11	0.00	0.09	0.63

Table 7: Standard Deviation of State Average Number of Axles per Truck

State	Axle group	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13
50	1	0.10	0.02	0.00	0.15	0.02	0.04	0.05	1.16	0.39	0.43
	2	0.09	0.01	0.00	0.37	0.02	0.02	0.72	0.54	0.37	0.50
	3	0.00	0.00	0.00	0.16	0.01	0.01	0.31	0.39	0.26	0.35
	4	0.00	0.00	0.00	0.06	0.00	0.01	0.12	0.11	0.15	0.39
27	1	0.19	0.03	0.00	0.15	0.09	0.09	0.03	0.95	0.76	0.25
	2	0.19	0.02	0.00	0.28	0.09	0.05	0.02	0.65	0.37	0.47
	3	0.00	0.00	0.01	0.14	0.01	0.01	0.02	0.37	0.32	0.33
	4	0.00	0.00	0.00	0.24	0.00	0.00	0.13	0.06	0.42	0.22
9	1	0.25	0.00	0.00	0.07	0.15	0.05	0.76	0.59	1.67	0.08
	2	0.16	0.00	0.00	0.17	0.07	0.03	0.04	0.11	0.44	0.59
	3	0.00	0.00	0.00	0.07	0.01	0.12	0.25	0.50	0.58	0.50
	4	0.00	0.00	0.00	0.06	0.00	0.00	0.07	0.00	0.00	0.25
53	1	0.20	0.01	0.11	0.31	0.14	0.10	0.08	0.58	0.29	0.24
	2	0.19	0.03	0.05	0.67	0.11	0.05	0.12	0.29	0.11	0.27
	3	0.00	0.00	0.01	0.23	0.08	0.01	0.12	0.21	0.14	0.20
	4	0.00	0.00	0.00	0.14	0.01	0.00	0.10	0.00	0.01	0.03
28	1	0.34	0.01	0.00	0.42	0.12	0.05	0.12	0.87	0.32	1.13
	2	0.32	0.01	0.00	0.35	0.10	0.02	0.12	0.23	0.11	0.54
	3	0.00	0.00	0.01	0.35	0.05	0.01	0.12	0.02	0.33	0.25
	4	0.00	0.00	0.00	0.13	0.01	0.00	0.18	0.00	0.10	0.30
18	1	0.14	0.07	0.00	0.22	0.15	0.12	0.20	0.35	0.75	0.70
	2	0.14	0.03	0.00	0.35	0.12	0.06	0.23	0.31	0.31	0.26
	3	0.00	0.00	0.02	0.23	0.04	0.02	0.21	0.16	0.38	0.50
	4	0.00	0.00	0.00	0.13	0.00	0.00	0.13	0.00	0.22	0.37
26	1	0.26	0.00	0.00	0.11	0.13	0.12	0.14	0.96	0.39	0.52
	2	0.24	0.01	0.05	0.26	0.11	0.09	0.12	0.40	0.08	0.12
	3	0.02	0.00	0.02	0.10	0.06	0.03	0.15	0.03	0.22	0.15
	4	0.00	0.00	0.00	0.12	0.04	0.04	0.12	0.00	0.18	0.13

3.4.3 Components 5 of the PDG Input (Axle Load Distribution):

For axle load distribution, from analysis of Chapter 4, normalized axle load distribution generally do not change greatly from month to month. Hence, each month's normalized axle load distribution within one season is assumed equal to the available month's site-specific data for that season.

3.5 Scenario 1-2: (SS WIM Data for 1 Week/Season)

This Scenario is simulated in a fashion similar to the one described under Scenario 1-1. The difference is that only 1 week per season of WIM data is considered available. For each season, a week is selected at random, excluding those involving national holidays and those having incomplete data. This simply yields a higher number of combinations to be simulated, (i.e., depending on data coverage, up to 20,736 combinations). The selected week is assumed representative of the entire month. The handling of the remaining elements of the PDG input is identical to that described under Scenario 1-1.

3.6 Scenario 2-0: (Continuous SS AVC Data and R WIM Data)

This Scenario utilizes only the vehicle classification information that is available from the 30 WIM sites being analyzed. The same as scenario 1-0, There is only one time coverage combination for this scenario. PDG inputs 1, 2, and 3 are obtained in identical fashion as for Scenario 1-0. For Input 4, that is the number of axles by configuration and vehicle class, the statewide average is used for reasons explained earlier. Input 5, that is the load frequency distribution by axle configuration, has to be estimated from R WIM data. In doing so, it is assumed that although there is no SS WIM data, there is sufficient qualitative information of truck weights for the site to allow classifying it into one of the axle load clusters distinguished within a particular State.

3.7 Scenario 2-1: (SS AVC Data for 1 Month/Season and R WIM Data)

This Scenario is simulated in a fashion similar to that of Scenario 1-1. The time coverage combination is same as scenario 1-1, up to 81 combinations. The difference is that the traffic data input component 5, that is the load distribution by axle configuration, is obtained from R WIM data as described under Scenario 2-0.

3.8 Scenario 2-2: (SS AVC Data for 1 Week/Season and R WIM Data)

This Scenario is simulated in a fashion similar to that of Scenario 1-2. The time coverage combination is same as scenario 1-2, up to 20,736 combinations. The difference is that the traffic data input component 5, that is the load distribution by axle configuration, is obtained from R WIM data as described under Scenario 2-0.

3.9 Scenario 2-3: (SS AVC Data for 1 Week/Year and R WIM Data)

This Scenario is simulated by assuming that the week of data considered available is representative of the month it belongs to. Weeks are selected at random, excluding those involving national holidays and those having incomplete data. Up to 48 possible weeks are available for one year, which defines a time coverage combination of 48. Traffic data input 3, which is the MAFs, is estimated from the regional vehicle classification cluster corresponding to the site in question. Traffic data input 1, i.e. AADTT, is estimated by dividing the available week's count data by the corresponding regional month's MAF for this vehicle class and then sum for all the classes. Traffic input 2 (Vehicle Classification) is estimated using the available 1 week's traffic data since vehicle classification is not sensitive to time change. Traffic input 4 is also estimated from state wide average data. Finally, traffic data element 5, which is the load distributions by axle type, is obtained from R WIM data.

3.10 Scenario 3-0: (Continuous SS ATR Data, R AVC Data and R WIM Data)

This scenario consists of continuous site-specific vehicle counts for an entire year combined with regional AVC and regional WIM data. These vehicle counts include vehicle classes 1 to 3, which are motorcycles, passenger cars and light 4-tire trucks. The percent trucks at the site, (i.e., vehicle classes 4 to 13) is assumed from regional dataset, which has similar truck classification distribution [14]. AADT is computed using the formula (1) recommended by TMG [12]. AADTT is then estimated using the regional percent truck. Traffic data input 2 is obtained as the average of the vehicle classification distribution for the sites that belong to the actual AVC cluster for the site. Similarly, traffic data input 3 is obtained as the average of the MAFs for the sites that belong to the actual AVC cluster for the site. Traffic data input 4, namely the number of axles by type and vehicle class, is assumed equal to the state-wide average for reasons described under Scenario 1-1. Traffic data input 5, that is the load distribution by axle configuration, is obtained as the average of data of the actual WIM cluster the site belongs to.

3.11 Scenario 3-1: (SS ATR Data for 1 Month/Season, R AVC Data and R WIM Data)

This Scenario is simulated in a fashion similar to Scenario 3-0. The only difference is that vehicle volume data is considered known only for 1 month for each of four seasons. Formula (1) is used to estimate the daily average total traffic volume for each of the 4 months. Using the regional vehicle classification information (traffic input 2) and percent truck, the average daily volume for each of the ten truck classes for each of the available 4 months is estimated. Traffic data input 1, namely the AADTT, is then computed as described under Scenario 1-1. Traffic data input 2, 3, 4 and 5 are obtained in a similar fashion to Scenario 3-0.

3.12 Scenario 4-0: (Continuous SS ATR Data, R AVC Data and N WIM Data)

This Scenario is similar to Scenario 3-0. The only difference is that the axle load information from the WIM cluster is replaced with information from national average WIM data. The latter is assumed equal to the default axle load distributions embedded into the PDG software [15]. This assumption affects only traffic data input 5, namely the load distribution by axle configuration.

3.13 Scenario 4-1: (SS ATR Data for 1 Week/Season, R AVC and N WIM Data)

This Scenario is simulated in a fashion similar to Scenario 3-1. The difference is that the axle load information from the WIM cluster is replaced with information from National average WIM data. The latter is assumed equal to the default axle load distributions embedded into the PDG software.

3.14 Scenario 4-2: (SS ATR Data for 1 Week/Year, R AVC and N WIM Data)

This Scenario is a variation of Scenario 4-1, whereby a single week of data only is available per year. As in Scenario 2-3, weeks are selected at random, excluding those that involve national holidays or incomplete traffic data. This week is assumed as representative of the entire month. As in Scenario 3-0, R AVC cluster data is used to compute percent of trucks and average MAF values are used to obtain the traffic volumes by month and truck class. National WIM data, (i.e., the defaults values in the PDG software) are used for traffic data input 5.

3.15 Scenario 4-3: (SS ATR Data for 1 Weekday+1 Weekend/Year, R AVC and N WIM Data)

This scenario involves ATR counts from one weekday and 1 weekend day. Traffic volumes in these days are weighed by 5 and 2, respectively, to compute, weekly traffic volumes. All weeks that do not involve holidays or missing data are considered at random under this Scenario. Subsequently, all traffic data input elements are computed as described under Scenario 4-2.

3.16 Scenario 4-4 to 4-7: (Various Coverage SS ATR Data, N AVC and N WIM Data)

These scenarios are essentially identical to Scenarios 4-0, 4-1, 4-2 and 4-3, respectively. The only difference is that traffic data input 2 and 3 are not computed from the regional average AVC data, but rather from National data. For the latter, the default vehicle classification values embedded into the PDG are used. In doing so, the default classification distribution for a Truck Traffic Classification (TTC) type 1 is arbitrarily selected, described as a major single-trailer truck route. The default MAF values embedded into the PDG are 1.00 for all months and vehicle classes. For each time coverage in SS ATR data, the method used for computing each of the traffic data input elements to the PDG is described earlier.

3.17 Implementation

The discussions above document in detail the methodology and assumptions used in obtaining each of the five traffic data input elements to the NCHRP 1-37A Design Guide. For each of the 17 traffic data collection scenarios considered, Table 8 shows the number of possible time coverage combinations analyzed for each scenario. Obviously, the continuous data coverage scenarios, (i.e., 1-0, 2-0, 3-0, 4-0 and 4-4), involve only a single time coverage combination and as a result, yield singular estimates of the traffic data input elements of the NCHRP 1-37A

Design Guide, (i.e., Table 2). On the other hand, the discontinuous scenarios yield one set of traffic data input elements per data coverage combination. Statistics of this traffic data input is computed and its range is established as a function of the desired level of confidence.

Table 8: Number of Possible Traffic Sampling Combinations by Scenario

Scenario	Time Coverage Combinations
1-0	1
1-1	81
1-2	20,736
2-0	1
2-1	81
2-2	20,736
2-3	48
3-0	1
3-1	81
4-0	1
4-1	20,736
4-2	48
4-3	480
4-4	1
4-5	20,736
4-6	48
4-7	480

For each confidence level, NCHRP 1-37A Design Guide simulations for the discontinuous time coverage scenarios are conducted by considering the low percentile for all traffic input elements simultaneously, (i.e., 1, 2, 3 and 5 as identified in Table 2). The reason for considering traffic under-prediction as critical is because it results in pavement designs thinner than required, which in turn will fail prematurely.

As described in the literature review, obtaining traffic input to the PDG from short-term traffic samples involves considerable calculations in factoring the site-specific data using representative R or N vehicle distribution and axle load data. *Trafload* [3] could be used to carry out these calculations. However, it accepts as input raw Card 4 and Card 7 data [8]. Hence, it is not directly applicable to the daily summary input format utilized in this study. Hence, it is decided to develop customized software for computing the traffic data input to the PDG. The software developed is written in Visual Basic 6.0 and it is called *TI-PG*. It reads daily traffic data from the MS Access™ database extracted from the LTPP database and computes the traffic input elements to the PDG following the procedures described in the 2001 TMG (12).

CHAPTER FOUR

LTPP WIM DATA ANALYSIS

4.1 LTPP WIM Data Extracted

The traffic data extracted from the LTPP database includes extended coverage of WIM data to allow simulating the selected traffic data collection scenarios defined in Table 5. The main criterion for selecting data from the LTPP database is the extent of WIM data coverage in terms of the total number of data days per year. A search of the LTPP database [4] is performed based on this criterion. Initially, a filter of 359 days per year or greater is selected, (i.e., 2% of days per year missing). This resulted in a total of 58 sites, some involving multiple data years. To increase the number of sites available for analysis, a lower threshold filter is used involving WIM coverage of 299 days per year or greater, (i.e., 20% of days per year missing). This results in a total of 178 sites, some involving multiple data years. The number of LTPP sites meeting these two criteria versus the number of data years available are plotted in Figures 1 and 2, respectively [14]. Figure 1, for example, suggests that 46 sites have more than 359 days per year WIM data for 1 year, 6 sites do so for 2 years and so on. The data quality for these sites is deemed as Level E, which is it has passed the quality control conducted by the State DOTs and the LTPP Regional Coordinating Offices. To further ensure data quality, the LTPP Quality Assurance Reports pertaining to these 178 sites were examined and reveal no particular problems with any of them.

The high resolution of traffic data necessary for simulating the scenarios in Table 3 is daily summaries, which is not contained in *DataPave*. Hence, data has to be retrieved from the Central Traffic Database (CTDB). It contains traffic data at five levels of resolution:

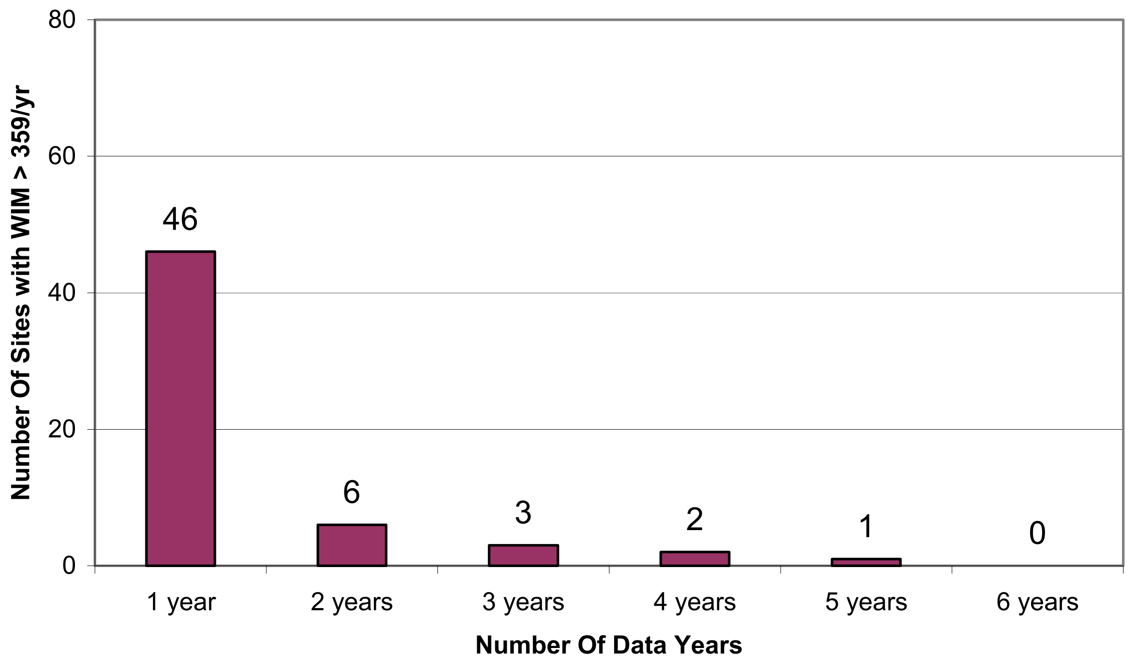


Figure 1: LTPP Sites with WIM Data Available for Periods Longer Than 359 Days Per Year

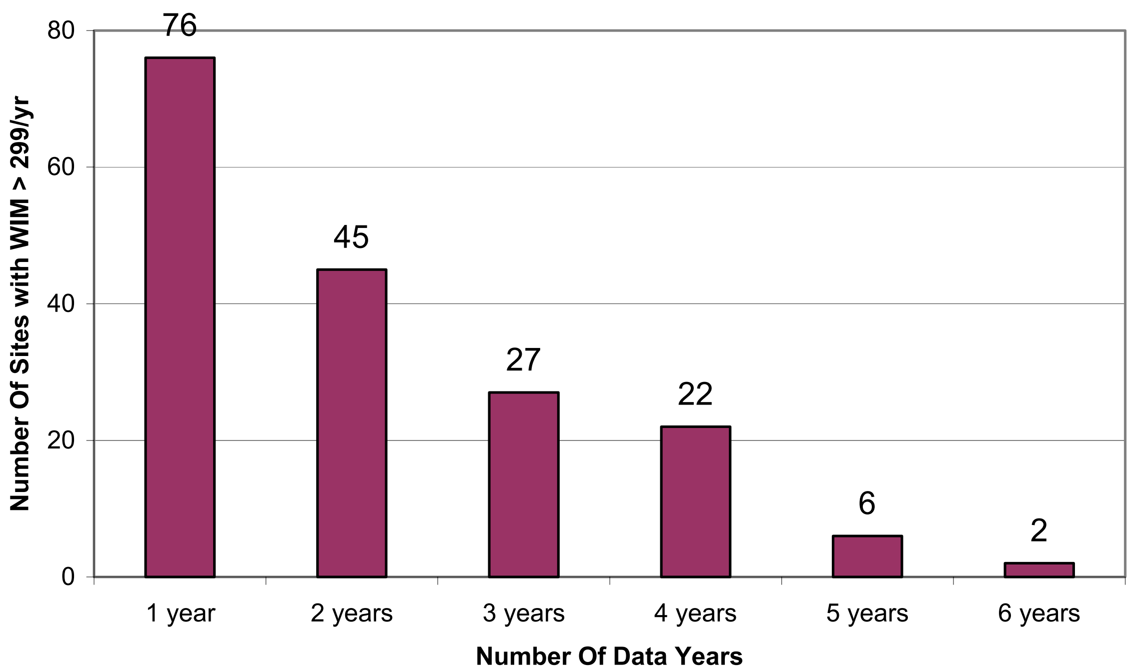


Figure 2: LTPP Sites with WIM Data Available for Periods Longer Than 299 Days Per Year

- Level 1: Annual Load/Count Summary Records by Axle (uploaded to the Information Management System database to become part of periodic *DataPave* releases).
- Level 2: Annual Loads by Vehicle Class and Annual Load Spectra by Truck Type.
- Level 3: Daily Summary Traffic Records.
- Level 4: Submitted Traffic Loading Records (i.e. raw individual Card 4 and Card 7 data).
- Level 5: Additional Traffic Loading Information.

Given the high resolution of daily data desired for simulating the 17 traffic scenarios, Level 3 WIM data is extracted from the CTDB for the 178 WIM sites for the data years identified. The data is in *MS Access* format. It contains the daily number of axle passes by truck class, axle type and load bin, that is it combines axle weight and vehicle classification information.

4.2 LTPP WIM Data Sites Selected For Scenario Simulation

A number of these extended WIM data coverage LTPP sites are selected for the detailed sensitivity analysis of the NCHRP 1-37A Design Guide with respect to the traffic input obtained from the simulated traffic data collection scenarios (Table 5). The remaining sites are used for obtaining the Regional traffic data sets, (i.e., vehicle classification and axle load distribution estimates), for the detailed sensitivity analysis sites.

The following criteria are used for selecting sites for the detailed sensitivity analysis:

1. WIM data coverage of preferably 359 days per year or greater.
2. Availability of WIM data over several years, to allow studying the effect of traffic growth.
3. Distribution of sites over a wide range of truck traffic volumes, (i.e., AADTT) and structural thickness.

The latter is indexed by the SN (structural number for flexible pavement) and the concrete slab thickness, for flexible and rigid pavement sites, respectively. Combining different AADTT level and pavement structures, 30 sites are selected to conduct the scenario simulation. 15 sites have flexible pavement structures; other 15 sites have rigid pavement structures. Detailed information about the 30 sites is given in Table 9 and Table 10.

Table 9: Background Information on the Flexible LTPP Sites Selected

Site	**State**	**SN (in)**	**Data years[1]**	**Data Days[2]**	**AADTT[2]**	**AADTT Level**
9_1803	CT	4.5	**1994**, 95	359	165	**AADTT ≤ 800**
26_1004	MI	1.7	1992,94,95,96,97,**98**	348	229	
27_1019	MN	3.0	1992,94,95,**96**	313	268	
28_2807	MS	5.5	1995,**96**	321	457	
53_1007	WA	2.6	1993,94,**95**	365	177	
18_2008	IN	6.2	1992,93,97,**98**	349	709	
18_2009	IN	9.2	**1998**	356	655	
26_1010	MI	4.8	1994,95,**98**	362	647	
53_6048	WA	4.2	**1994**	365	783	
26_1012	MI	5.3	1994,95,**98**	355	977	**AADTT > 800**
18_1028	IN	7.0	1997,**98**	319	1535	
18_6012	IN	9.1	1992,97,**98**	324	1473	
26_1013	MI	5.9	1994,**98**	334	1395	
28_3081	MS	4.8	**1993**	356	1120	
28_3093	MS	4.0	**1995**	341	1920	

[1]Data year used in traffic data collection scenario simulation is in bold
[2] AADTT Volumes and Data Days are for the year in bold

Table 10: Background Information on the Rigid LTPP Sites Selected

Site	State	Slab (in)	Config.	Data years[1]	Data Days[2]	AADTT[2]	AADTT Level
9_4020	CT	9.0	JRCP	**1994**	308	546	**AADTT ≤ 1200**
26_3069	MI	9.0	JRCP	1994,95,**97**	319	577	
28_4024	MS	8.0	JRCP	**1995**	360	99	
50_1682	VT	8.0	JRCP	1992,94,95,**97**	363	419	
53_3813	WA	7.8	JRCP	1992,93,**94**	365	548	
18_5022	IN	9.0	CRCP	**1997**	313	1164	
9_4008	CT	9.0	JRCP	**1994**	364	1496	**AADTT > 1200**
26_5363	MI	9.0	CRCP	1993,94,95,**97**	355	1247	
27_4055	MN	8.9	JRCP	**1994**,97	300	1381	
27_5076	MN	9.0	CRCP	**1997**	344	1438	
9_5001	CT	8.0	CRCP	**1995**	323	1590	
18_5518	IN	9.0	CRCP	1994,**97**,98	365	3746	
26_4015	MI	9.0	JRCP	1994,96,97,**98**	341	1807	
28_5006	MS	8.0	CRCP	1993,94,**95**,97	361	1559	
28_5805	MS	8.0	CRCP	1993,94,**95**	361	2024	

[1] Data year used in traffic data collection scenario simulation is in bold
[2] Volumes and Data Days are for the year in bold

4.3 Constancy of Some Parameters

From the data analysis (Figure 3) and the literature [11][13], vehicle classification distribution appears relatively constant throughout the years and the months within a year. The same conclusion can be reached by studying the normalized axle load distributions.

From plotting the statewide average of DOW factors (Figure 4), it is found that from class 4 to class 13 the DOW factors have similar trends. And the weekday factors (from Monday to Friday) are similar. While the weekend factors (Saturday and Sunday) are same. Thus, if 1 work weekday and 1 weekend day's data are available, the weekly or monthly average traffic volume can be predicted as (5* 1 work weekday and 2* 1 weekend day)/7.

In summary, the assumptions above allow computation of PDG traffic input from a discontinuous short-term data coverage of traffic data, as described in Chapter 3.

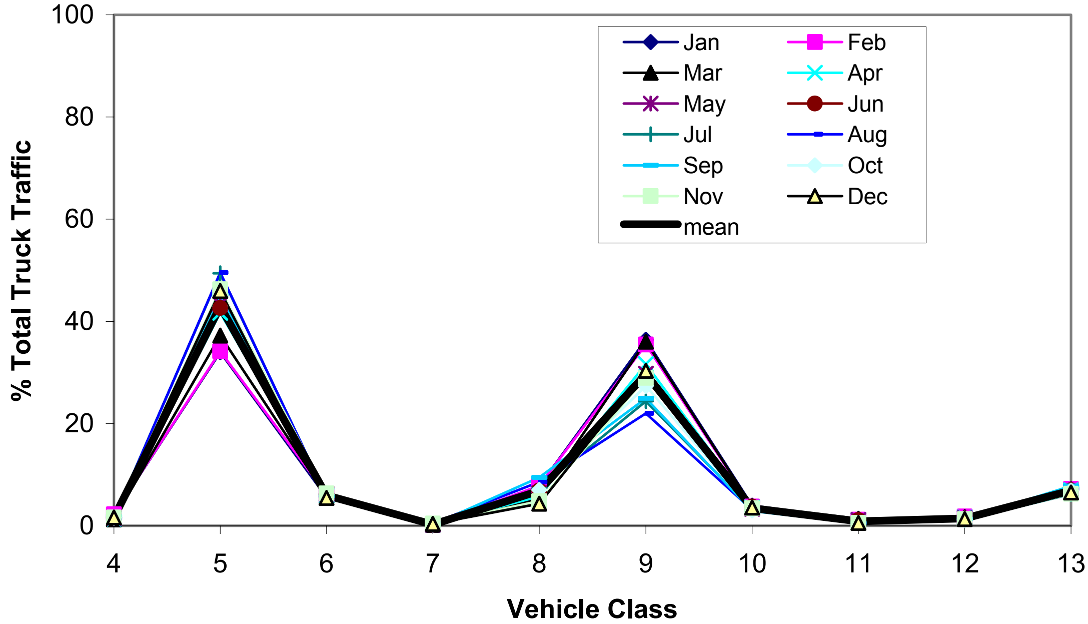


Figure 3: Monthly versus Annual Vehicle Class Distribution, AVC Cluster; WA Site 6048

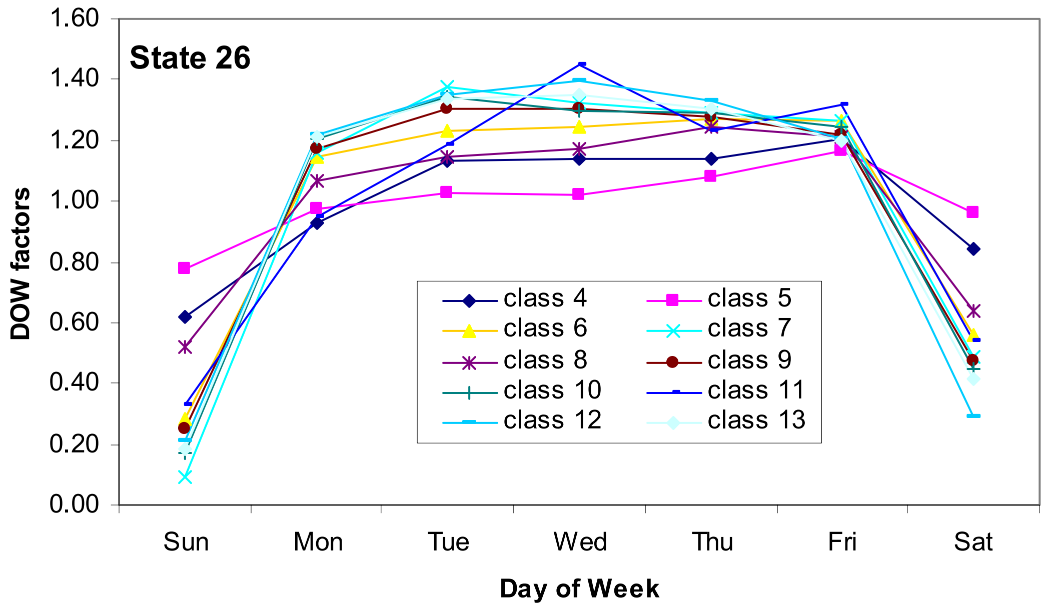


Figure 4: Average Day of Week factors for FHWA class 4-13, State 26

CHAPTER FIVE

SOFTWARE FOR GENERATING TRAFFIC INPUT FOR THE NEW PDG

5.1 Introduction

The NCHRP 1-37A Pavement Design Guide requires detailed traffic loading data, including traffic volume, class distribution, MAF, and axle load distribution. With a number of WIM or AVC systems available in a jurisdiction, the traffic data collected can be conveniently computed using software *TI-PG* to generate traffic input components for the new pavement design. Where site-specific traffic data is not available, regional or national data can be used to estimate the necessary traffic input (Table 5).

TI-PG uses the daily traffic data summary as input. The advantage of using daily summary is that the data required by *TI-PG* is independent of the equipment collecting them, since each type of equipment may use different algorithms to extract the traffic data. *TI-PG* can be used to generate traffic data components if the data is stored in the required format, which is currently the standard *Microsoft Access*™ format in LTPP database. The output of *TI-PG* is the traffic input components directly required by the NCHRP 1-37A Pavement Design (Table 2). *TI-PG* can also be used to analyze traffic characteristics with its output data. Figure 5 is the flow chart for *TI-PG*. The source code of *TI-PG* is included in the Appendix.

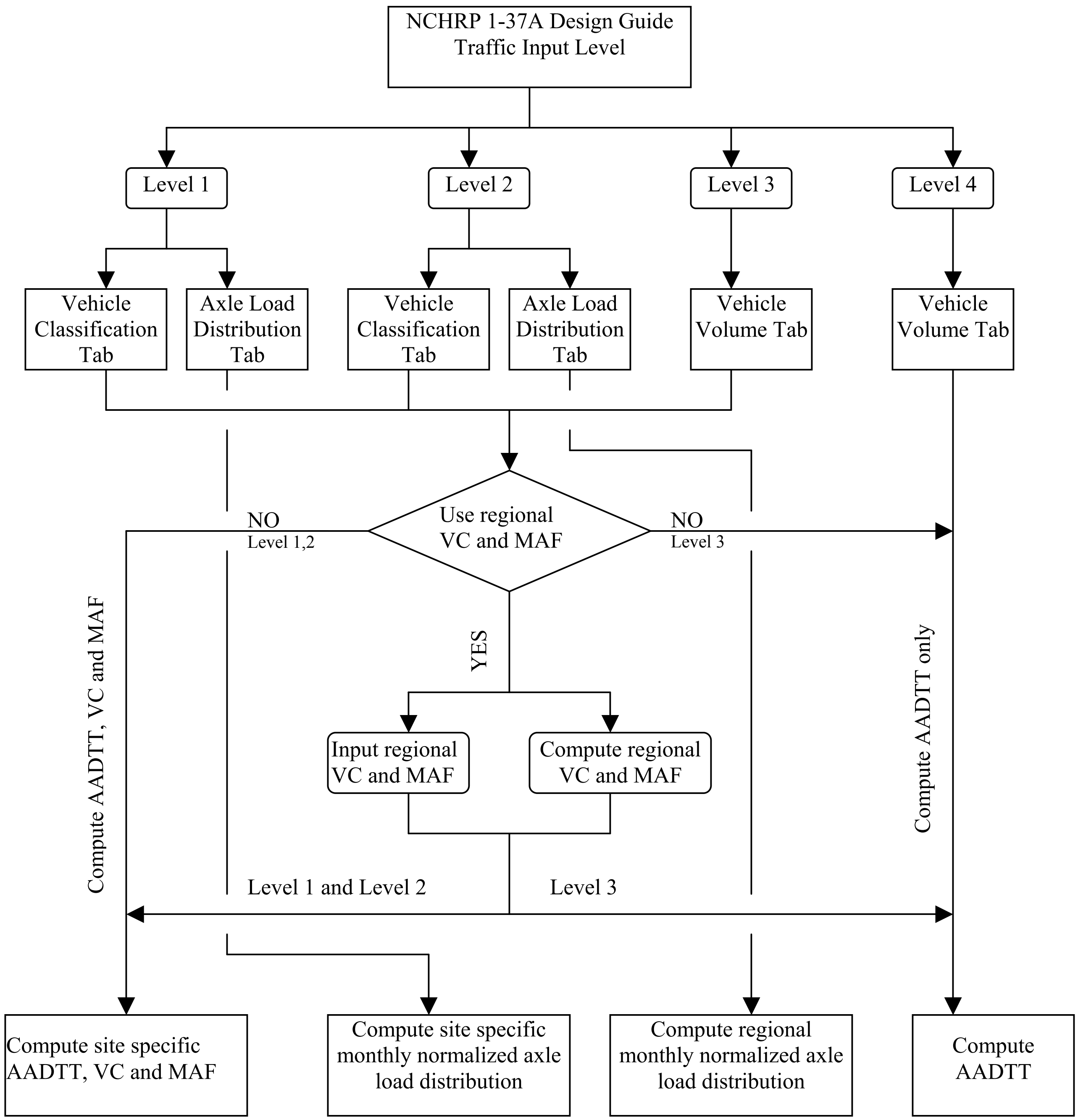


Figure 5: Flow Chart for TI-PG Software

5.2 Input Data Format

TI-PG uses daily traffic data in *Microsoft Access* format to generate traffic input component for the NCHRP 1-37A new Pavement Design Guide. The format used is identical to that used by the LTPP CTDB Level 3. The field names used in these databases are described in Table 11.

Table 11: Definition of Variables Extracted from the CTDB [4]

Variable Name	Definition
STATE_CODE	State/Province ID
SHRP_ID	Test section LTPP identifier
LANE_TRF	Lane identifier, where 1 is the one near the shoulder right-hand-side
DIR_TRF	Traffic direction, where 1, 2, 3 and 4 indicate east, west, north and south, respectively
VEH_CLASS	FHWA vehicle classes 1 to 13, with 14 indicating "other" and 15 indicating unknown
AXLE_GROUP	Axle configuration, 1, 2, 3 and 4 indicating single, tandem, tridem and quad axles, respectively.
YEAR	Year the data was collected
MONTH	Month the data was collected
DAY	Date the data was collected
RECORD_STATUS	Quality Control code from A to E
DAY_OF_WEEK	Day of Week from Sunday to Saturday
COUNT	Total vehicle count
COUNT01 To COUNT20	Vehicle counts for FHWA vehicle class 1 to 20
AX_CT_01 to AX_CT_40	Number of axle passes by load bin. Depending on axle type, these bins are: Singles: AX_CT_01 is 0-999 lbs and subsequent bins are in increments of 1000 lbs Tandems: AX_CT_01 is 0-1,999 lbs and subsequent bins are in increments of 2000 lbs Triples/Quads: AX_CT_01 is 0-2,999 lbs and subsequent bins are in increments of 3,000 lbs

The input data is in *Microsoft Access*™ table format. Tables 12, 13 and 14 are examples of the data table for axle load data, vehicle classification (VC) data and traffic volume counts (ATR) data, respectively. The fields shown in these tables are necessary as input data, the field columns, however, can be in any order other than the one shown. The access file may include additional fields than the fields in the tables. *TI-PG* uses SQL statements to search the data tables for the required data fields.

Table 12: Axle Load Data Format

STATE_CODE	SHRP_ID	LANE_TRF	DIR_TRF	VEH_CLASS	AXLE_GROUP	YEAR	MONTH	DAY	RECORD_STATUS	DAY_OF_WEEK	AX_CT_01 to AX_CT_40
28	2807	1	3	10	1	1993	10	8	0	6	0
28	2807	1	3	10	1	1993	10	9	0	7	0
28	2807	1	3	10	1	1993	10	10	0	1	0
28	2807	1	3	10	1	1993	10	11	0	2	0
28	2807	1	3	10	1	1993	10	12	0	3	0
28	2807	1	3	10	1	1993	10	13	0	4	0
28	2807	1	3	10	1	1993	10	14	0	5	0
28	2807	1	3	10	1	1993	10	15	0	6	0
28	2807	1	3	10	1	1993	10	18	0	2	0
28	2807	1	3	10	1	1993	10	19	0	3	0
28	2807	1	3	10	1	1993	10	20	0	4	0
28	2807	1	3	10	1	1993	10	24	0	1	0

Table 13: Vehicle Classification (AVC) Data Format

STATE_CODE	SHRP_ID	LANE_TRF	DIR_TRF	YEAR	MONTH	DAY	RECORD_STATUS	DAY_OF_WEEK	COUNT01 TO COUNT20
28	1802	1	3	1993	12	28	0	3	0
28	1802	1	3	1993	12	29	0	4	0
28	1802	1	3	1993	12	30	0	5	0
28	1802	1	3	1993	12	31	0	6	0
28	1802	1	3	1993	9	30	0	5	0
28	1802	1	3	1993	10	1	0	6	0
28	1802	1	3	1993	10	2	0	7	0
28	1802	1	3	1993	10	3	0	1	0
28	1802	1	3	1993	10	4	0	2	0
28	1802	1	3	1993	10	5	0	3	0
28	1802	1	3	1993	10	6	0	4	0
28	1802	1	3	1993	10	7	0	5	0
28	1802	1	3	1993	10	8	0	6	0
28	1802	1	3	1993	10	9	0	7	0
28	1802	1	3	1993	10	10	0	1	0
28	1802	1	3	1993	10	11	0	2	0
28	1802	1	3	1993	10	12	0	3	0

Table 14: Traffic Volume (ATR) Data Format

STATE_CODE	SHRP_ID	LANE_TRF	DIR_TRF	YEAR	MONTH	DAY	RECORD_STATUS	DAY_OF_WEEK	COUNT
28	2807	2	7	1997	12	18	E	5	1927
28	2807	2	7	1997	12	19	E	6	2189
28	2807	2	7	1997	12	20	E	7	2007
28	2807	2	7	1997	12	21	E	1	1439
28	2807	2	7	1997	12	22	E	2	1989
28	2807	2	7	1997	12	23	E	3	1976
28	2807	2	7	1997	12	24	E	4	1776
28	2807	2	7	1997	12	25	E	5	1257
28	2807	2	7	1997	12	26	E	6	1765
28	2807	2	7	1997	12	27	E	7	1663
28	2807	2	7	1997	12	28	E	1	1316
28	2807	2	7	1997	12	29	E	2	1389

5.3 Traffic Input Levels

Four traffic input levels are defined corresponding to the traffic input requirement for the new pavement design, as described in Table 1.

Traffic input level 1 requires site-specific vehicle classification data and axle loading data. The data is in the form of year-long daily summaries. The time length of data collection needs not be continuous (i.e., it can be 1 week, 1 month, etc). If the vehicle classification data is not continuous, regional data set can be used to adjust the available site-specific data to compute AADTT, VC distribution and MAFs. The regional data set may be default values incorporated into the *TI-PG*, it can be input by the user, or it can be computed by *TI-PG* if the user can identify the sites in the jurisdiction that exhibit similar vehicle classification characteristics and supply daily data for them. *TI-PG* computes regional VC and MAF by averaging the VCs and MAFs that are in the sites specified by the user. The format requirement for the *MS Access*[TM] file, which is used to compute the regional VC and MAF, is the same as shown in Table 13. Traffic input level 2 require site-specific vehicle classification data and regional axle load data. For regional axle load data, after the user identifies the sites that belong to the regional axle load distribution group, *TI-PG* computes the regional axle load distribution by averaging the monthly axle load distribution for the selected sites. The access file (used to compute site-specific or regional axle load distribution) format is shown in Table 12.

Level 3 input requires site-specific total traffic volume (ATR) data and regional axle load data. The user can choose to use regional VC, MAF and percent truck to estimate AADTT.

Level 4 inputs require site-specific total traffic volume data and national average VC, MAF and axle load data (default value in new pavement design).

When the user starts the *TI-PG* software, will need to choose the traffic input level for the new pavement design. As described next, selecting the traffic input level, activates tabs to allow specifying disk location/file name/table name where the necessary input is located.

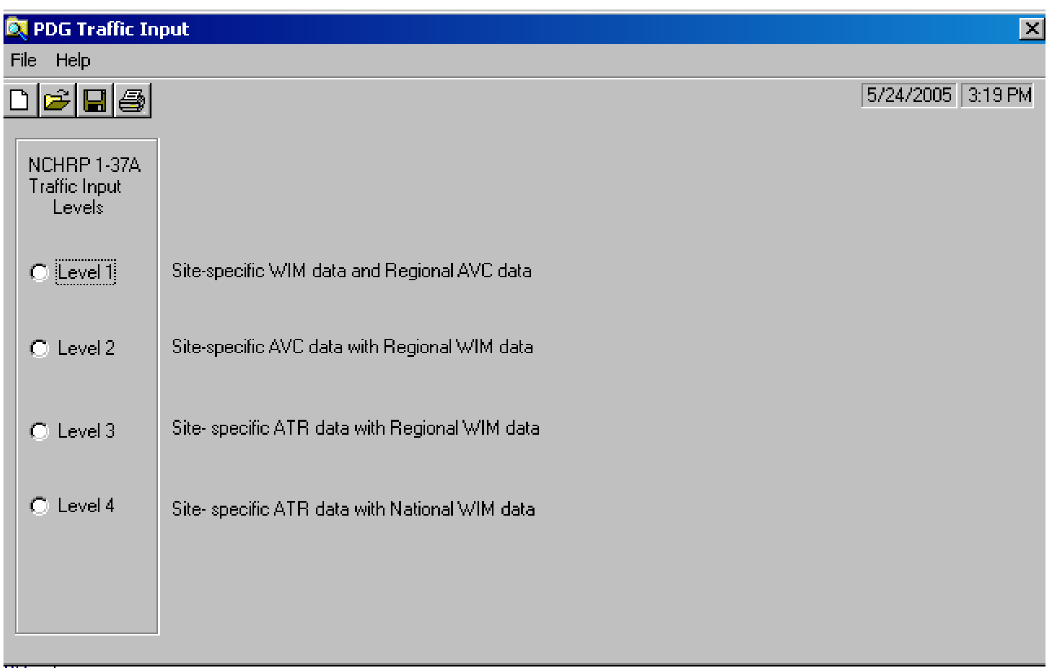


Figure 6: Initial Menu for TI-PG Software

5.4 Input and Output

Three menu screens, (i.e., tabs) are available for the traffic data computation, namely "Vehicle Volume", "Vehicle Classification" and "Axle Load Distribution". "Vehicle Volume" corresponds to the total traffic volume computation with ATR source data. "Vehicle Classification" corresponds to AADTT and truck class distribution computation with AVC source data. "Axle Load Distribution" corresponds to the normalized axle load distribution computation with WIM source data.

If traffic input Level 1 is selected, Vehicle Classification and Axle Load Distribution tabs are activated for computing site specific traffic input components. If traffic input Level 2 is selected, the Vehicle Classification tab is activated for computing site specific AADTT , VC and MAFs, The Axle Load Distribution tab is activated for computing regional normalized axle load distribution. If traffic input Level 3 is selected, Vehicle Volume and Vehicle Classification tabs are activated to compute site specific AADT and regional VC and MAFs. If traffic input Level 4 is selected, Vehicle Volume tab is activated to compute site specific AADT.

5.4.1 Vehicle Classification

After a traffic input level is selected, the Microsoft Access database file name needs to be input as the data source file. The user can manually input the file and path name or browse from the windows. After the database file name is found, the user needs to click button "Select" to make the connection to the database file

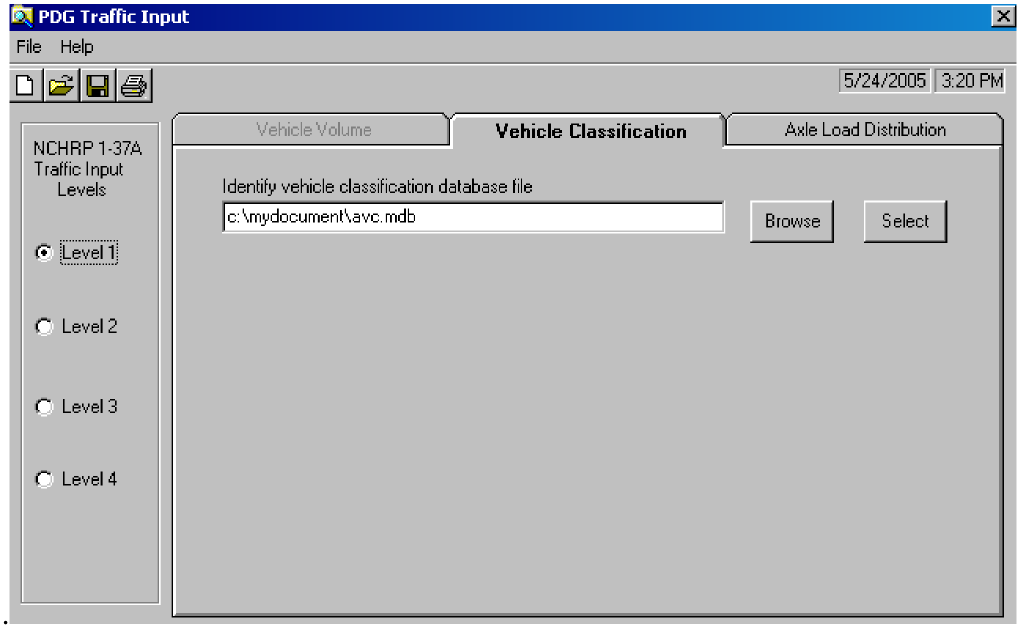


Figure 7: Connect to Daily Traffic Database File for Traffic Volume by Class (VC)

Once the data file is found, the user needs to choose the data table from the database file, as there may be multiple data tables in one *Microsoft Access*™ file (Figure 8).

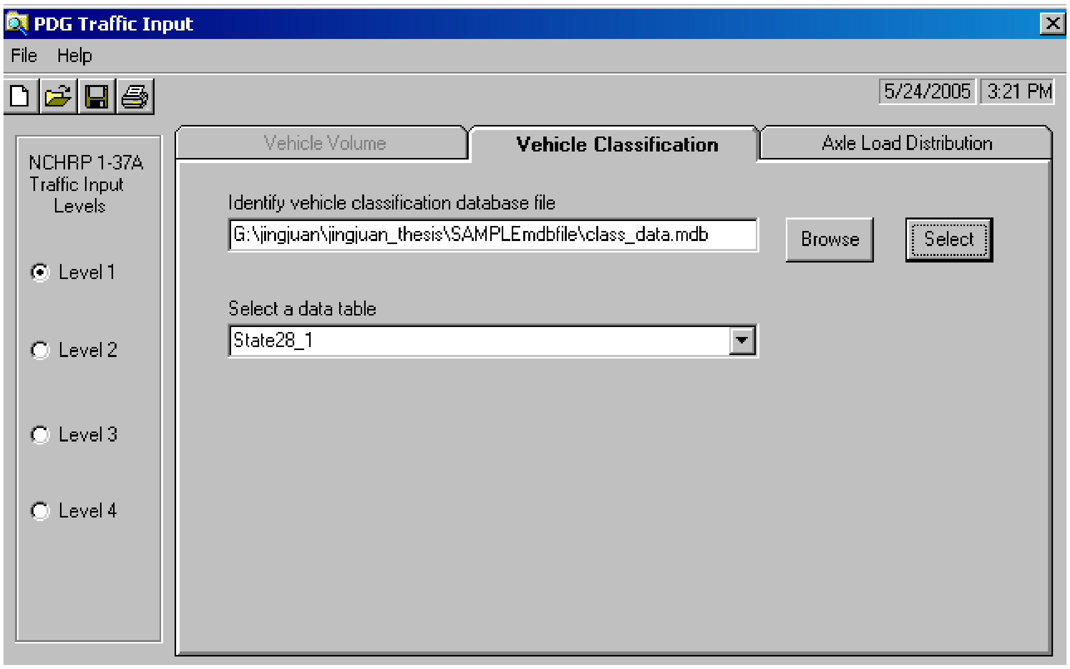


Figure 8: Data Tables in the Connected Database File

After the user select the data table, the data sites' information are shown automatically to facilitate identification (Figure 9).

For vehicle classification calculation, the "Input Regional VC and MAF" button is for manually inputting the regional VC and MAF. The "Compute Regional VC and MAF" button is for computing the regional VC and MAF from the multiple sites selected. Figure 10 shows the default regional VC and MAFs in the software. To compute site-specific VC and MAF, only one site should be selected. The site-specific VC and MAF from discontinuous daily data will be adjusted using the regional VC and MAF if the user has finished inputting or computing the regional VC and MAF. The output site-specific AADTT, VC and MAF are in the output table (Figure 11). The user can also choose to import or export MAF data from an external ASCII format file.

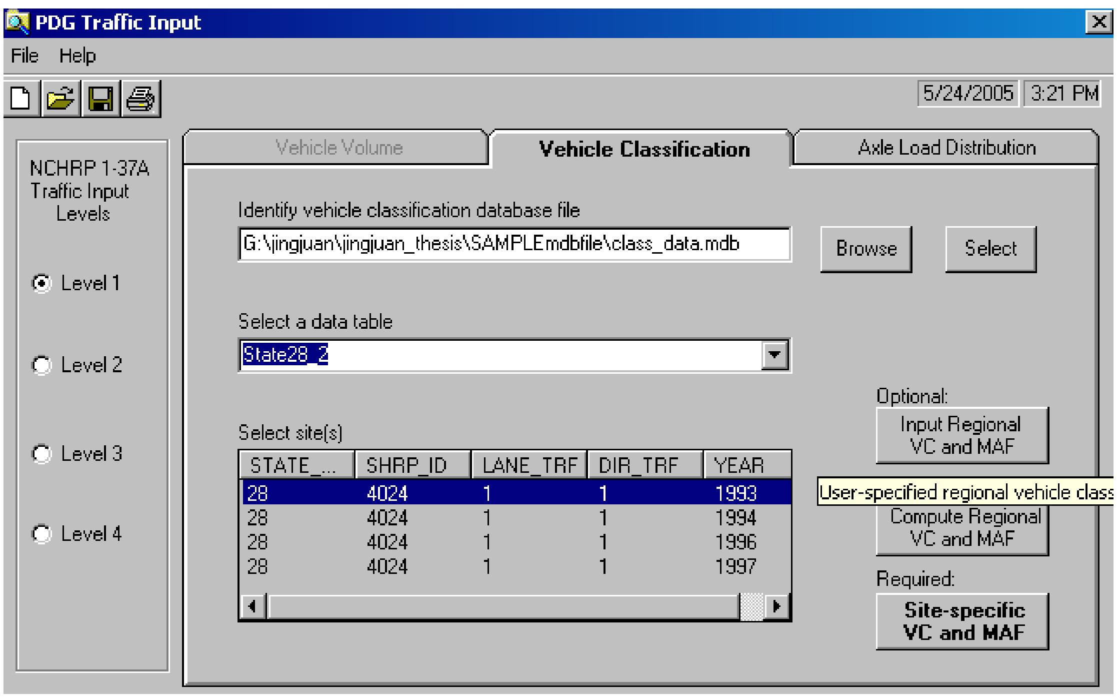
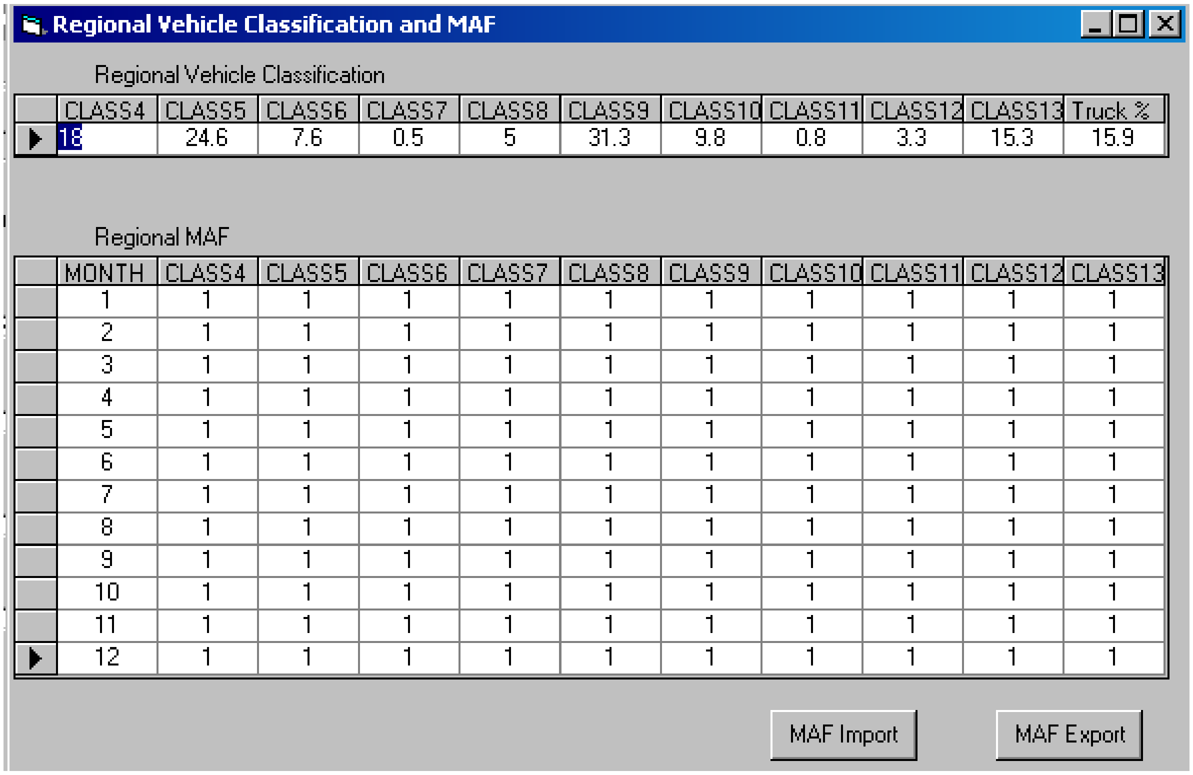


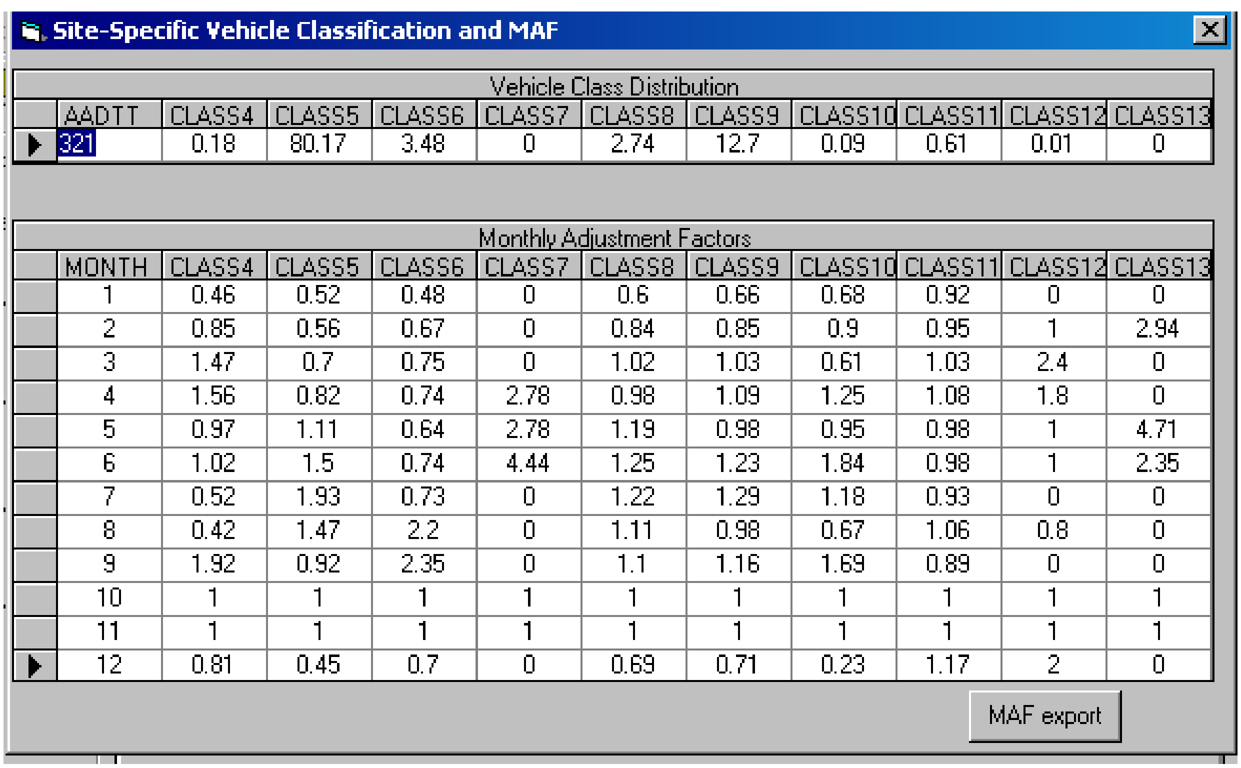
Figure 9: Data Sites Information in the Selected Data Table and the Command Buttons



CLASS4	CLASS5	CLASS6	CLASS7	CLASS8	CLASS9	CLASS10	CLASS11	CLASS12	CLASS13	Truck %
18	24.6	7.6	0.5	5	31.3	9.8	0.8	3.3	15.3	15.9

MONTH	CLASS4	CLASS5	CLASS6	CLASS7	CLASS8	CLASS9	CLASS10	CLASS11	CLASS12	CLASS13
1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1	1
8	1	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	1	1

Figure 10: Default Regional VC and MAF



AADTT	CLASS4	CLASS5	CLASS6	CLASS7	CLASS8	CLASS9	CLASS10	CLASS11	CLASS12	CLASS13
321	0.18	80.17	3.48	0	2.74	12.7	0.09	0.61	0.01	0

MONTH	CLASS4	CLASS5	CLASS6	CLASS7	CLASS8	CLASS9	CLASS10	CLASS11	CLASS12	CLASS13
1	0.46	0.52	0.48	0	0.6	0.66	0.68	0.92	0	0
2	0.85	0.56	0.67	0	0.84	0.85	0.9	0.95	1	2.94
3	1.47	0.7	0.75	0	1.02	1.03	0.61	1.03	2.4	0
4	1.56	0.82	0.74	2.78	0.98	1.09	1.25	1.08	1.8	0
5	0.97	1.11	0.64	2.78	1.19	0.98	0.95	0.98	1	4.71
6	1.02	1.5	0.74	4.44	1.25	1.23	1.84	0.98	1	2.35
7	0.52	1.93	0.73	0	1.22	1.29	1.18	0.93	0	0
8	0.42	1.47	2.2	0	1.11	0.98	0.67	1.06	0.8	0
9	1.92	0.92	2.35	0	1.1	1.16	1.69	0.89	0	0
10	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1	1
12	0.81	0.45	0.7	0	0.69	0.71	0.23	1.17	2	0

Figure 11: Output Data Table: Site Specific VC and MAF

5.4.2 Axle Load Distribution

The "Axle Load Distribution" tab is shown in Figure 12. The input Access data format is shown in Table 12. The process of connecting the database file is the same with the vehicle classification calculation described above. For level 1 traffic input, site-specific axle load distribution is needed. For Level 2 input, regional axle load distribution is needed. To compute the regional axle load distribution, sites belonging to same axle load distribution group need to be identified in a data table. The output axle load distribution (Site-Specific or Regional) is shown in Figure 13.

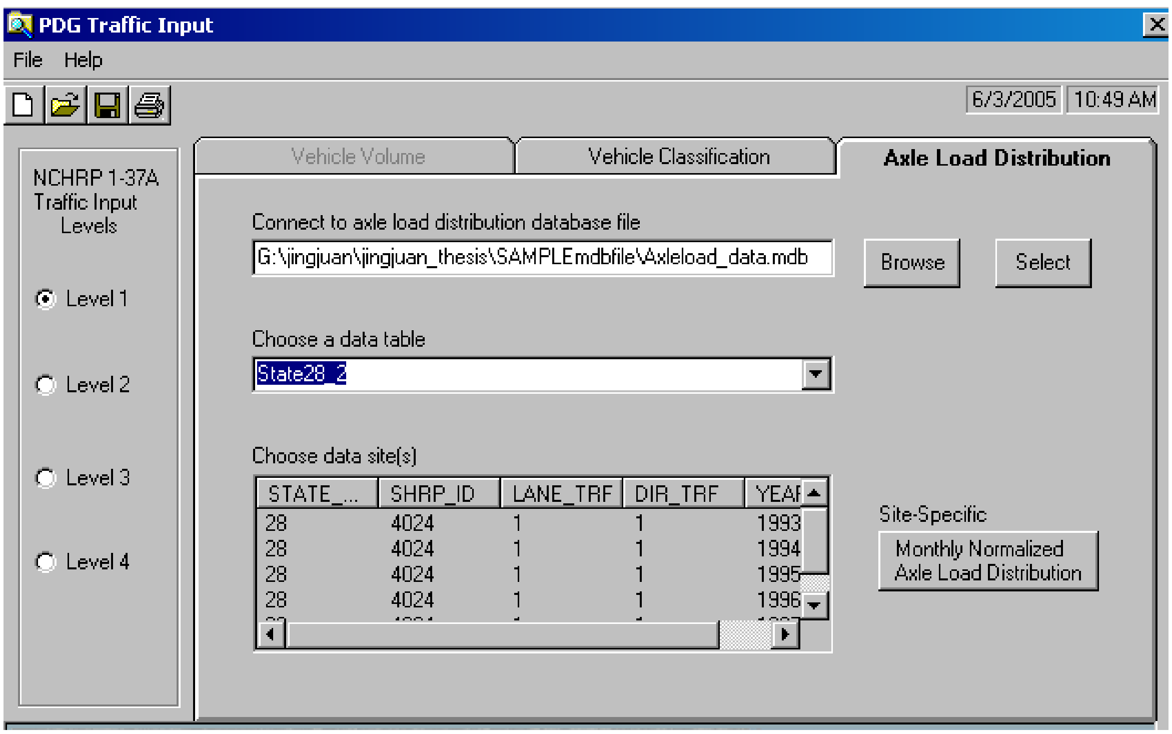
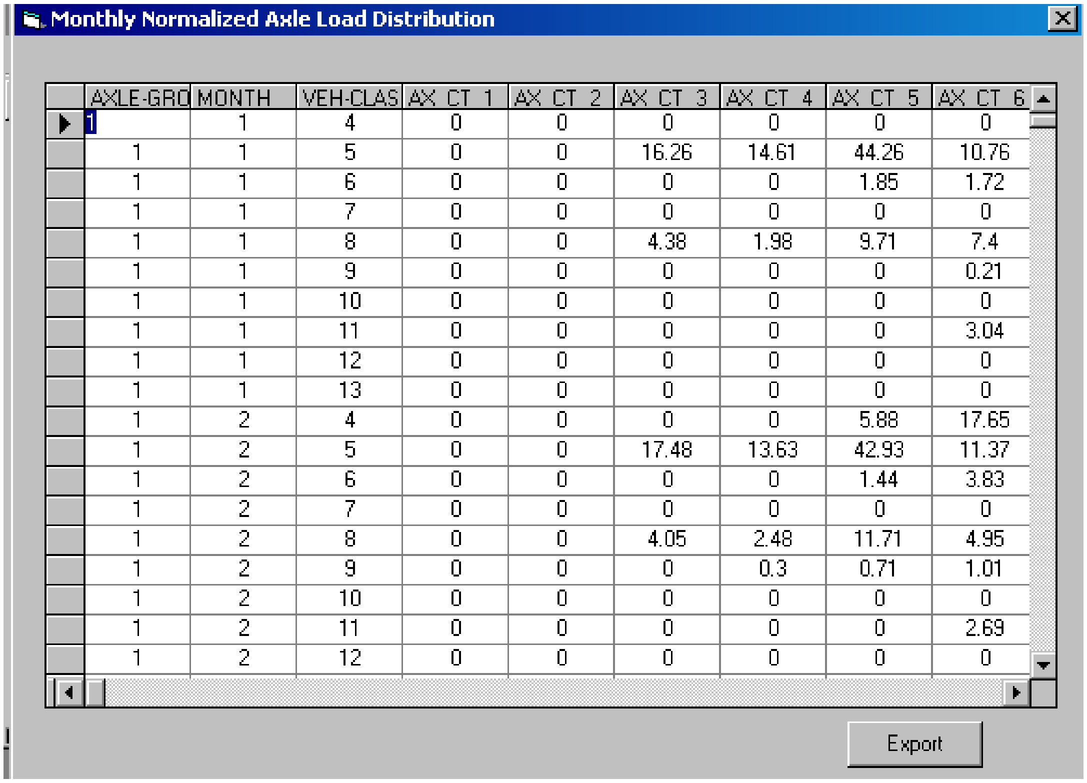


Figure 12: Menu Screen for Axle Load Distribution Computation



AXLE-GRO	MONTH	VEH-CLAS	AX CT 1	AX CT 2	AX CT 3	AX CT 4	AX CT 5	AX CT 6
1	1	4	0	0	0	0	0	0
1	1	5	0	0	16.26	14.61	44.26	10.76
1	1	6	0	0	0	0	1.85	1.72
1	1	7	0	0	0	0	0	0
1	1	8	0	0	4.38	1.98	9.71	7.4
1	1	9	0	0	0	0	0	0.21
1	1	10	0	0	0	0	0	0
1	1	11	0	0	0	0	0	3.04
1	1	12	0	0	0	0	0	0
1	1	13	0	0	0	0	0	0
1	2	4	0	0	0	0	5.88	17.65
1	2	5	0	0	17.48	13.63	42.93	11.37
1	2	6	0	0	0	0	1.44	3.83
1	2	7	0	0	0	0	0	0
1	2	8	0	0	4.05	2.48	11.71	4.95
1	2	9	0	0	0	0.3	0.71	1.01
1	2	10	0	0	0	0	0	0
1	2	11	0	0	0	0	0	2.69
1	2	12	0	0	0	0	0	0

Figure 13: Result Table for Axle Load Distribution Computation

5.4.3 Vehicle Volume

The "Vehicle Volume" tab is shown in Figure 14. The input *Microsoft Access*™ data format is shown in Table 14. The process of connecting the database file is same with vehicle classification calculation described above. For Level 3 traffic input, the regional VC and MAF can be used to adjust the site-specific ATR data. Regional VC AND MAF can be obtained in same way as described in 5.4.1. The "AADTT" command button will give the single value output of AADTT.

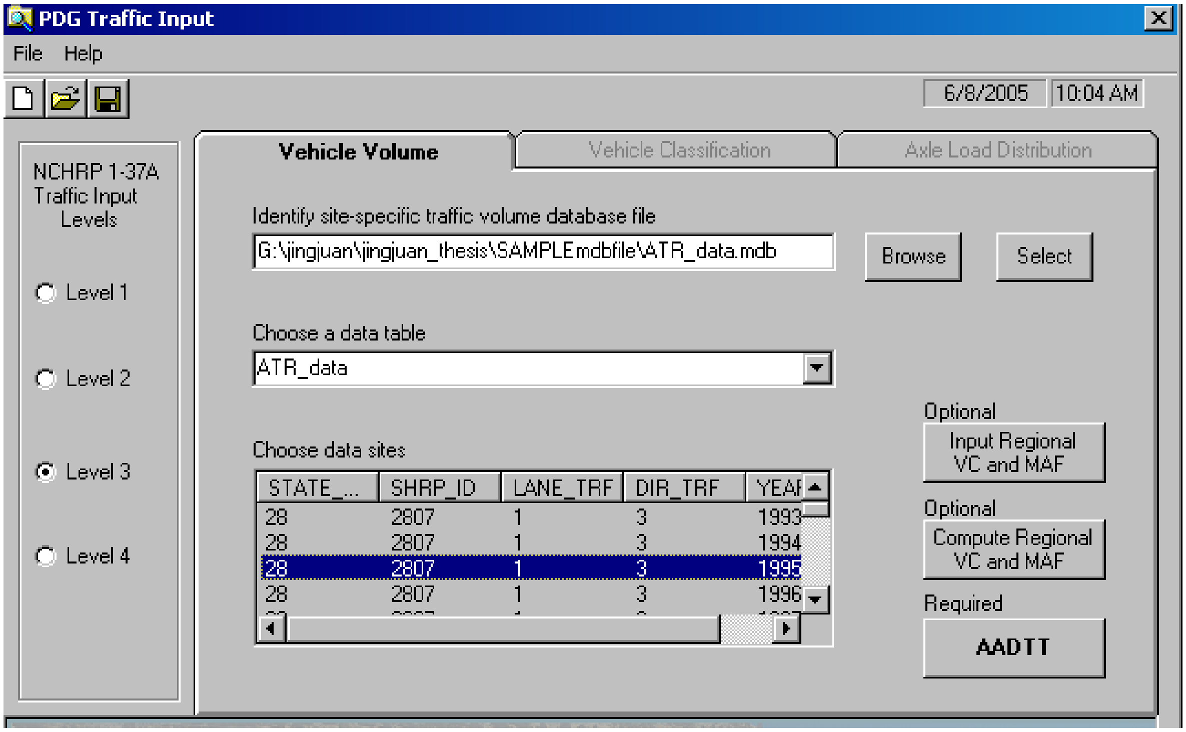


Figure 14: Input Menu for Traffic Volume Computation (ATR Data)

CHAPTER SIX

RESULTS AND DISCUSSION

6.1 Introduction

This Chapter presents the results of the statistical analysis of the traffic input to the NCHRP 1-37A Pavement Design as a result of the traffic data collection scenarios identified earlier (Table 5). The traffic statistics discussed here are produced with the *TI-PG* software described in the previous chapter. As mentioned already, only 4 of the 5 input components to the NCHRP 1-37A Pavement Design Guide are varied, namely:

- AADTT
- VC (Vehicle Class Distribution)
- MAF
- Load frequency distributions

There is no need to vary the number of axles by truck configuration, because it varies little within each state, especially for the most populous truck classes, namely 5 and 9 (Table 7).

Variations in these inputs come from two sources:

1. Data source (i.e., site-specific, regional and national as simulated from the extended coverage WIM data): For example, scenario group 3- uses regional AVC data to adjust the ATR data, which has only total traffic volume information. The regional AVC data is used to compute the regional vehicle classification and MAF data. The regional vehicle classification and MAF are average values of the data for the sites that have similar truck class distribution, which is established through cluster analysis [11]. The regional data sets are only reasonable estimates for the site analyzed. Hence, estimation errors exist due to the difference between the true data and the estimated data.

2. Time coverage for those scenarios that involve discontinuous data coverage: (e.g., for Scenario 1-1, the traffic data is collected for time period of 1 month for each season, which results in 81= 3^4 time coverage combinations).

The statistical parameters for the input are obtained as described under Scenario Description (Chapter 3). Data is presented for all 30 sites for which a detailed analysis is conducted, regardless of whether they produce reasonable pavement lives or not, (i.e., only 17 of these sections did).

For each of these 30 sites and traffic data collection scenario, the statistical mean and standard deviation are computed for each of the four traffic input components to the NCHRP 1-37A Design Guide. Scenario 1-0, involving continuous coverage of site-specific WIM data, represents the "truth" in traffic input and serves as the reference for all accuracy calculations. Due to the different data source and time coverage, the various scenarios are expected to yield different accuracy and precision in traffic estimates.

6.2 AADTT

The true AADTT volumes for the 30 sites analyzed are plotted in Figure 15 in increasing order. They range from a low value of 100 to a high value of almost 4000 vehicles per day. To compare the accuracy of each data collection scenario in predicting AADTT, the ratio of the mean AADTT over the true AADTT is used. Figure 16 shows these AADTT ratios by scenario for each of the 30 sites. Table 15 lists these AADTT ratio values. Both Scenarios 1-1 and 2-1 include 1 month/season site-specific AVC data, thus they are identical in predicting AADTT. The same is the case for Scenarios 1-2 and 2-2, which include 1 week/season site-specific AVC data. Furthermore, Scenario 2-0 involves continuous AVC data. Hence, it is equivalent to

Scenario 1-0 in computing AADTT and therefore it is omitted from this ensuing discussion.

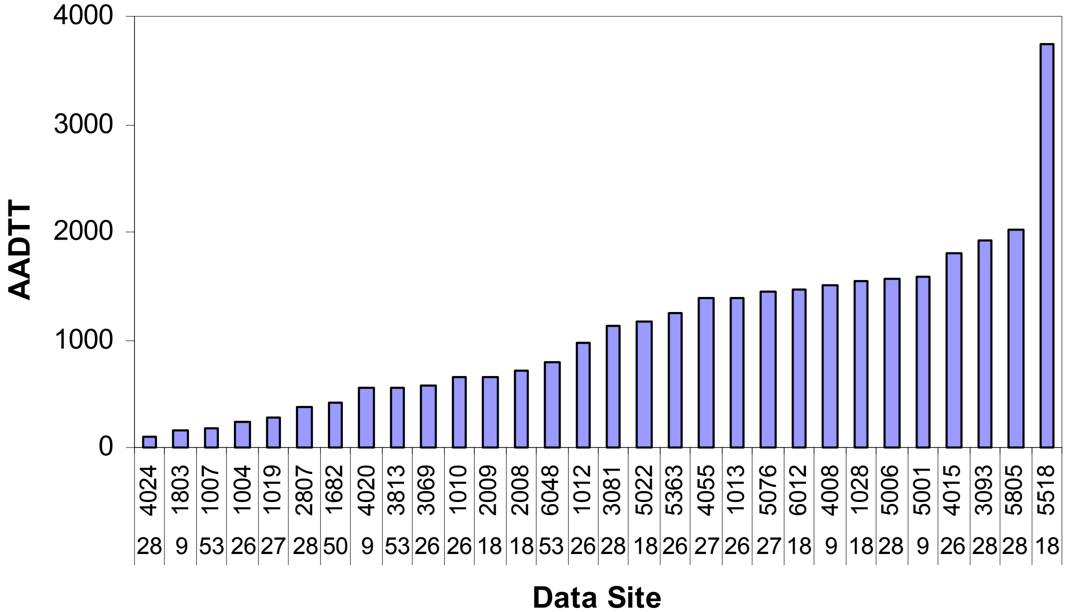


Figure 15: AADTT for 30 Sites Analyzed

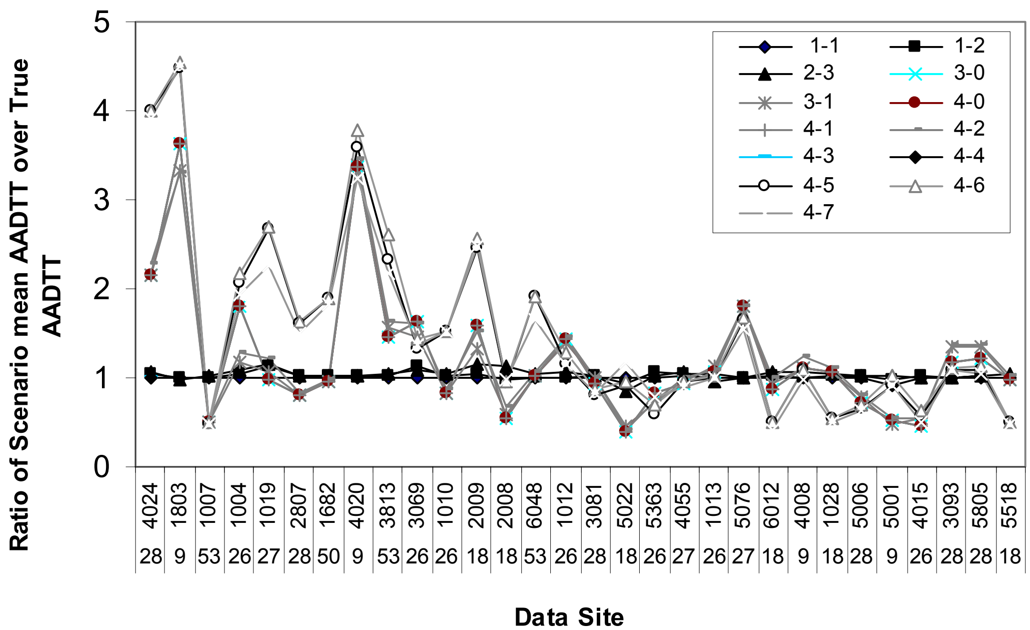


Figure 16: Ratio of Mean AADTT over True AADTT for Each Scenario for 30 Sites

Table 15: Ratio of Scenario Mean AADTT over True AADTT

AADTT Ratio		Scenario ID												
State ID	Site ID	1-1/ 2-1	1-2/ 2-2	2-3	3-0	3-1	4-0	4-1	4-2	4-3	4-4	4-5	4-6	4-7
28	4024	1.0019	1.0508	1.0656	2.1426	2.1450	2.1426	2.2477	2.2831	2.0977	4.0279	4.0087	4.0099	3.9190
9	1803	1.0006	0.9928	0.9768	3.6344	3.3288	3.6344	3.2670	3.3087	3.2092	4.9688	4.4696	4.5491	4.5038
53	1007	1.0018	0.9952	1.0279	0.5023	0.5034	0.5023	0.4999	0.5130	0.5239	0.5150	0.4861	0.4940	0.4736
26	1004	0.9993	1.0533	1.0849	1.7943	1.1797	1.7943	1.2225	1.2912	1.0897	3.0000	2.0631	2.1715	1.9296
27	1019	1.0022	1.1281	1.1523	0.9819	1.0656	0.9819	1.1953	1.2278	1.0594	2.2083	2.6681	2.6860	2.2523
28	2807	1.0025	1.0275	1.0311	0.8063	0.8078	0.8063	0.8281	0.8321	0.8019	1.6735	1.6073	1.6205	1.5072
50	1682	1.0000	1.0142	1.0114	0.9630	0.9630	0.9630	0.9762	0.9787	0.9640	1.9886	1.8863	1.8932	1.8328
9	4020	1.0017	1.0115	1.0155	3.3778	3.3849	3.3778	3.4155	3.4525	3.0245	3.5333	3.5862	3.7914	3.2329
53	3813	1.0025	1.0212	1.0434	1.4573	1.5721	1.4573	1.5865	1.6307	1.4762	2.1200	2.3257	2.6165	2.1700
26	3069	1.0013	1.1284	1.0764	1.6303	1.4595	1.6303	1.6357	1.6143	1.6913	1.3361	1.3353	1.4416	1.3671
26	1010	1.0052	1.0223	1.0470	0.8301	0.8334	0.8301	0.8482	0.8765	0.8478	1.5365	1.5228	1.5226	1.5216
18	2009	1.0047	1.0410	1.1624	1.5818	1.3326	1.5818	1.3580	1.5257	1.4212	2.8909	2.4629	2.5563	2.4681
18	2008	1.0076	0.9806	1.1353	0.5534	0.5950	0.5534	0.5692	0.6717	0.9088	0.9138	0.9413	0.9593	0.9793
53	6048	1.0018	1.0069	1.0449	1.0219	1.0247	1.0219	1.0302	1.0670	1.0359	1.9879	1.9076	1.9077	1.6566
26	1012	1.0022	1.0083	1.0652	1.4259	1.3846	1.4259	1.3925	1.4593	1.6404	1.1778	1.1575	1.2786	1.1443
28	3081	1.0001	1.0258	1.0150	0.9285	0.9985	0.9285	1.0065	1.0097	1.0382	0.7430	0.8104	0.8663	0.8209
18	5022	1.0007	0.9406	0.8483	0.4017	0.4461	0.4017	0.4013	0.4148	0.5101	0.9244	0.9234	0.9544	1.1737
26	5363	1.0008	1.0646	1.0173	0.8174	0.7171	0.8174	0.7109	0.7482	0.8682	0.6598	0.5770	0.7010	0.7819
27	4055	1.0260	1.0519	1.0603	0.9426	0.9649	0.9426	0.9899	1.0009	1.0053	0.9441	0.9502	0.9462	0.8883
26	1013	1.0012	1.0514	0.9522	1.0751	1.1273	1.0751	1.1476	1.0824	1.1503	0.9191	0.9934	1.0183	1.0051
27	5076	1.0014	1.0019	1.0017	1.7953	1.7977	1.7953	1.7999	1.8046	1.7822	1.7071	1.6517	1.6697	1.5490
18	6012	1.0013	1.0209	1.0585	0.8797	0.9279	0.8797	0.9521	0.9902	0.8338	0.4556	0.4947	0.5020	0.4080
9	4008	1.0055	1.0013	1.0701	1.1118	1.1177	1.1118	1.1137	1.2336	1.2576	1.1118	1.0762	1.0783	0.9759
18	1028	1.0023	1.0298	1.0384	1.0559	1.0573	1.0559	1.0865	1.1023	1.0799	0.5596	0.5454	0.5459	0.4949
28	5006	1.0001	1.0274	1.0154	0.7084	0.7912	0.7084	0.8049	0.8052	0.7778	0.5803	0.6627	0.7015	0.6387
9	5001	0.9157	0.9837	1.0180	0.5325	0.4882	0.5325	0.5222	0.5456	0.5056	0.9408	0.9235	1.0163	0.9087
26	4015	0.9992	1.0313	0.9934	0.4480	0.5366	0.4480	0.5541	0.5527	0.5546	0.4595	0.5751	0.6199	0.5041
28	3093	1.0001	1.0098	1.0085	1.1701	1.3545	1.1701	1.3734	1.3704	1.3382	0.9138	1.0769	1.1082	1.0763
28	5805	1.0003	1.0198	1.0155	1.2119	1.3546	1.2119	1.3773	1.3779	1.2888	0.9464	1.0805	1.1411	1.0362
18	5518	1.0008	1.0295	1.0435	0.9706	0.9711	0.9706	0.9978	1.0145	0.9892	0.5200	0.5034	0.5079	0.4796
Average		**0.9997**	**1.0257**	**1.0365**	**1.2251**	**1.2077**	**1.2251**	**1.2304**	**1.2595**	**1.2257**	**1.5421**	**1.5091**	**1.5625**	**1.4567**
SD		**0.0166**	**0.0377**	**0.0588**	**0.7521**	**0.7016**	**0.7521**	**0.7052**	**0.7099**	**0.6417**	**1.1418**	**1.0528**	**1.0755**	**1.0045**

Figures 16 shows that the mean AADTT is very close to the true AADTT for scenario groups 1- and 2- (i.e., site-specific WIM or AVC data, respectively), regardless of the length of coverage. This is not the case for scenario groups 3- and 4-, where the mean AADTT is significantly different than the true AADTT. The reason is that lack of site-specific WIM and AVC data necessitates use of regional or national truck percentage values, which can be drastically different from the site-specific values. As mentioned earlier regional truck percentage values are obtained from the average of the percent trucks for the vehicle classification cluster for the particular site. The national percentage of trucks of 15.9% is computed as the average of the percentage of trucks for the 178 extended WIM coverage sites analyzed. It appears that for sites with lower AADTT level, AADTT ratios tend to be higher than 1, while for sites with higher AADTT level, the ratios tend to be lower than 1. This is due to a correlation between the percent trucks and the AADTT level at the sites analyzed. As can be seen from Table 16, the *Pearson* correlation coefficient between AADTT and truck percentage for the 30 sites analyzed is 0.62. It should be noted that the outliers for scenario groups 3- and 4- are identified as sites 9_1803, 28_4024 and 9_4020 with tuck percentages (i.e., 3.2%, 4.2%, 4.5%, respectively) much lower than either the assumed regional or national averages.

Figure 17 shows a box-plot of these AADTT ratios. The lower and upper lines of the "box" are the 25th and 75th percentiles of the sample. The distance between the top and bottom of the box is the inter-quartile range. The line in the middle of the box is the sample median. The whiskers are lines extending 1.5 times of inter-quartile range from each end of the box to show the extent of the rest of the data. An outlier is a value that is more/less than 1.5 times the inter-quartile range away from the top or bottom of the box. Clearly, the distributions of AADTT ratios are positively skewed. This is typical of ratios that exhibit a log-symmetric distribution, whereby an overestimation by a factor of 3 and an underestimation by a factor of 3 have logarithms with an average of 0. Figure 18 is box plot of the natural log AADTT ratios.

Table 16: Percent Truck For The 30 Sites Analyzed

STATE_ID	SHRP_ID	AADTT	Site-Specific Percent Truck	Regional Percent Truck	National Percent Truck
28	4024	99	4.2	9.0	15.9
9	1803	165	3.2	11.6	15.9
53	1007	178	32.8	16.5	15.9
26	1004	229	5.3	9.5	15.9
27	1019	268	7.2	7.1	15.9
28	2807	376	10.1	8.1	15.9
50	1682	419	8.5	8.2	15.9
9	4020	546	4.5	15.2	15.9
53	3813	548	7.5	10.9	15.9
26	3069	577	11.9	19.4	15.9
26	1010	647	11.0	9.1	15.9
18	2009	655	5.5	8.7	15.9
18	2008	709	17.4	9.6	15.9
53	6048	783	8.5	8.7	15.9
26	1012	977	13.5	19.3	15.9
28	3081	1120	21.4	19.9	15.9
18	5022	1164	17.2	6.9	15.9
26	5363	1247	24.1	19.7	15.9
27	4055	1381	17.9	16.9	15.9
26	1013	1395	17.3	18.6	15.9
27	5076	1438	9.9	17.8	15.9
18	6012	1473	34.9	30.7	15.9
9	4008	1496	15.2	16.9	15.9
18	1028	1535	30.2	31.9	15.9
28	5006	1559	27.4	19.4	15.9
9	5001	1590	16.9	9.0	15.9
26	4015	1807	34.6	15.5	15.9
28	3093	1920	17.4	20.4	15.9
28	5805	2024	16.8	20.4	15.9
18	5518	3746	32.5	31.5	15.9

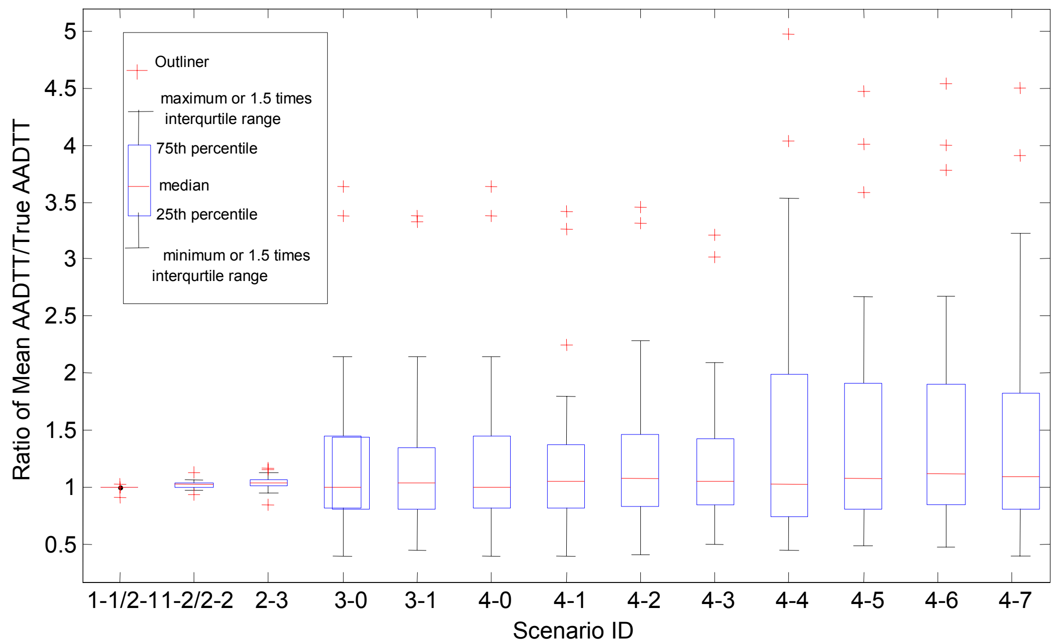


Figure 17: Box-Plot of the Ratio of the Scenario Mean AADTT over the True AADTT

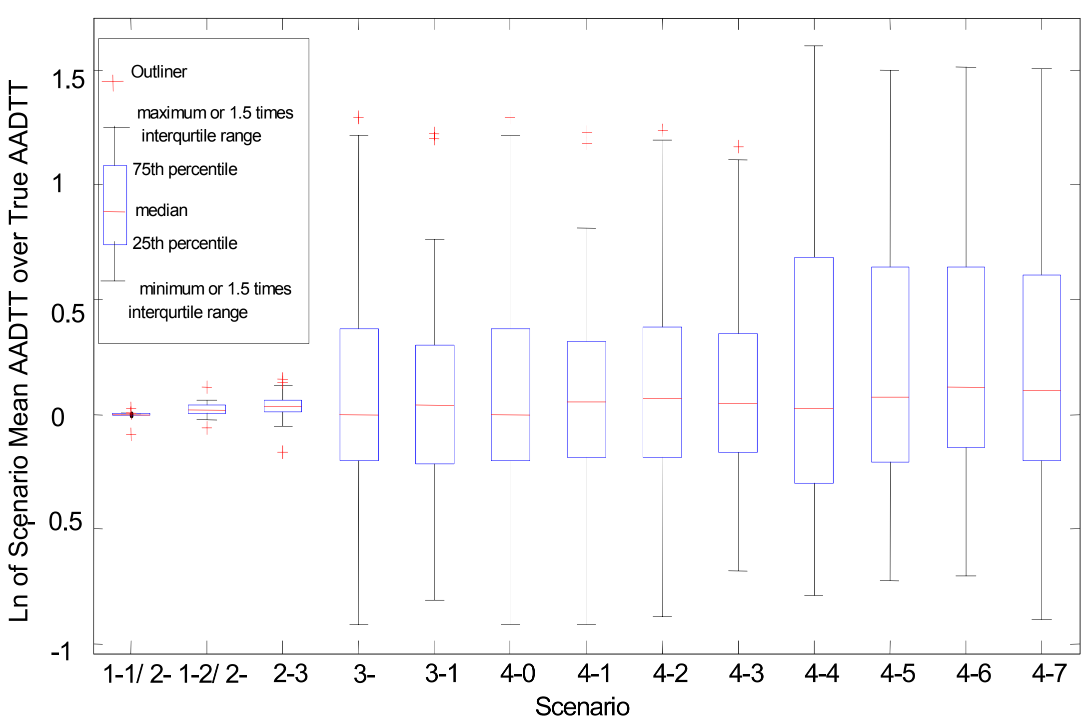


Figure 18: Box-Plot of the Natural Log of the Scenario Mean AADTT over the True AADTT

The range in AADTT estimation is of interest, especially its underestimation, since it will lead to pavement life over-prediction and hence, result in unsafe pavement designs. K-S hypothesis test was conducted to test the goodness of fit of the lognormal distribution for the ratios. Results show that the K-S test statistic is less than the critical value for lognormal distribution for 95% reliability. Hence, it is reasonable to assume lognormal distribution for the ratios. The percent range of AADTT under-estimation corresponding to each reliability level is computed as follows [9].

Compute the mean and standard deviation of nature log value of the 30 AADTT ratios for each scenario, denoted by $\mu_{\ln(x)}$ and $\sigma_{\ln(x)}$, respectively. For each reliability level (75%, 85% or 95%), the inverse values for the corresponding cumulative standard normal deviate are Z =0.6745, 1.0364 and 1.6449, respectively. The under estimated ln(ratio) (natural log value of mean AADTT ratio) for each reliability level is:

$$\ln(ratio) = \mu_{\ln(x)} - Z * \sigma_{\ln(x)} \tag{5}$$

The $\mu_{\ln(x)}$ are assumed to equal 0, since the natural log value of the mean AADTT ratios are symmetrical to zero. As the ratios and natural log ratios are in same increasing order, the mean AADTT ratio for each reliability level can be obtained as:

$$\text{Mean AADTT ratio} = e^{\ln(\text{ratio})} \tag{6}$$

The error in estimating the mean AADTT ratio corresponding to each reliability level is:

$$\text{Percent Error in under estimating mean AADTT} = 1 - \text{Mean AADTT ratio} \tag{7}$$

For example, for scenario 1-1/2-1, the standard deviation of natural log mean AADTT ratio is 0.016583 (which is the standard deviation of the 30 natural log value of mean AADTT ratios in Table 15). For 75% reliability from equation (5):

ln(ratio)=0- 0.6745*0.016583=-0.011185

Mean AADTT ratio= $e^{(-0.011185)}$=0.9889, from equation (6)

Percent Error in under estimating mean AADTT =1-0.988877=0.0111, from equation (7)

Results are shown in Table 17 and Figure 19.

Table 17: Percent Error in Under-Predicting Mean AADTT by Confidence Level

	Scenario ID												
Reliability	1-1/ 2-1	1-2/ 2-2	2-3	3-0	3-1	4-0	4-1	4-2	4-3	4-4	4-5	4-6	4-7
75%	1.11%	2.45%	3.75%	31.71%	30.49%	31.71%	30.20%	29.83%	28.25%	35.98%	34.61%	34.30%	34.34%
85%	1.70%	3.73%	5.70%	44.35%	42.82%	44.35%	42.44%	41.98%	39.96%	49.60%	47.94%	47.56%	47.61%
95%	2.69%	5.86%	8.90%	60.55%	58.81%	60.55%	58.38%	57.85%	55.50%	66.29%	64.51%	64.10%	64.15%

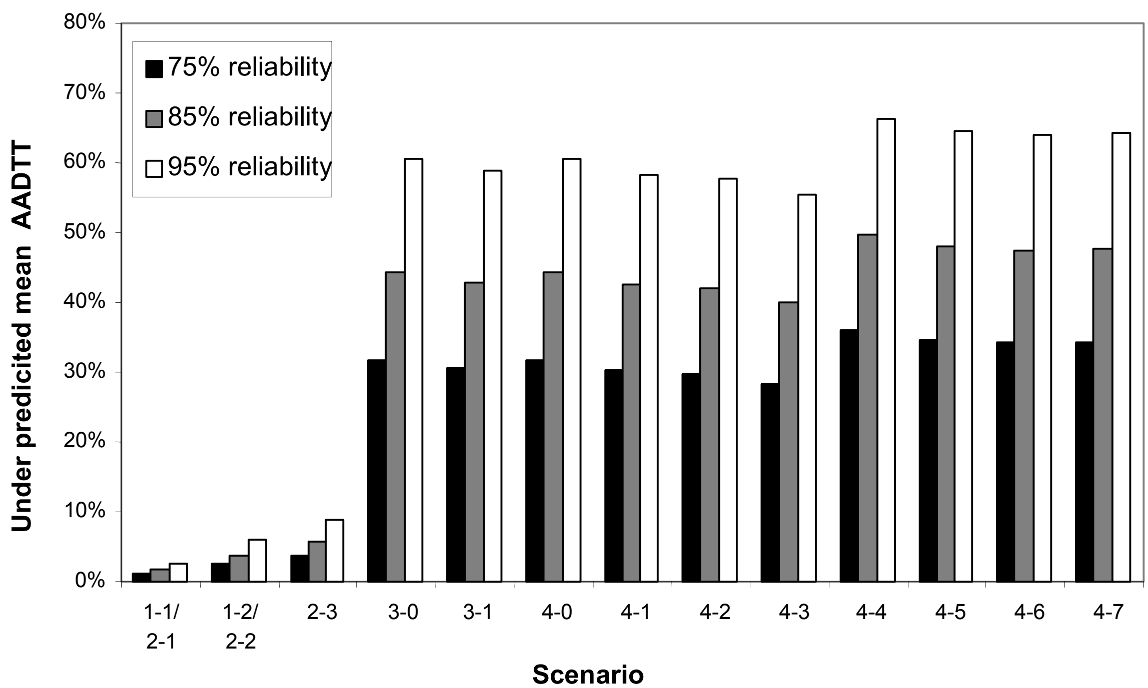


Figure 19: Percentile Range in Mean AADTT Under-Prediction

The error ranges described above are obtained from data source error (such as using regional data to estimate site-specific data). Another source of error is from the short time data collection coverage, such as 1 month/season. This source of error is related to the Coefficient of Variance (CV) in predicting AADTT within each scenario (Table 18).

Table 18: Coefficient of Variance (CV) For AADTT Estimation from Different Traffic Data Collection Scenarios

AADTT CV		Scenario ID									
State ID	Site ID	1-1/ 2-1	1-2/ 2-2	2-3	3-1	4-1	4-2	4-3	4-5	4-6	4-7
28	4024	0.1566	0.2121	0.3818	0.0358	0.0694	0.2078	0.2916	0.0708	0.2102	0.3340
9	1803	0.1477	0.1618	0.3108	0.0674	0.0830	0.2658	0.3789	0.0846	0.3242	0.3538
53	1007	0.1461	0.1791	0.9513	0.0537	0.0634	0.1756	0.2188	0.0473	0.1758	0.2358
26	1004	0.1821	0.2971	0.5969	0.0745	0.1720	0.4931	0.6698	0.1817	0.4556	0.6442
27	1019	0.1575	0.1925	0.4239	0.0642	0.0893	0.1943	0.3965	0.0859	0.2789	0.4283
28	2807	0.0881	0.1398	0.2566	0.0382	0.1066	0.2837	0.4199	0.0811	0.2010	0.3131
50	1682	0.0261	0.0516	0.0917	0.0066	0.0221	0.0732	0.1429	0.0357	0.0907	0.2578
9	4020	0.0742	0.0707	0.1485	0.0534	0.0383	0.1439	0.3408	0.0209	0.2480	0.4030
53	3813	0.1094	0.1552	0.2713	0.0500	0.1012	0.2001	0.3896	0.0921	0.5158	0.4511
26	3069	0.2132	0.1810	0.3902	0.1435	0.1031	0.2927	0.4250	0.1058	0.5608	0.4825
26	1010	0.1180	0.1857	0.3161	0.0522	0.0489	0.1301	0.1697	0.1251	0.2626	0.3263
18	2009	0.1668	0.1770	0.4193	0.0363	0.0425	0.3126	0.3952	0.0412	0.2283	0.3886
18	2008	0.2413	0.2754	0.6844	0.1483	0.1705	0.6448	0.8105	0.1366	0.3626	0.4802
53	6048	0.0892	0.1067	0.0795	0.0244	0.0373	0.1243	0.1536	0.0361	0.0876	0.3339
26	1012	0.1028	0.1198	0.2937	0.0329	0.0428	0.1798	0.2553	0.0312	0.2868	0.2651
28	3081	0.0406	0.0451	0.1107	0.0181	0.0347	0.0818	0.2461	0.0360	0.2741	0.2635
18	5022	0.4329	0.4221	0.9634	0.1345	0.1687	0.3656	0.3424	0.1687	0.3656	0.3424
26	5363	0.2692	0.2644	0.6177	0.1268	0.1484	0.5807	0.4392	0.1503	0.6869	0.4703
27	4055	0.0534	0.0718	0.1203	0.0363	0.0400	0.1004	0.1855	0.0590	0.1305	0.2507
26	1013	0.2971	0.3119	0.5779	0.1571	0.1870	0.4932	0.5426	0.1894	0.5868	0.6100
27	5076	0.0730	0.0955	0.1846	0.0348	0.0680	0.1857	0.2219	0.0331	0.1186	0.2769
18	6012	0.1461	0.1857	0.3187	0.0432	0.0757	0.1852	0.3398	0.0794	0.1962	0.3334
9	4008	0.1229	0.1227	0.4007	0.0649	0.0621	0.3484	0.4251	0.0348	0.1406	0.2958
18	1028	0.0261	0.0528	0.0919	0.0099	0.0244	0.0670	0.1349	0.0192	0.0467	0.2180
28	5006	0.0376	0.0450	0.0969	0.0141	0.0261	0.0664	0.2675	0.0283	0.2377	0.3213
9	5001	0.1765	0.1040	0.2589	0.0750	0.0634	0.2362	0.3719	0.0688	0.3773	0.4409
26	4015	0.1914	0.2265	0.4550	0.0797	0.0779	0.2744	0.4018	0.0879	0.4682	0.4302
28	3093	0.0377	0.0549	0.1071	0.0108	0.0291	0.0773	0.2068	0.0315	0.2438	0.2279
28	5805	0.0475	0.0691	0.1299	0.0202	0.0365	0.0834	0.2079	0.0410	0.2474	0.3134
18	5518	0.1218	0.1405	0.2876	0.0483	0.0618	0.2349	0.2567	0.0532	0.2025	0.3031
Average		**0.1364**	**0.1573**	**0.3446**	**0.0585**	**0.0765**	**0.2367**	**0.3349**	**0.0752**	**0.2871**	**0.3598**
SD		**0.0909**	**0.0917**	**0.2385**	**0.0431**	**0.0485**	**0.1535**	**0.1530**	**0.0494**	**0.1579**	**0.1066**

Let A_{CV} represent the average of the 30 CVs and S_{CV} represent the standard deviation of the 30 CVs. For each reliability level (75%, 85%, 95%), the AADTT under-prediction percentile due to this second source of error is:

Using central limit theory [9], the average AADTT under prediction percentile for each scenario and for each reliability, denoted by P_B, is given by:

$$P_B = \left(A_{CV} + \frac{S_{CV} * Z}{\sqrt{30}} \right) * Z \qquad (8)$$

For example, for Scenario 1-1/2-1, the average CV is 0.1364; the SD of CV is 0.0909. For 75% reliability, The AADTT under-prediction percentile for scenario 1-1/2-1 $=[0.1364+0.0909*0.6745 /30^{0.5}]*0.6745=0.09958$, from equation (8)

The results are shown in Table 19 and Figure 20. In predicting AADTT, Scenarios 1-1 or 2-1 have approximately the same variation with Scenarios 2-1 or 2-2. This suggests that high quality AVC data for 1 week per season can provide AADTT estimates with accuracy comparable to that obtained from the 1 month per season scenario. For Scenario 2-3, only 1 week of site-specific AVC data is available, the variation in AADTT is much higher, which means that seasonal changes in truck volume data are significant.

Scenario groups 3- and 4- have similar time coverage of site-specific data with scenario groups 1- and 2-, therefore it is not surprising that they exhibit similar variations in AADTT ratios. It should be noticed that although the variation within each scenario for scenario group 3- and 4- are relatively low, the mean AADTT is significantly different than the true AADTT, as seen in Figure 15. Hence, no high accuracy in predicting AADTT from scenario groups 3- and 4- should be expected.

Table 19: Range in AADTT Under Estimation Due to Different Data Collection Period

Reliability	Scenario ID												
	1-1/ 2-1	1-2/ 2-2	2-3	3-0	3-1	4-0	4-1	4-2	4-3	4-4	4-5	4-6	4-7
75%	9.96%	11.37%	25.22%	0.00%	4.30%	0.00%	5.56%	17.24%	23.86%	0.00%	5.48%	20.67%	25.16%
85%	15.92%	18.10%	40.39%	0.00%	6.91%	0.00%	8.88%	27.55%	37.72%	0.00%	8.77%	32.85%	39.38%
95%	26.93%	30.40%	68.46%	0.00%	11.75%	0.00%	14.98%	46.52%	62.65%	0.00%	14.81%	55.02%	64.45%

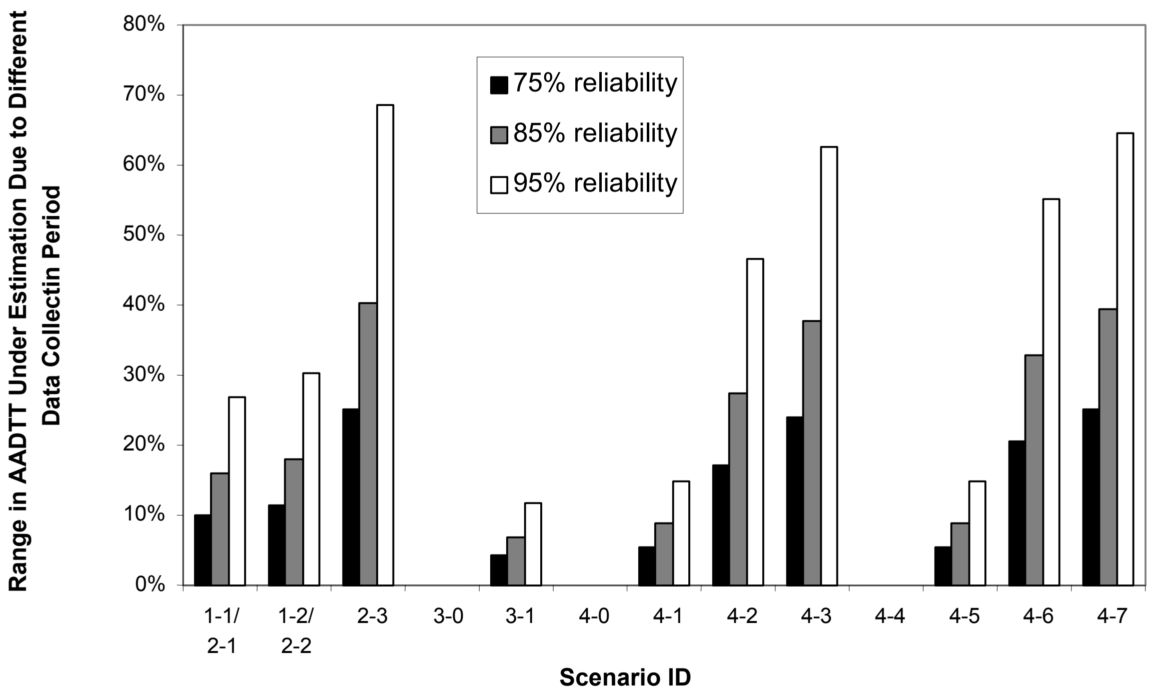


Figure 20: Range in AADTT Under Estimation by Scenario

The two sources of errors in predicting AADTT are due to different sources: time and data sources, which are independent variables. Hence, the overall range in AADTT under-prediction is computed as the sum of the low percentile range of mean AADTT underestimation plus the low percentile range of the AADTT underestimation from different data collection time. This approach is very conservative, but answers the question of reliability in predicting AADTT, (i.e., certainty that the error range estimated will not be exceeded). Results are shown in Table 20 and Figure 21.

Table 20: Under Estimated AADTT Percentile

	Scenario ID												
Reliability	1-1/ 2-1	1-2/ 2-2	2-3	3-0	3-1	4-0	4-1	4-2	4-3	4-4	4-5	4-6	4-7
75%	11.07%	13.81%	28.97%	31.71%	34.80%	31.71%	35.76%	47.07%	52.11%	35.98%	40.09%	54.97%	59.50%
85%	17.63%	21.83%	46.09%	44.35%	49.72%	44.35%	51.32%	69.52%	77.67%	49.60%	56.70%	80.41%	87.00%
95%	29.62%	36.26%	77.36%	60.55%	70.56%	60.55%	73.36%	104.37%	118.15%	66.29%	79.32%	119.11%	128.61%

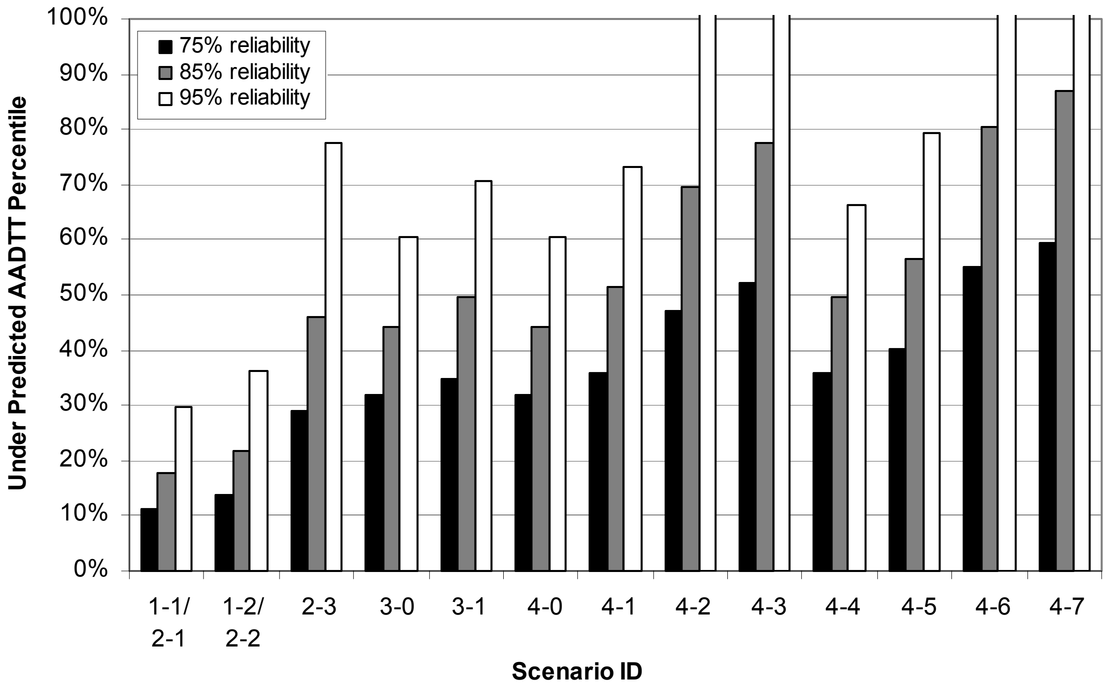


Figure 21: Under Predicted AADTT Percentile

6.3 Vehicle Class Distribution for Class 5 and Class 9

Of the 10 FHWA truck classes, Class 5 and Class 9 are the most common. They comprise roughly 80% of total truck volume. Therefore identifying them and counting their volumes accurately is very important. From the analysis presented in Section 6.1 (AADTT), it is evident that for scenario groups 1- and 2-, the mean AADTTs are very close to the true AADTTs because site-specific VC information is available. Hence, for these scenario groups, the source of variation for Class 5 and Class 9 prediction is from the time coverage of data only. Using Equation (8) for Class 5 and Class 9 separately, errors in traffic volume estimation for Class 5 and Class 9 are obtained for different reliability levels (Table 21). Figure 22 is a chart plot of the results for Class 5. Figure 23 is a chart plot of the results for Class 9. Figure 22 and 23 clearly show that Scenario 1-1/2-1 and Scenario 1-2/2-2 have similar accuracy in predicting truck volumes for these two truck classes, which agrees with the previous results on AADTT estimation (Figure 20 and Figure 21). For Scenario 2-3, truck volume estimation for Class 5 and Class 9 could be under predicted by more than 40% for 95% reliability.

Table 21: Truck Volume Under Prediction Percentile for Class 5 and Class 9

	Class 5 (Reliability)			Class 9 (Reliability)		
Scenario ID	75%	85%	95%	75%	85%	95%
1-1/2-1	10.92%	17.48%	29.59%	8.83%	14.30%	24.65%
1-2/2-2	12.25%	19.52%	32.85%	9.64%	15.57%	26.74%
2-3	26.36%	42.10%	71.10%	21.37%	34.77%	60.34%

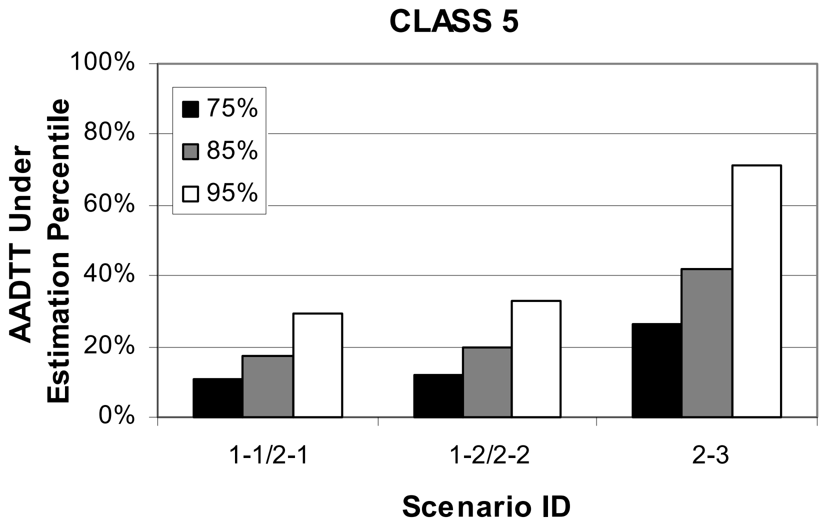


Figure 22: AADTT Under Estimation Percentile for FHWA Class 5

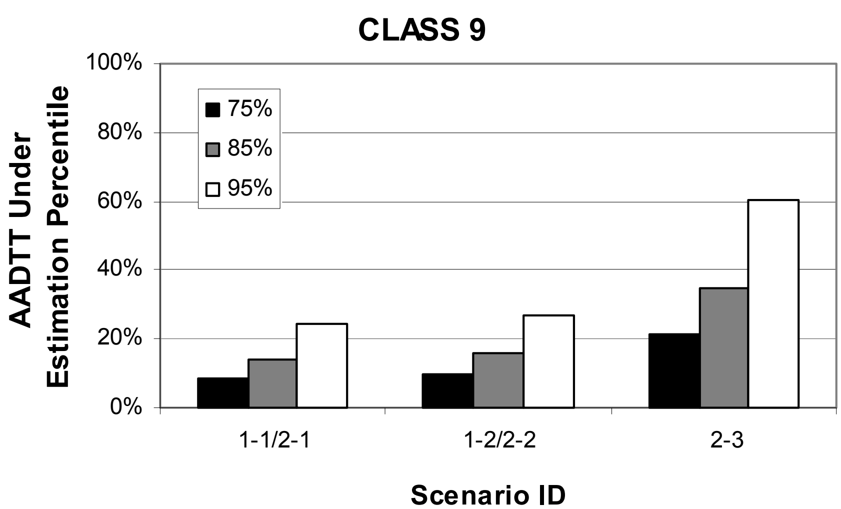


Figure 23: AADTT Under Estimation Percentile for FHWA Class 9

6.4 MAF

The analysis presented earlier suggests that different data collection periods result in different traffic prediction errors in predicting AADTTs by vehicle class. Scenario 2-3 results in twice as many errors as 1-1/2-1 and Scenario 1-2/2-2 (Figure 21). This suggests that the seasonal changes in truck volume are obvious. Since new pavement design emphasizes the combination of environmental and mechanical pavement behavior, MAFs will play an important role in pavement design.

Table 22 and 23 show the errors in estimating MAF for different scenarios for vehicle classes 5 and 9 separately. The method in computing the errors is the same with that described in Section 6.3. Figure 24 to 29 are chart plots of the results. For MAF estimation, only Scenario 1-1/2-1 and Scenario 1-2/2-2 have variation since other scenarios simply use regional MAFs, which are constant between scenarios.

For both Scenario 1-1/2-1 and Scenario 1-2/2-2: for reliability, the errors of MAF estimations are around 10% and 30% for 75% and 95% reliability respectively, for both Class 5 and Class 9. However, for Class 5, the errors in the winter season are larger than that in summer season. It is because there are fewer truck Class 5 volume in the winter season than that in the summer season.

Table 22 and 23 also show that Scenario 1-1/2-1 and 1-2/2-2 do not have great difference in estimating MAF.

Table 22: MAF Estimation Errors Percentile for Vehicle Class 5

Reliability	Scenario ID	January	February	March	April	May	June	July	August	September	October	November	December
75%	1-1/2-1	16.5%	16.1%	11.8%	10.5%	9.9%	10.0%	11.0%	9.3%	9.0%	10.8%	11.8%	13.0%
75%	1-2/2-2	19.4%	17.7%	14.4%	9.9%	13.0%	11.6%	12.6%	11.0%	10.1%	12.9%	11.1%	11.9%
85%	1-1/2-1	26.7%	26.0%	19.2%	17.1%	16.0%	16.1%	17.7%	14.8%	14.4%	17.5%	18.9%	21.2%
85%	1-2/2-2	31.4%	28.6%	23.1%	15.9%	21.0%	18.7%	20.3%	17.5%	16.2%	20.8%	17.9%	19.0%
95%	1-1/2-1	45.9%	44.8%	33.3%	30.0%	27.8%	27.7%	30.3%	25.1%	24.7%	30.1%	32.2%	36.6%
95%	1-2/2-2	54.1%	49.2%	39.7%	27.0%	36.1%	31.7%	34.7%	29.3%	27.6%	35.5%	30.3%	32.3%

Table 23: MAF Estimation Errors Percentile for Vehicle Class 9

reliability	scenaion ID	January	February	March	April	May	June	July	August	September	October	November	December
75%	1-1/2-1	9.5%	10.1%	9.7%	9.2%	6.5%	8.0%	10.8%	11.7%	8.8%	9.6%	11.6%	10.4%
75%	1-2/2-2	11.5%	9.6%	11.0%	8.7%	8.8%	11.9%	11.0%	13.2%	9.2%	8.6%	12.4%	11.8%
85%	1-1/2-1	15.6%	16.4%	15.8%	15.1%	10.4%	13.3%	17.7%	19.2%	14.5%	15.8%	18.9%	17.2%
85%	1-2/2-2	18.7%	15.5%	17.8%	14.0%	14.2%	19.9%	17.9%	22.0%	15.0%	13.8%	20.4%	19.5%
95%	1-1/2-1	27.4%	28.4%	27.5%	26.4%	17.8%	23.5%	31.1%	34.1%	25.7%	27.8%	33.1%	30.5%
95%	1-2/2-2	32.6%	26.6%	30.7%	23.9%	24.6%	36.2%	31.3%	39.5%	26.1%	23.6%	36.1%	34.4%

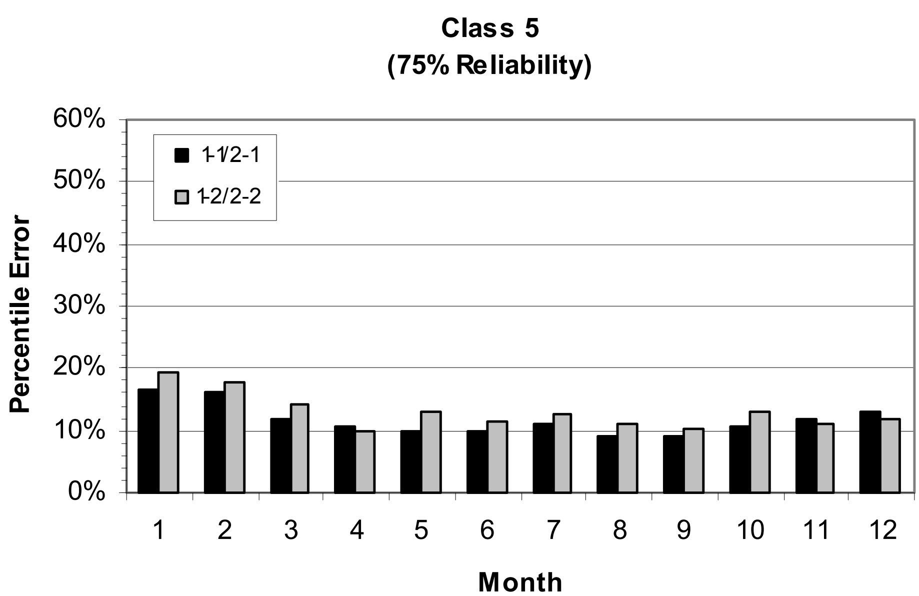


Figure 24: MAF Estimation Error Percentile for FHWA Class 5 (75% Reliability)

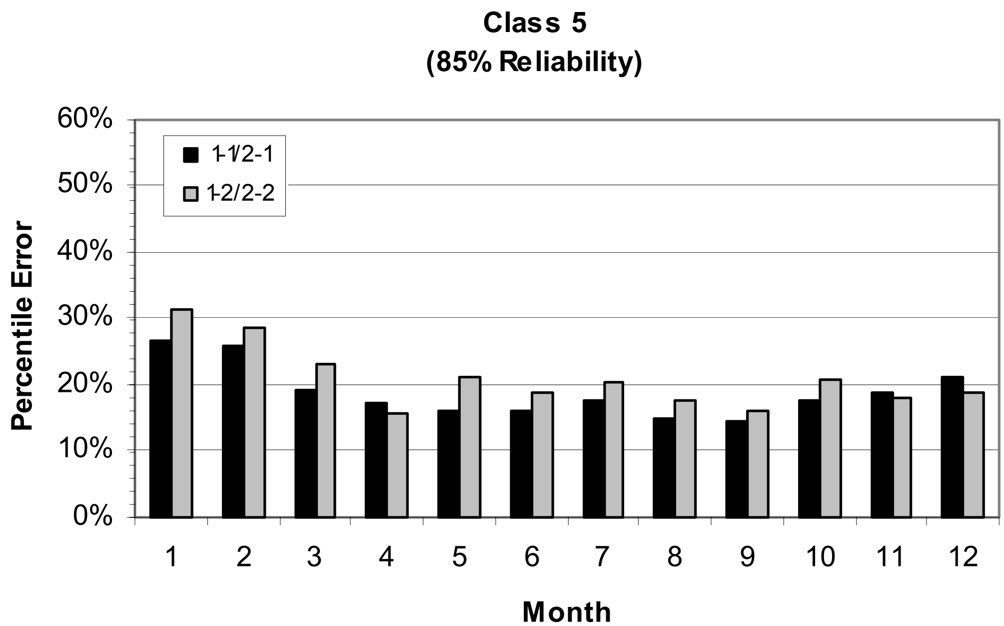


Figure 25: MAF Estimation Error Percentile for FHWA Class 5 (85% Reliability)

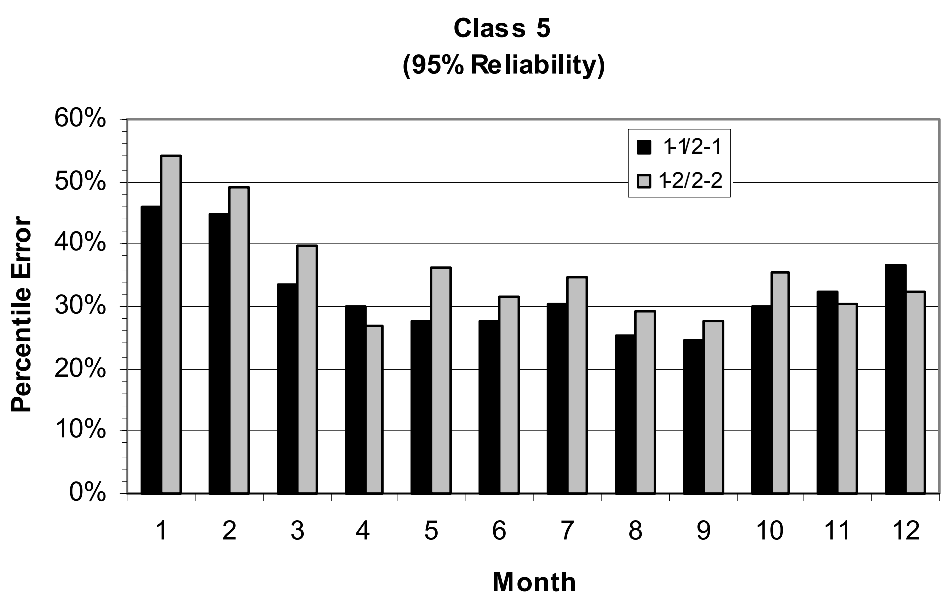


Figure 26: MAF Estimation Error Percentile for FHWA Class 5 (95% Reliability)

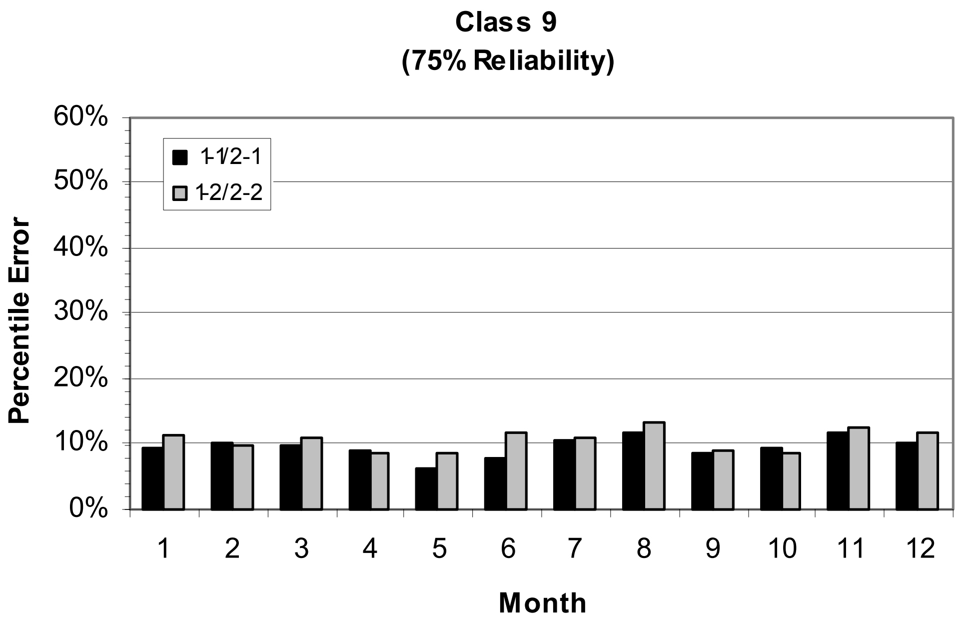


Figure 27: MAF Estimation Error Percentile for FHWA Class 9 (75% Reliability)

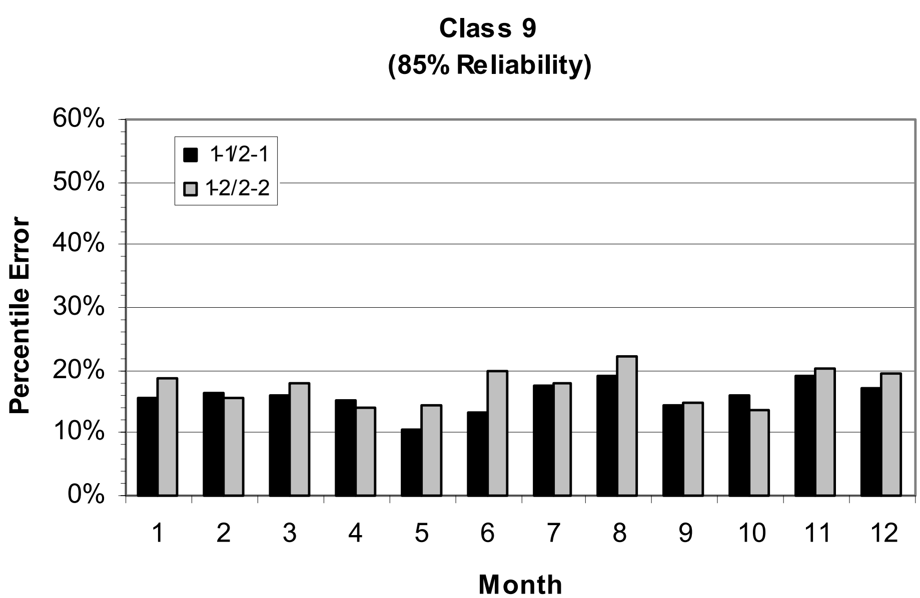


Figure 28: MAF Estimation Error Percentile for FHWA Class 9 (85% Reliability)

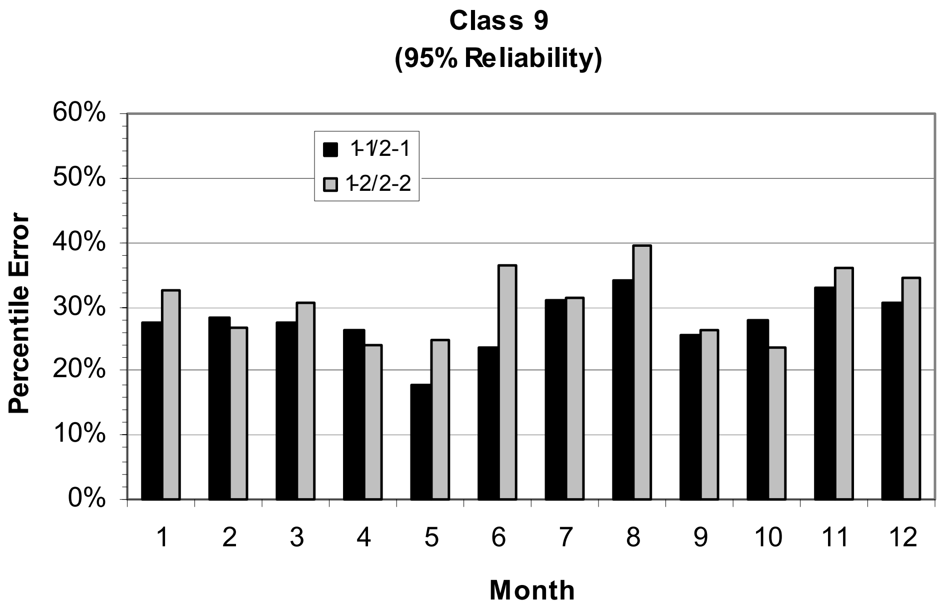


Figure 29: MAF Estimation Error Percentile for FHWA Class 9 (95% Reliability)

6.5 Axle Load Distribution

The discussion above dealt with traffic volumes, either in terms of overall AADTT, AADTT by class and their monthly fluctuation expressed in terms of MAFs. The fundamental mechanism of pavement damage is the failure due to repetitive traffic loading. Hence, the truck axle load will determine if the pavement will fail under given number of loading cycles. Obviously, heavy axle load will lead to pavement failure with a few number of axle passes, while light axle load may never do damage to the pavement. Figure 30 is an example of single axle load distribution for FHWA Class 5. Figure 31 is an example of tandem axle load distribution for FHWA Class 9.

To estimate the error in computing the frequency distribution of axles by configuration, 5000 lbs load interval is used for single axle of Class 5, and a 10,000 lbs load interval is used for tandem axle of Class 9. The use of wider load range is to avoid the zero value in conducting the statistical analysis, since there are no axle passes for certain small load ranges. For axle load distribution errors, only Scenario 1-1 and 1-2 are considered, as constant regional or national normalized axle load distribution is used in other scenarios.

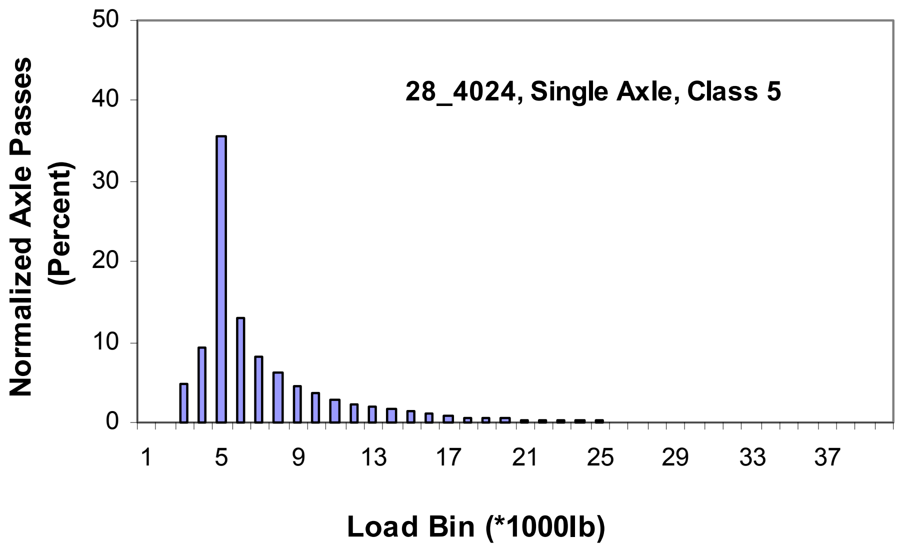


Figure 30: Single Axle Load Distribution Example

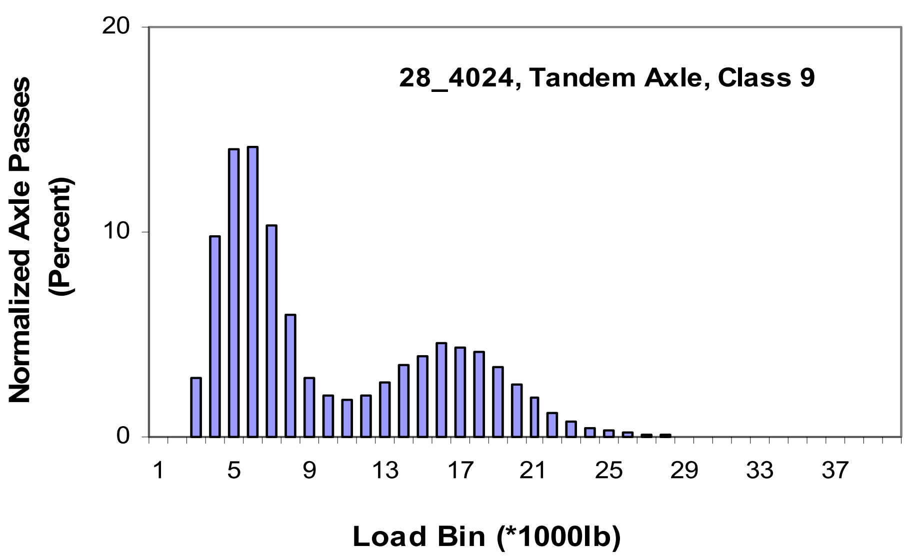


Figure 31: Tandem Axle Load Distribution Example

Similarly, Equation 8 is used for under prediction estimation of axle passes. Results are shown in Table 24 and Figures 32 to 37. Previous analyses show that for truck volume prediction, Scenario 1-1 and 1-2 have similar accuracy. However, for axle load distribution, Scenario 1-1 has much lower percentile errors than Scenario 1-2, as shown by figure 32-37. For the single axles of Class 5 vehicles, for example, percentile errors for axle load frequency estimation for load range under 15000 lbs are lower than 15.2% and 22.7% for Scenario 1-1, and Scenario 1-2, respectively (Figure 34). This difference is more obvious for the heavy load range, such as axle load more than 15000 lbs, in which Scenario 1-2 has more than twice the percentile errors than Scenario 1-1. Similar results are obtained for Class 9 tandem axle.

In summary, for axle load distribution, Scenario 1-1 has much better accuracy than Scenario 1-2. Within each scenario, the heavy load range has more percentile errors than the light load range. This is apparently due to the low volume of heavy load trucks. Low volume truck traffic requires long time coverage to collect accurate data.

Table 24: Axle Loading Estimation Percentile Errors for FHWA Class 5 and 9

		Class 5 (Load Range)					Class 9 (Load Range)				
Reliability	Scenario ID	<5000	<10000	<15000	<20000	>20000	<10000	<20000	<30000	<40000	>40000
75%	1-1	4.3%	3.6%	5.6%	8.7%	11.9%	7.7%	2.5%	4.2%	7.2%	14.0%
	1-2	8.1%	5.2%	8.6%	17.5%	31.0%	15.2%	4.3%	7.1%	13.8%	124.4%
85%	1-1	6.8%	5.7%	9.0%	13.9%	18.9%	12.3%	4.0%	6.7%	11.5%	22.2%
	1-2	13.3%	8.3%	13.6%	28.5%	51.3%	24.7%	7.0%	11.5%	22.5%	214.7%
95%	1-1	11.6%	9.7%	15.2%	23.7%	31.7%	20.8%	6.9%	11.4%	19.5%	37.2%
	1-2	23.5%	13.9%	22.7%	49.3%	91.2%	42.7%	12.0%	19.8%	39.4%	403.5%

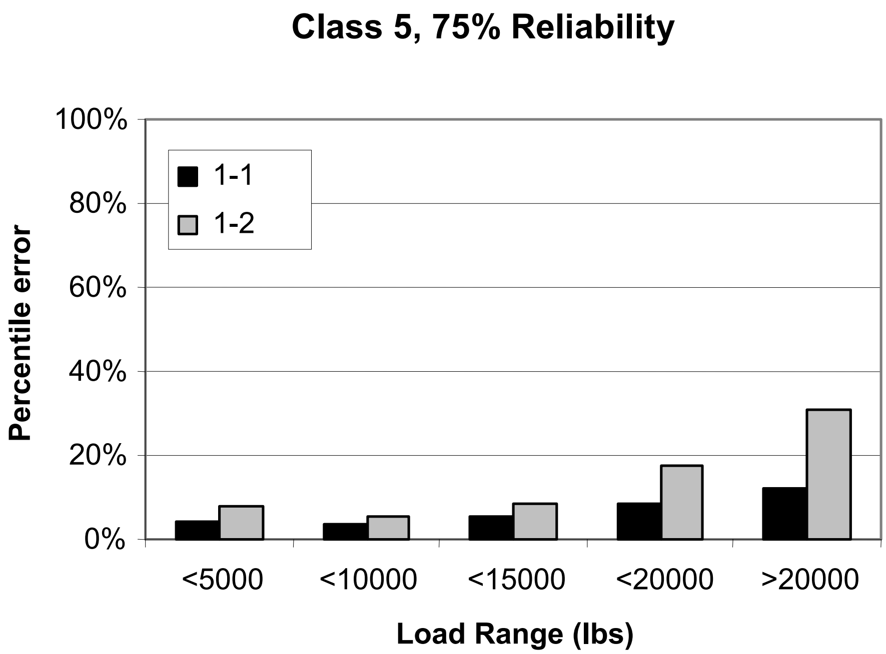


Figure 32: Single Axle Loading Estimation Error Percentile for FHWA Class 5 (75% Reliability)

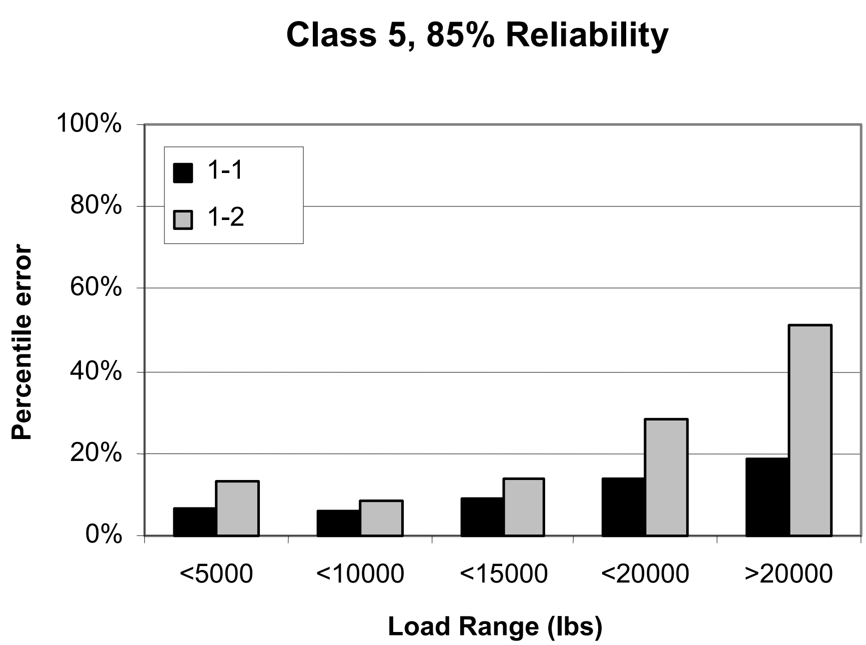


Figure 33: Single Axle Loading Estimation Error Percentile for FHWA Class 5 (85% Reliability)

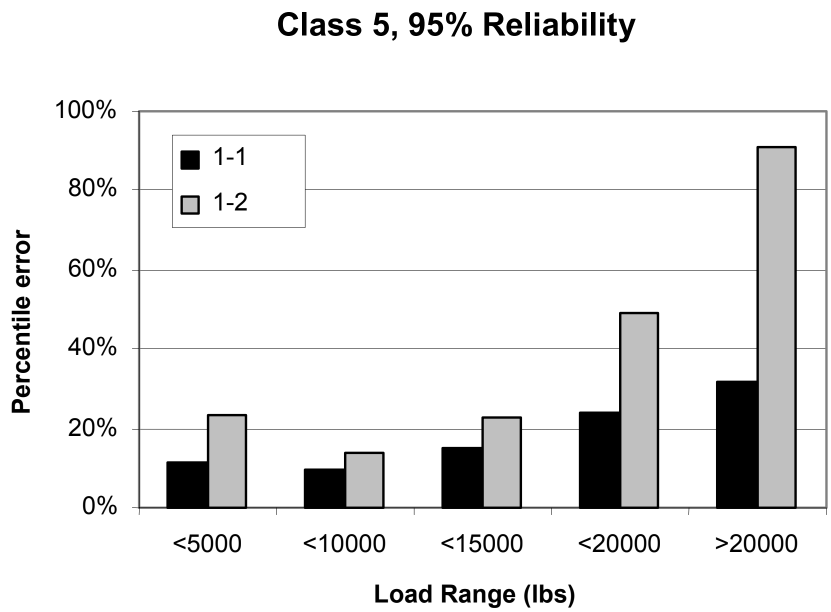


Figure 34: Single Axle Loading Estimation Error Percentile for FHWA Class 5 (95% Reliability)

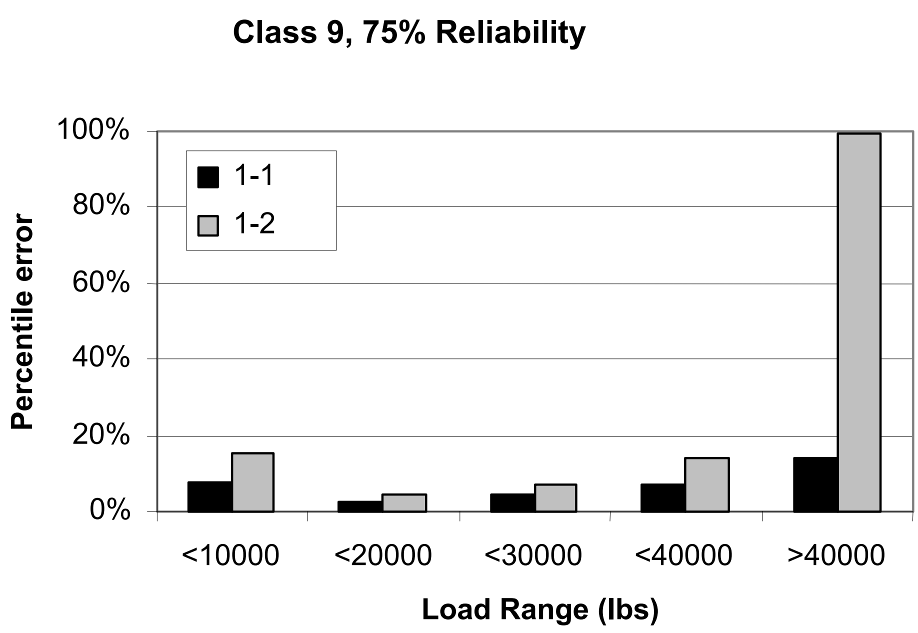


Figure 35: Tandem Axle Loading Estimation Error Percentile for FHWA Class 9 (75% Reliability)

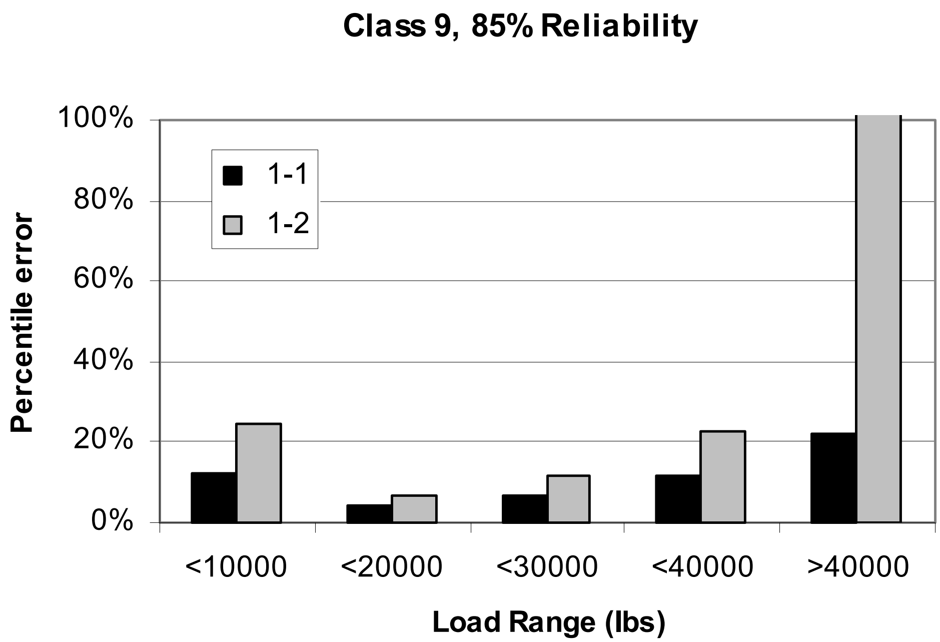


Figure 36: Tandem Axle Loading Estimation Error Percentile for FHWA Class 9 (85% Reliability)

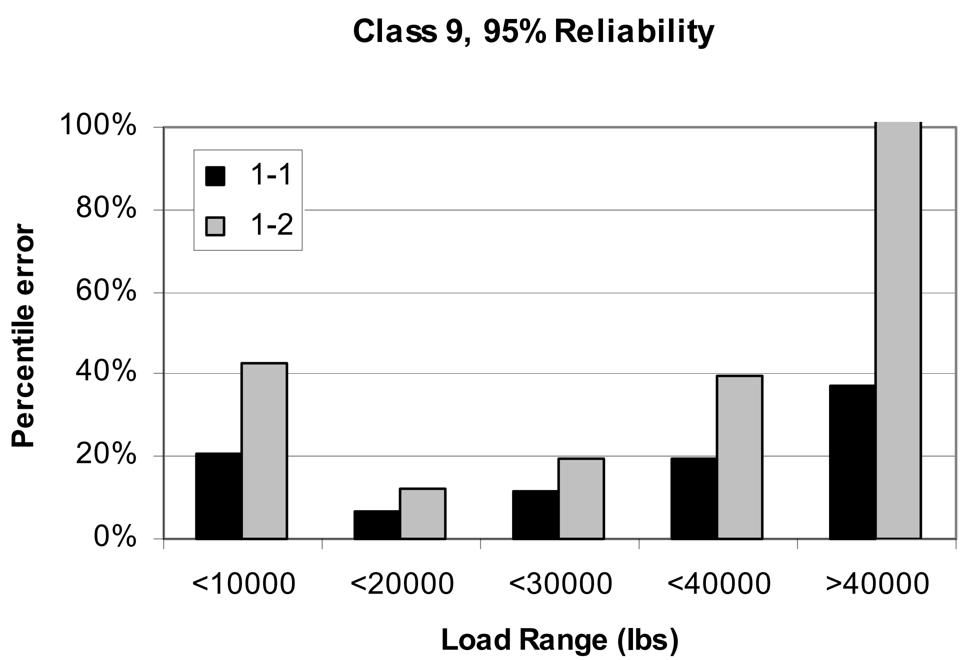


Figure 37: Tandem Axle Loading Estimation Error Percentile for FHWA Class 9 (95% Reliability)

6.6 Summary

The preceding sections prescribed a statistical analysis for traffic input elements for the PDG. For each of the four traffic input elements (AADTT, Vehicle Classification, MAF, and Axle Load Distribution) in the new PDG, percent error in predicting the input is conducted for 75%, 85% and 95% reliability respectively.

For AADTT prediction, for 75% reliability, the percent errors are 11.07% for Scenario 1-1/2-1, 13.81% for Scenario 1-2/2-2, 28.97% for Scenario 2-3, and more than 30% for other scenarios. For 85% reliability, the percent errors are 17.63% for Scenario 1-1/2-1, 21.83% for Scenario 1-2/2-2, 46.09% for Scenario 2-3, and more than 40% for all other scenarios. For 95% reliability, the percent errors are 29.62% for Scenario 1-1/2-1, 36.26% for Scenario 1-2/2-2, 77.36% for Scenario 2-3, and more than 60% for all other scenarios. Hence, Scenario 1-1/2-1 and 1-2/2-2, with one month per season or one week per season site specific truck class data, result in much higher accuracy than other scenarios. Although Scenario 2-3 involves site specific truck class data, the percent error is high due to the very short period of time of data collection (1 week only). High percent errors exist in Scenario group 3- and 4- due to the lack of site specific truck class data.

For truck Class 5 and 9 volume prediction, the results are similar with AADTT prediction for scenario groups 1- and 2-. For MAF estimation, the percent errors are about 10%, 20% and 30% for 75%, 85% and 95% reliability respectively, for both truck class 5 and truck class 9.

For axle load distribution estimation, truck Class 5 single axle and Class 9 tandem axle are analyzed for the percent errors in load distribution. For Class 5 single axle, for Scenario 1-1, about 10%, 15% and 24% errors are expected for load range lower than 20,000 lbs, about 12%, 20% and 32% errors are expected for load range higher than 20,000 lbs, for 75%, 85% and 95%

reliability separately. For Scenario 1-2, about 20%, 30% and 50% errors are expected for load range lower than 20,000 lbs, about 30%, 50% and 90% errors are expected for load range higher than 20,000 lbs, for 75%, 85% and 95% reliability separately. Similar results are obtained for Class 9 tandem axle. Finally, figures 32-37 suggest gross under estimations of the percentage of heavy axles, which are known to cause most of the pavement damage.

CHAPTER SEVEN

CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

Instead of using a single number EASLs as traffic input for pavement design, the NCHRP 1-37A Pavement Design Guide requires comprehensive data as traffic input. *TI-PG* provides a useful tool to generate traffic input for the new pavement design utilizing daily traffic data from LTPP database. In addition, *TI-PG* can also be used to analyze data from other data resources if the data is stored in the required format, which is a very common way of data storage (Microsoft Access™ format).

Chapter 6 presents the detailed results of traffic input prediction errors from the selected data collection scenarios. Some conclusions are summarized in this chapter.

In traffic volume predictions, such as AADTT, one month per season site-specific truck class volume data (Scenario 1-1/2-1) has similar accuracy with one week per season site-specific truck class volume data (Scenario 1-2/2-2) in predicting AADTT. For 95% reliability, the percent errors are 29.62% and 36.26% respectively. While for Scenario 2-3, with only 1 week per year site-specific truck data available, the percent error in predicting AADTT are 77.36% for 95% reliability. It shows that uniformly distributed data collection time can improve the quality of data greatly. It also shows that the seasonal changes in traffic volume are evident. For scenario group 3- and 4-, where no site-specific truck class data is available, the percent errors in predicting AADTT are more than 50% for 95% reliability. Hence, site-specific class data is very important in predicting AADTT accurately.

Simulation of scenario group 1- and 2- also provides the results for volume prediction for truck class 5 and 9. Similar conclusions can be obtained for truck class 5 and 9.

MAF play an important role in predicting pavement performance from traffic loading. Simulation of Scenario 1-1/2-1 and 1-2/2-2 provides results of percent error in predicting MAF from limited truck data. For 95% reliability, the percent errors are about 30% for Class 5 and Class 9, for both Scenario 1-1/2-1 and Scenario 1-2/2-2. However, different seasonal trend can be observed. For Class 5, the winter season shows more errors than the summer season. For class 9, this trend is not very obvious.

For axle load distribution, two kinds of results are presented in Chapter 6. They are Class 5 single axle and Class 9 tandem axle load distribution. The percent errors in number of axles within certain load ranges are computed.

For Class 5 single axle, 15.2% (Scenario 1-1) and 23.5% (Scenario 1-2) errors in number of axle for load range of less than 15000 lbs are expected for 95% reliability, While 23.7% (Scenario 1-1) and 49.3% (Scenario 1-2) errors for load range of 15000~20000 lbs. For axle load greater than 20000 lbs, site-specific continuous data is needed to obtain the axle passes since very few passing occurs in this load range.

For Class 9 tandem axle, about 20% (Scenario 1-1) and 40% (Scenario 1-2) errors are expected for load range less than 10,000 lbs and 30,000~40,000lbs for 95% reliability, while for load range 10,000~30,000 lbs, the errors are less than 11.4% (Scenario 1-1) and 19.8% (Scenario 1-2). For load ranges greater than 40000 lbs, the errors are very large. Hence, only site-specific continuous data collection can predict accurately the axle loading repetitions for this load range. Different from AADTT predictions, Scenario 1-1 and 1-2 have major difference in percent errors of number of axles prediction for each load range. It shows that the axle passes for each load range is very sensitive to time. Continuous time coverage is necessary for collecting axle passes data, especially to capture the very low passes of heavy trucks.

7.2 Recommendations

Multiple input formats are expected for future improvement of *TI-PG,* such as the raw traffic data (Level 4) in central database (i.e. raw individual Card 4 and Card 7 data).

The current version of *TI-PG* uses a database file from local resources. It is recommended to improve to web-based version in the future for remote data access and communication. By developing remote data communication, the users do not need to store the huge amount of traffic data in local resources and hence save time and disk space.

In simulating the data scenarios described in Chapter 3, some formal means of establishing the regional datasets are needed. Further work is expected to provide traffic input reliability information for the new pavement design users and to estimate the induced errors in predicting pavement performance.

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APPENDIX: SOURCE CODE FOR TI-PG SOFTWARE

```
'-----------------------------------------------------------------------------------------------------------
' Site-specific AADT calculation
' rcd: obtained recordset from the database file
' apomonth(): calculated monthly average daily traffic data
' tname: path name of database file

Function ATRrecordset()
Dim il As Integer, nl As Integer, cat As New Catalog, rcd As New ADODB.Recordset
Dim j As Integer, stateid As String, shrpid As String, lanetrf As String, dirtrf As String
Dim year As String, kl As Integer, nr As Integer, fieldstring As String
Dim tname As String, apomonth() As Double
Dim ss As Double
Dim msg, Style

' set regional VC and MAF data
    For j = 1 To 11
     regionalVC(j) = rcd1.Fields(j - 1).Value
    Next j

    rcd2.MoveFirst
    For il = 1 To 12
    For j = 1 To 10
     regionalMAF(il, j) = rcd2.Fields(j).Value
    Next j
    rcd2.MoveNext
    Next il

'Connect database file
   cat.ActiveConnection = _
      "Provider=Microsoft.Jet.OLEDB.4.0;" & _
      "Data Source=" & PDGINPmain.ATRfile.Text

  tname = PDGINPmain.ATRtable.Text
  nl = PDGINPmain.ATRsites.ListItems.Count
For il = 1 To nl
 If PDGINPmain.ATRsites.ListItems(il).Selected = True Then
   stateid = PDGINPmain.ATRsites.ListItems(il).Text
   shrpid = PDGINPmain.ATRsites.ListItems(il).SubItems(1)
   lanetrf = PDGINPmain.ATRsites.ListItems(il).SubItems(2)
   dirtrf = PDGINPmain.ATRsites.ListItems(il).SubItems(3)
   year = PDGINPmain.ATRsites.ListItems(il).SubItems(4)

     fieldstring = "STATE_CODE, SHRP_ID, LANE_TRF, DIR_TRF,YEAR," _
                 & "MONTH, DAY, RECORD_STATUS, DAY_OF_WEEK, COUNT "
```

```
  On Error GoTo errhandler
  rcd.CursorType = adOpenKeyset
  rcd.Open "SELECT " & fieldstring _
     & "FROM " & tname _
     & " WHERE STATE_CODE=" & stateid & " and SHRP_ID=" & CStr(shrpid) & _
      " and LANE_TRF=" & lanetrf & " and DIR_TRF=" & dirtrf & " and YEAR=" & year & _
      " ORDER BY STATE_CODE ASC, SHRP_ID ASC, LANE_TRF ASC, DIR_TRF
         ASC,YEAR ASC, MONTH ASC, DAY ASC", cat.ActiveConnection
 nr = rcd.RecordCount
 Call ATRdata(rcd, apomonth())
 rcd.Close
 aposum = 0

 For j = 1 To 12
   aposum = aposum + apomonth(j)
 Next j
 msg = "AADTT=" + CStr(Format(aposum * rcd1.Fields(10).Value / 100 / 12, "######"))
 Style = vbOKOnly   ' Define buttons.
 ATRrecordset = MsgBox(msg, Style)

 End If
Next il

Exit Function

errhandler:

 msg = "cannot find one or more of required fields in the data table," + _
"make sure the data table includes the fields required for the vehicle classification calculation"
Style = vbOK   ' Define buttons.
ATRMAFrecordset = MsgBox(msg, Style)

End Function

‘-----------------------------------------------------------------------------------------------------------


Sub ATRdata(rcd As ADODB.Recordset, apomonth() As Double)

 Dim i As Long, cname As String, item As Long
 Dim j As Long, k As Long, l As Long, kl As Long, ii As Long, m As Long, N As Long
 Dim iii As Long, ss As Double, aposum As Double
 Dim nyear As Long, year() As Long, iyear As Long, dowf() As Double
 Dim col As New Column, rcd1 As New ADODB.Recordset
     traffi = rcd.GetRows
```

```
      nr = rcd.RecordCount
      iyear = traffi(4, 1)
      Call month__ATR(iyear, apomonth(), dowf)

  End Sub

'-------------------------------------------------------------------------------------------------------------
     Sub month__ATR(iyear As Long, apomonth() As Double, dowf() As Double)

Dim j As Long, m As Long, N As Long, iii As Long, inr As Long, nweekday() As Long
Dim apoyear() As Double, dayofyear As Long, sdmonth As Double, sdyear As Double,
tndayofweek As Long
Dim tot As Double, apoclass As Double, numdayofweek As Long, idayofweek As Long,
monthid() As Long, nmonth As Long
Dim srMAF() As Double
ReDim dowf(12, 7)
ReDim apomonth(12)
ReDim monthid(12)
For N = 1 To 12
  Call numweekday(iyear, N, nweekday())
    numdayofweek = 0
    apoclass = 0
     For idayofweek = 1 To 7
      If nweekday(idayofweek) <> 0 Then
        numdayofweek = numdayofweek + 1

      For inr = 0 To nr - 1
       If (traffi(5, inr) = N And traffi(8, inr) = idayofweek) Then
           apoclass = apoclass + traffi(9, inr) / nweekday(idayofweek)
           dowf(N, idayofweek) = dowf(N, idayofweek) + traffi(9, inr) / nweekday(idayofweek)
        End If
      Next inr

     End If
    Next idayofweek

      If numdayofweek <> 0 Then
        apoclass = apoclass / numdayofweek
        monthid(N) = 1
      Else
        monthid(N) = 0
     End If
      apomonth(N) = apoclass
       For idayofweek = 1 To 7
       If nweekday(idayofweek) = 0 Then
         dowf(N, idayofweek) = apoclass
```

```
      End If
     Next idayofweek

  Next N

     ' use regional VC and MAF to adjust the site-specific data
    ReDim srMAF(10)
    nmonth = 0
    apoclass = 0
     For N = 1 To 12
      If monthid(N) = 1 Then
        nmonth = nmonth + 1
        apoclass = apoclass + apomonth(N)
        For iii = 1 To 10
          srMAF(iii) = srMAF(iii) + regionalMAF(N, iii)
        Next iii
      End If
     Next N

      For N = 1 To 12
      If monthid(N) = 0 Then
       For iii = 4 To 13
        apomonth(N) = apomonth(N) + apoclass * regionalVC(iii - 3) / srMAF(iii - 3) *
regionalMAF(N, iii - 3) / 100
       Next iii
      End If
      Next N

End Sub

‘-------------------------------------------------------------------------------------------------------------
' This module is used to compute the site-specific and regional vehicle class distribution and
MAF data
' rcd1 is the record storing the site specific vehicle classification data
'rcd2 is the record storing the site-specific MAF data

Public rcd1 As ADODB.Recordset, rcd2 As ADODB.Recordset, rcd1reg As ADODB.Recordset,
rcd2reg As ADODB.Recordset
Public nmissing As Long, imonth() As Long, idayweek() As Long, traffi() As Variant, nr As
Long
 Public regionalVC(11) As Double, regionalMAF(12, 10) As Double
‘-------------------------------------------------------------------------------------------------------------
Sub MAFdatasource()
Set AVCMAFtable.AVCMAFDataGrid.DataSource = rcd2
End Sub
‘-------------------------------------------------------------------------------------------------------------
```

```
Sub defaultregionalVCMAF()
Dim i As Integer, j As Integer, avcvalue() As Double
 Set rcd1 = New ADODB.Recordset
 Set rcd2 = New ADODB.Recordset
 ReDim avcvalue(10)
   avcvalue(0) = 18
   avcvalue(1) = 24.6
   avcvalue(2) = 7.6
   avcvalue(3) = 0.5
   avcvalue(4) = 5
   avcvalue(5) = 31.3
   avcvalue(6) = 9.8
   avcvalue(7) = 0.8
   avcvalue(8) = 3.3
   avcvalue(9) = 15.3

    For j = 4 To 13
     rcd1.Fields.Append "CLASS" + CStr(j), adDouble, 800
    Next j

    rcd1.Fields.Append "Percent Truck", adDouble, 800
     rcd1.CursorType = adOpenKeyset
     rcd1.LockType = adLockOptimistic
     rcd1.Open
     rcd1.AddNew
     For i = 0 To 9
      rcd1.Fields(i).Value = avcvalue(i)
     Next i
     rcd1.Fields(10).Value = 15.9
     rcd2.Fields.Append "MONTH", adInteger, 750

    For j = 4 To 13
     rcd2.Fields.Append "CLASS" + CStr(j), adDouble, 750
    Next j

      rcd2.CursorType = adOpenKeyset
      rcd2.LockType = adLockOptimistic
      rcd2.Open
      For i = 1 To 12
        rcd2.AddNew
        rcd2.Fields(0).Value = i
        For j = 4 To 13
        rcd2.Fields(j - 3).Value = 1
        Next j
     Next i
Set RegionVCMAF.regionalMAFtable.DataSource = rcd2
```

```
Set RegionVCMAF.regionalVCtable.DataSource = rcd1

' set regional VC and MAF data
    For j = 1 To 11
     regionalVC(j) = rcd1.Fields(j - 1).Value
    Next j

    rcd2.MoveFirst
    For il = 1 To 12
    For j = 1 To 10
     regionalMAF(il, j) = rcd2.Fields(j).Value
    Next j
    rcd2.MoveNext
    Next il

End Sub

‘-------------------------------------------------------------------------------------------------------------
'save MAF data to ASCII FILE, Which is directly
'required by the new pavement design

Sub MAFtxtsavefile(filename As String)
Dim i As Integer, j As Integer, k As Integer, ij As Integer
Dim ss As String
Open filename For Output As #1

rcd2.MoveFirst
ss = "Month,"
For ij = 4 To 12
 ss = ss + "Class " + CStr(ij) + ","
Next ij
ss = ss + "Class 13"
Print #1, ss

  For i = 1 To 12
  ss = MonthName(i) + ","
   For j = 4 To 12
   ss = ss + CStr(rcd2.Fields(j - 3).Value) + ","
   Next j
  ss = ss + CStr(rcd2.Fields(10).Value)
  Print #1, ss
  rcd2.MoveNext
  Next i

  Close #1
```

```
 End Sub
‘------------------------------------------------------------------------------------------------------------------
 'Import MAF data ASCII FILE, Which is directly required by the new pavement design

 Sub MAFtxtOpenfile(filename As String)
 Dim i As Integer, j As Integer, k As Integer, ij As Integer
 Dim ss As String, amaf As Double
 Open filename For Input As #1

   Set rcd2 = New ADODB.Recordset
   rcd2.Fields.Append "MONTH", adInteger
   For j = 4 To 13
   rcd2.Fields.Append "CLASS" + CStr(j), adDouble
   Next j

   rcd2.CursorType = adOpenKeyset
   rcd2.LockType = adLockOptimistic
   rcd2.Open

 For i = 1 To 11
   Input #1, ss
 Next i

For i = 1 To 12
 rcd2.AddNew
 rcd2.Fields(0).Value = i
 Input #1, ss
 For j = 1 To 10
  Input #1, amaf
  rcd2.Fields(j).Value = amaf
 Next j
Next i

 Close #1
 ' rcd2.Close

Set RegionVCMAF.regionalMAFtable.DataSource = rcd2
End Sub
‘------------------------------------------------------------------------------------------------------------------

' site-specific vehicle classification and MAF calculation
' rcd: obtained recordset from the database file
' apomonth(): calculated monthly average daily traffic data by class
' tname: path name of database file
```

```
Function AVCMAFrecordset()
Dim il As Integer, nl As Integer, cat As New Catalog, rcd As New ADODB.Recordset
Dim j As Integer, stateid As String, shrpid As String, lanetrf As String, dirtrf As String
Dim year As String, kl As Integer, nr As Integer, fieldstring As String
Dim tname As String, apomonth() As Double
Dim ss As Double
Dim msg, Style
Dim rcd3 As ADODB.Recordset, rcd4 As ADODB.Recordset

' set regional VC and MAF data
   For j = 1 To 11
    regionalVC(j) = rcd1.Fields(j - 1).Value
   Next j

   rcd2.MoveFirst
   For il = 1 To 12
   For j = 1 To 10
    regionalMAF(il, j) = rcd2.Fields(j).Value
   Next j
   rcd2.MoveNext
   Next il


'Connect database file
 cat.ActiveConnection = _
     "Provider=Microsoft.Jet.OLEDB.4.0;" & _
     "Data Source=" & PDGINPmain.AVCfile.Text

   Set rcd3 = New ADODB.Recordset
   Set rcd4 = New ADODB.Recordset

   rcd3.Fields.Append "AADTT", adDouble, 800

   For j = 4 To 13
     rcd3.Fields.Append "CLASS" + CStr(j), adDouble, 800
   Next j

     rcd3.CursorType = adOpenKeyset
     rcd3.LockType = adLockOptimistic
     rcd3.Open

   rcd4.Fields.Append "MONTH", adInteger

   For j = 4 To 13
     rcd4.Fields.Append "CLASS" + CStr(j), adDouble
   Next j
```

```
      rcd4.CursorType = adOpenKeyset
      rcd4.LockType = adLockOptimistic
      rcd4.Open

tname = PDGINPmain.AVCtable.Text
nl = PDGINPmain.AVCsites.ListItems.Count
For il = 1 To nl
 If PDGINPmain.AVCsites.ListItems(il).Selected = True Then
   stateid = PDGINPmain.AVCsites.ListItems(il).Text
   shrpid = PDGINPmain.AVCsites.ListItems(il).SubItems(1)
   lanetrf = PDGINPmain.AVCsites.ListItems(il).SubItems(2)
   dirtrf = PDGINPmain.AVCsites.ListItems(il).SubItems(3)
   year = PDGINPmain.AVCsites.ListItems(il).SubItems(4)

     fieldstring = "STATE_CODE, SHRP_ID, LANE_TRF, DIR_TRF,YEAR," _
                & "MONTH, DAY, RECORD_STATUS, DAY_OF_WEEK, "

       For j = 1 To 9
        fieldstring1 = fieldstring & "COUNT0"
        fieldstring = fieldstring1 & CStr(j)
        fieldstring = fieldstring & ", "
       Next j
       For j = 10 To 19
       fieldstring1 = fieldstring & "COUNT"
        fieldstring = fieldstring1 & CStr(j)
       fieldstring = fieldstring & ", "
       Next j
        fieldstring = fieldstring & "COUNT20 "

 '  On Error GoTo errhandler
    rcd.CursorType = adOpenKeyset
    rcd.Open "SELECT " & fieldstring _
       & "FROM " & tname _
       & " WHERE STATE_CODE=" & stateid & " and SHRP_ID=" & CStr(shrpid) & _
        " and LANE_TRF=" & lanetrf & " and DIR_TRF=" & dirtrf & " and YEAR=" & year & _
        " ORDER BY STATE_CODE ASC, SHRP_ID ASC, LANE_TRF ASC, DIR_TRF
ASC,YEAR ASC, MONTH ASC, DAY ASC", cat.ActiveConnection
   nr = rcd.RecordCount
   Call classdata(rcd, apomonth())
   rcd.Close
   ReDim aposum(20)

       For j = 1 To 12
         For kl = 1 To 20
         aposum(kl) = aposum(kl) + apomonth(j, kl)
```

```
        Next kl
       Next j

       For j = 1 To 12
         rcd4.AddNew
         rcd4.Fields(0).Value = j

         For kl = 4 To 13
         If aposum(kl) > 0 Then
         rcd4.Fields(kl - 3).Value = Format(apomonth(j, kl) * 12 / aposum(kl), "#####0.00")
         Else
         rcd4.Fields(kl - 3).Value = 0
         End If
         Next kl
         rcd4.Update
        Next j

       rcd3.AddNew

       ss = 0
       For kl = 4 To 13
       ss = ss + aposum(kl)
       Next kl

       rcd3.Fields(0).Value = Format(ss / 12, "#####0")

       For kl = 4 To 13
       If ss > 0 Then
       rcd3.Fields(kl - 3).Value = Format(aposum(kl) * 100 / ss, "#####0.00")
       Else
       rcd3.Fields(kl - 3).Value = 0
       End If
       Next kl
       rcd3.Update

  End If

Next il


Set AVCresult.AVCMAFtable.DataSource = rcd4
Set AVCresult.AVCVCtable.DataSource = rcd3

'AVCresult.Show
AVCMAFrecordset = "true"
Exit Function
```

```
'errhandler:

' msg = "cannot find one or more of required fields in the data table," + _
'"make sure the data table includes the fields required for the vehicle classification calculation"
'Style = vbOK   ' Define buttons.
'AVCMAFrecordset = MsgBox(msg, Style)

End Function
'-----------------------------------------------------------------------------------------------------------

Function regionalAVCMAFrecordset()
Dim il As Integer, nl As Integer, cat As New Catalog, rcd As New ADODB.Recordset
Dim j As Integer, stateid As String, shrpid As String, lanetrf As String, dirtrf As String
Dim year As String, kl As Integer, nr As Integer
Dim tname As String, apomonth() As Double, apomonthtotal() As Double, iselected As Integer
Dim ss As Double, sstotal As Double
Dim msg, Style

 cat.ActiveConnection = _
     "Provider=Microsoft.Jet.OLEDB.4.0;" & _
     "Data Source=" & PDGINPmain.AVCfile.Text

    Set rcd1 = New ADODB.Recordset
    Set rcd2 = New ADODB.Recordset

    For j = 4 To 13
     rcd1.Fields.Append "CLASS" + CStr(j), adDouble, 750
    Next j
    rcd1.Fields.Append "Percent Truck", adDouble, 750

      rcd1.CursorType = adOpenKeyset
      rcd1.LockType = adLockOptimistic
      rcd1.Open

    rcd2.Fields.Append "MONTH", adInteger

    For j = 4 To 13
     rcd2.Fields.Append "CLASS" + CStr(j), adDouble, 750
    Next j

      rcd2.CursorType = adOpenKeyset
      rcd2.LockType = adLockOptimistic
      rcd2.Open

tname = PDGINPmain.AVCtable.Text
```

```
nl = PDGINPmain.AVCsites.ListItems.Count

iselected = 0
ReDim apomonthtotal(12, 20)

For il = 1 To nl
 If PDGINPmain.AVCsites.ListItems(il).Selected = True Then
   iselected = iselected + 1
   stateid = PDGINPmain.AVCsites.ListItems(il).Text
   shrpid = PDGINPmain.AVCsites.ListItems(il).SubItems(1)
   lanetrf = PDGINPmain.AVCsites.ListItems(il).SubItems(2)
   dirtrf = PDGINPmain.AVCsites.ListItems(il).SubItems(3)
   year = PDGINPmain.AVCsites.ListItems(il).SubItems(4)

  '  On Error GoTo errhandler
    rcd.CursorType = adOpenKeyset

    fieldstring = "STATE_CODE, SHRP_ID, LANE_TRF, DIR_TRF,YEAR," _
                  & "MONTH, DAY, RECORD_STATUS, DAY_OF_WEEK, "

        For j = 1 To 9
         fieldstring1 = fieldstring & "COUNT0"
         fieldstring = fieldstring1 & CStr(j)
         fieldstring = fieldstring & ", "
        Next j
        For j = 10 To 19
        fieldstring1 = fieldstring & "COUNT"
         fieldstring = fieldstring1 & CStr(j)
        fieldstring = fieldstring & ", "
        Next j
         fieldstring = fieldstring & "COUNT20 "

    rcd.Open "SELECT " & fieldstring _
        & "FROM " & tname _
        & " WHERE STATE_CODE=" & stateid & " and SHRP_ID=" & CStr(shrpid) & _
         " and LANE_TRF=" & lanetrf & " and DIR_TRF=" & dirtrf & " and YEAR=" & year & _
         " ORDER BY STATE_CODE ASC, SHRP_ID ASC, LANE_TRF ASC, DIR_TRF
ASC,YEAR ASC, MONTH ASC, DAY ASC", cat.ActiveConnection

' nr: total number of records, ie. total number of data days in one year
   nr = rcd.RecordCount
   Call classdata(rcd, apomonth())
   For j = 1 To 12
   For kl = 1 To 20
    apomonthtotal(j, kl) = apomonthtotal(j, kl) + apomonth(j, kl)
   Next kl
```

```
  Next j
  rcd.Close
 End If

Next il

  For j = 1 To 12
  For kl = 1 To 20
   apomonth(j, kl) = apomonthtotal(j, kl) / iselected
  Next kl
  Next j

  'rcd.Close
  ReDim aposum(20)

      For j = 1 To 12
        For kl = 1 To 20
        aposum(kl) = aposum(kl) + apomonth(j, kl)
        Next kl
      Next j

       For j = 1 To 12
         rcd2.AddNew

         rcd2.Fields(0).Value = j

         For kl = 4 To 13
         If aposum(kl) > 0 Then
         rcd2.Fields(kl - 3).Value = Format(apomonth(j, kl) * 12 / aposum(kl), "#####0.00")
         Else
         rcd2.Fields(kl - 3).Value = 0
         End If
         Next kl
         rcd2.Update
       Next j

      rcd1.AddNew

      ss = 0
      For kl = 4 To 13
      ss = ss + aposum(kl)
      Next kl

      sstotal = 0
      For kl = 1 To 20
      sstotal = sstotal + aposum(kl)
```

```
        Next kl

        For kl = 4 To 13
        If ss > 0 Then
        rcd1.Fields(kl - 4).Value = Format(aposum(kl) * 100 / ss, "#####0.00")
        Else
        rcd1.Fields(kl - 4).Value = 0
        End If
        Next kl

        rcd1.Fields(10).Value = Format(ss / sstotal * 100, "#####0.0")

        rcd1.Update

Set RegionVCMAF.regionalMAFtable.DataSource = rcd2
Set RegionVCMAF.regionalVCtable.DataSource = rcd1
regionalAVCMAFrecordset = "true"
Exit Function

'errhandler:

' msg = "cannot find one or more of required fields in the data table," + _
'"make sure the data table includes the fields required for the vehicle classification calculation"
'Style = vbOK   ' Define buttons.
'regionalAVCMAFrecordset = MsgBox(msg, Style)

' RegionVCMAF.Show

End Function
'-------------------------------------------------------------------------------------------------------------

Sub classdata(rcd As ADODB.Recordset, apomonth() As Double)

   Dim i As Long, cname As String, item As Long
   Dim j As Long, k As Long, l As Long, kl As Long, ii As Long, m As Long, N As Long
   Dim iii As Long, ss As Double, aposum() As Double
   Dim nyear As Long, year() As Long, iyear As Long, dowf() As Double
   Dim col As New Column, rcd1 As New ADODB.Recordset

        traffi = rcd.GetRows
        nr = traffi(13, 20)
        nr = rcd.RecordCount
        iyear = traffi(4, 1)
        Call month__spectra(iyear, apomonth(), dowf)

  End Sub
```

```
‘-----------------------------------------------------------------------------------------------------------

     Sub month__spectra(iyear As Long, apomonth() As Double, dowf() As Double)

Dim j As Long, m As Long, N As Long, iii As Long, inr As Long, nweekday() As Long
Dim apoyear() As Double, dayofyear As Long, sdmonth As Double, sdyear As Double,
tndayofweek As Long
Dim tot As Double, apoclass() As Double, numdayofweek As Long, idayofweek As Long,
monthid() As Long, nmonth As Long
Dim srMAF() As Double
ReDim dowf(12, 7, 20)
ReDim apomonth(12, 20)
ReDim monthid(12)
For N = 1 To 12
  Call numweekday(iyear, N, nweekday())
    numdayofweek = 0

    ReDim apoclass(20)

    For idayofweek = 1 To 7
     If nweekday(idayofweek) <> 0 Then
       numdayofweek = numdayofweek + 1

     For inr = 0 To nr - 1
      If (traffi(5, inr) = N And traffi(8, inr) = idayofweek) Then
         For iii = 0 To 19
           apoclass(iii) = apoclass(iii) + traffi(iii + 9, inr) / nweekday(idayofweek)
           dowf(N, idayofweek, iii + 1) = dowf(N, idayofweek, iii + 1) + traffi(iii + 9, inr) /
nweekday(idayofweek)
         Next iii
      End If
     Next inr

     End If

     Next idayofweek

     If numdayofweek <> 0 Then
     For iii = 0 To 19
       apoclass(iii) = apoclass(iii) / numdayofweek
     Next iii
     monthid(N) = 1
     Else

     monthid(N) = 0
```

```
    End If

    For iii = 0 To 19
      apomonth(N, iii + 1) = apoclass(iii)
    Next iii

    For idayofweek = 1 To 7
     If nweekday(idayofweek) = 0 Then
      For iii = 0 To 19
       dowf(N, idayofweek, iii + 1) = apoclass(iii)
      Next iii
     End If
    Next idayofweek

Next N

   ' use regional MAF adjust missing month's VC data
  ReDim srMAF(10)
  nmonth = 0
   ReDim apoclass(20)
   For N = 1 To 12
    If monthid(N) = 1 Then
      nmonth = nmonth + 1
      For iii = 0 To 19
        apoclass(iii) = apoclass(iii) + apomonth(N, iii + 1)
      Next iii

      For iii = 1 To 10
      srMAF(iii) = srMAF(iii) + regionalMAF(N, iii)
      Next iii

     End If
    Next N

    For N = 1 To 12
    If monthid(N) = 0 Then
     For iii = 4 To 13
       If (srMAF(iii - 3) > 0) Then
        apomonth(N, iii) = apoclass(iii - 1) / srMAF(iii - 3) * regionalMAF(N, iii - 3)
       Else
       apomonth(N, iii) = apoclass(iii - 1) / nmonth * regionalMAF(N, iii - 3)
       End If
     Next iii

     End If
    Next N
```

```
End Sub

'-----------------------------------------------------------------------------------------------------------

Sub numweekday(nyear As Long, imonth As Long, nweekday() As Long)
Dim day() As Long, dow() As Long
Dim i As Long, j As Long, ii As Long, dayofmissing() As Long, imissingday As Long


ReDim day(31)
ReDim dow(31)
ReDim dayofmissing(100)

      ReDim nweekday(7)
      i = 0
     For ii = 0 To nr - 1

         If traffi(4, ii) = nyear And traffi(5, ii) = imonth Then
          For j = 0 To i
            If (traffi(6, ii) = day(j)) Then
            Exit For
           End If
          Next j

          If j = i + 1 Then
            i = i + 1
            day(i) = traffi(6, ii)
            dow(i) = traffi(8, ii)

           End If
          End If
      Next ii

      If (i < dayofmonth(imonth, nyear)) Then
        For ii = 1 To i
         nweekday(dow(ii)) = nweekday(dow(ii)) + 1
        Next ii

        imissingday = 0
        For ii = 1 To dayofmonth(imonth, nyear)
           For j = 1 To i
            If (day(j) = ii) Then
             Exit For
            End If
            Next j
```

```
      If j = i + 1 Then
        imissingday = imissingday + 1
        dayofmissing(imissingday) = ii
       End If
     Next ii

    Else
    Call numdayweekpmonth(imonth, nyear, nweekday())

    End If

End Sub

'-------------------------------------------------------------------------------------------------------------

' Calculate the number of day of week (Sunday to Saturday) for each month of a specific year
Sub numdayweekpmonth(imonth As Long, nyear As Long, ndw() As Long)
Dim i As Long, j As Long
Dim Mydate As Date, MyweekDay As Long
ReDim ndw(7)

   For i = 1 To dayofmonth(imonth, nyear)
     Mydate = CStr(imonth) + "/" + CStr(i) + "/" + CStr(nyear)
     MyweekDay = Weekday(Mydate)
      ndw(MyweekDay) = ndw(MyweekDay) + 1
   Next i
  End Sub

'-------------------------------------------------------------------------------------------------------------
Function dayofmonth(imonth, nyear)

If imonth = 2 Then
 If (nyear = 1988 Or nyear = 1992 Or nyear = 1996 Or nyear = 2000) Then
  dayofmonth = 29
 Else
  dayofmonth = 28
 End If

 ElseIf imonth = 1 Or imonth = 3 Or imonth = 5 Or imonth = 7 Or imonth = 8 Or imonth = 10 Or
imonth = 12 Then
  dayofmonth = 31
 Else
  dayofmonth = 30
End If
```

```
End Function

‘-------------------------------------------------------------------------------------------------------------

Public Sub defineregionalVCMAFdatatable()
 Dim i As Integer, message As String

   For i = 0 To 9
    With RegionVCMAF.regionalVCtable.Columns(i)
      .Visible = True
      .Width = 750
      .Caption = "CLASS" + CStr(i + 4)
      .DataField = "CLASS" + CStr(i + 4)
      .Alignment = dbgCenter
     End With
   Next i

    With RegionVCMAF.regionalVCtable.Columns(10)
      .Visible = True
      .Width = 750
      .Caption = "Truck %"
      .DataField = "Percent Truck"
      .Alignment = dbgCenter
     End With

  With RegionVCMAF.regionalMAFtable.Columns(0)
      .Visible = True
      .Width = 750
      .Caption = "MONTH"
      .DataField = "MONTH"
      .Alignment = dbgCenter
   End With

   For i = 1 To 10
     With RegionVCMAF.regionalMAFtable.Columns(i)
      .Visible = True
      .Width = 750
      .Caption = "CLASS" + CStr(i + 3)
      .DataField = "CLASS" + CStr(i + 3)
      .Alignment = dbgCenter
     End With
   Next i

 'RegionVCMAF.Show
End Sub
‘-------------------------------------------------------------------------------------------------------------
```

```
Sub tablelist(Fname As String, list1 As ComboBox)

  Dim tb() As New Table, nt As Long
  Dim i As Long
  Dim cat As New ADOX.Catalog, tname As String

   cat.ActiveConnection = _
     "Provider=Microsoft.Jet.OLEDB.4.0;" & _
     "Data Source=" & Fname

    nt = cat.Tables.Count
    list1.Clear

    For i = 0 To nt - 1
     If cat.Tables(i).Type = "TABLE" Then
      tname = cat.Tables(i).Name
      list1.AddItem (tname)
     End If
    Next i
    list1.Text = list1.List(0)
    list1.Refresh
    list1.Visible = True

 End Sub
'--------------------------------------------------------------------------------------------------------------
' find the sites information in one data table
Function EXTRACT1(list1 As ComboBox, lvwDB As ListView, Fname As String)

  Dim rcd1 As New ADODB.Recordset, nt As Long
  Dim i As Long, j As Long, nr As Long, nitem As Long, titem() As Long, itable As Long
  Dim traffi() As Variant, cat As New ADOX.Catalog
  Dim msg, Style

  cat.ActiveConnection = _
     "Provider=Microsoft.Jet.OLEDB.4.0;" & _
     "Data Source=" & Fname

   lvwDB.ListItems.Clear
   lvwDB.FullRowSelect = True
   lvwDB.Font.Size = 5
   lvwDB.LabelEdit = lvwManual

  nitem = 1
'  For j = 0 To list1.ListCount - 1
'   If list1.Selected(j) = True Then
```

```
   rcd1.CursorType = adOpenKeyset

    On Error GoTo errhandler
 '  rcd1.Open list1.List(j), cat.ActiveConnection
    rcd1.Open "SELECT STATE_CODE,SHRP_ID, LANE_TRF, DIR_TRF,YEAR" _
       & " FROM " & list1.Text _
        & " ORDER BY STATE_CODE ASC, SHRP_ID ASC, LANE_TRF ASC,DIR_TRF ASC,
YEAR ASC", cat.ActiveConnection

   rcd1.MoveFirst

   nr = rcd1.RecordCount

   traffi = rcd1.GetRows
   rcd1.Close
   lvwDB.ListItems.Add 1
    lvwDB.ListItems(1).Text = CStr(traffi(0, 0))
    lvwDB.ListItems(1).ListSubItems.Add , , CStr(traffi(1, 0))
    lvwDB.ListItems(1).ListSubItems.Add , , CStr(traffi(2, 0))
    lvwDB.ListItems(1).ListSubItems.Add , , CStr(traffi(3, 0))
    lvwDB.ListItems(1).ListSubItems.Add , , CStr(traffi(4, 0))

    For i = 1 To nr - 1
     If (traffi(4, i) <> traffi(4, i - 1) Or traffi(3, i) <> traffi(3, i - 1) Or traffi(2, i) <> traffi(2, i - 1)
_
      Or traffi(1, i) <> traffi(1, i - 1) Or traffi(0, i) <> traffi(0, i - 1)) Then
       nitem = nitem + 1

       lvwDB.ListItems.Add nitem
       lvwDB.ListItems(nitem).Text = CStr(traffi(0, i))
       lvwDB.ListItems(nitem).ListSubItems.Add , , CStr(traffi(1, i))
       lvwDB.ListItems(nitem).ListSubItems.Add , , CStr(traffi(2, i))
       lvwDB.ListItems(nitem).ListSubItems.Add , , CStr(traffi(3, i))
       lvwDB.ListItems(nitem).ListSubItems.Add , , CStr(traffi(4, i))

      End If
    Next i

 ' End If

'  Next j

  lvwDB.Visible = True
  EXTRACT1 = "true"
  Exit Function
```

```
errhandler:


msg = "cannot find one or more of required fields in the data table," + _
"make insure fields: STATE_CODE,SHRP_ID, LANE_TRF, DIR_TRF and YEAR are included
in table"

Style = vbOK   ' Define buttons.

EXTRACT1 = MsgBox(msg, Style)

 End Function
‘-------------------------------------------------------------------------------------------------------------

'data site information
  Sub MakeColumns(lvwDB As ListView)
    ' Clear the ColumnHeaders collection.
    lvwDB.ColumnHeaders.Clear
    ' Add four ColumnHeaders.
    lvwDB.Font.Size = 5
    lvwDB.ColumnHeaders.Add , , "STATE_CODE", 1000
    lvwDB.ColumnHeaders.Add , , "SHRP_ID", 1000
    lvwDB.ColumnHeaders.Add , , "LANE_TRF", 1000
    lvwDB.ColumnHeaders.Add , , "DIR_TRF", 1000
    lvwDB.ColumnHeaders.Add , , "YEAR", 1000
    ' Set the EventFlag variable so this doesn't get done again and again.
   'lvwDB.Visible = True
   lvwDB.Refresh
   lvwDB.View = lvwReport

End Sub

‘-------------------------------------------------------------------------------------------------------------

' export regional MAF to txt type file
Function exportMAFresultfile() As String
Dim fs, a, mes As String
Dim aex As Boolean
Dim appAccess As New Access.Application
Dim aw As EXCEl.Application
' open save file window
On Error GoTo errhandler
    With PDGINPmain.dlgDialog
        .DialogTitle = "exporting axle load distribution file"
        .Filter = "(*.maf)|*.maf"
        .DefaultExt = "maf"
```

```
        .filename = "*.maf"
        .CancelError = True
        .ShowSave
    End With
'get file name
    exportMAFresultfile = PDGINPmain.dlgDialog.filename

    Set fs = CreateObject("Scripting.FileSystemObject")
    aex = fs.FileExists(exportMAFresultfile)
    If aex = False Then
      Call MAFtxtsavefile(exportMAFresultfile)
    Else
        If messages = "Yes" Then
          Call MAFtxtsavefile(exportMAFresultfile)
         Else
          Resume
         End If
    End If

errhandler:
End Function

'-------------------------------------------------------------------------------------------------------------

' import regional MAF data file
Public Function importregionalMAFfile() As String
Dim fs, a, mes As String
Dim aex As Boolean
Dim appAccess As New Access.Application
Dim aw As EXCEl.Application
Dim msg, Style, Title, help, Ctxt, Response, MyString
' open save file window
On Error GoTo errhandler
    With PDGINPmain.dlgDialog
        .DialogTitle = "Importing MAF file"
        .Filter = "(*.maf)|*.maf"
        .DefaultExt = "maf"
        .filename = "*.maf"
        .CancelError = True
        .ShowOpen
    End With


'get file name
    importregionalMAFfile = PDGINPmain.dlgDialog.filename
```

```
    Set fs = CreateObject("Scripting.FileSystemObject")
    aex = fs.FileExists(importregionalMAFfile)
    If aex = False Then

        msg = "The file doesn't exist, try again ?"   ' Define message.
        Style = vbOK + vbCritical + vbDefaultButton2   ' Define buttons.
        Title = "Open File"   ' Define title.

        Response = MsgBox(msg, Style, Title)
        If Response = vbOK Then   ' User chose Yes.
          messages = "Yes"   ' Perform some action.
        Else   ' User chose No.
          messages = "No"   ' Perform some action.
        End If

    Else
      Call MAFtxtOpenfile(importregionalMAFfile)
    End If

errhandler:
Exit Function

End Function


'-------------------------------------------------------------------------------------------------------------

Function messages()
Dim msg, Style, Title, help, Ctxt, Response, MyString
msg = "The file has existed, Do you want to replace it ?"   ' Define message.
Style = vbYesNo + vbCritical + vbDefaultButton2   ' Define buttons.
Title = "Save File"   ' Define title.

Response = MsgBox(msg, Style, Title)
If Response = vbYes Then   ' User chose Yes.
  messages = "Yes"   ' Perform some action.
Else   ' User chose No.
  messages = "No"   ' Perform some action.
End If

End Function
'-------------------------------------------------------------------------------------------------------------

' find if a named file exists
Function fileexist(filename As String)
```

```
Dim fs
Dim aex As Boolean
Dim msg, Style, Title, help, Ctxt, Response, MyString
msg = " file doesn't exist, please reinput the filename!"
Style = vbOK
' open database file window

   Set fs = CreateObject("Scripting.FileSystemObject")
   aex = fs.FileExists(filename)
   If aex = False Then
  fileexist = MsgBox(msg, Style)

'    Resume
   End If

 '   If Err = 32755 Then
 '     End
 '   End If

End Function

'-----------------------------------------------------------------------------------------------------------------
'Following codes are computing monthly normalized axle load distribution data
Option Explicit

Public rcdWIM As New ADODB.Recordset
Dim traffi() As Variant, nr As Long, nitem As Long, titem() As Variant, titem1() As Variant
Dim tb1 As New Table, tb2 As New Table, tb3 As New Table, tb4 As New Table

Dim nmissing As Long, imonth() As Long, idayweek() As Long
' save monthly normalized axle load distribution to ACCESS FILE
Sub axleload(filename As String)

   Dim tname As String, cat As New ADOX.Catalog
   Dim nt As Long, i As Long, nc As Long, cname As String, item As Long
   Dim j As Long, k As Long, l As Long, kl As Long, ii As Long, m As Long, N As Long

   Dim apomonth() As Double, iii As Long, ss As Double, aposum() As Double
   Dim nyear As Long, year() As Long, iyear As Long, msgstring As String
   Dim col As New Column, rcdwim1 As New ADODB.Recordset

   cat.ActiveConnection = _
     "Provider=Microsoft.Jet.OLEDB.4.0;" & _
     "Data Source=" & filename

     Set tb2 = New Table
```

```
  tb2.Name = "monthly_normalized_axle_load"

  nt = cat.Tables.Count
  For i = 0 To nt - 1
   If cat.Tables(i).Name = tb2.Name Then
     Call messages(msgstring)
     If msgstring = "Yes" Then
       cat.Tables.Delete tb2.Name
     ElseIf msgstring = "No" Then
     '  exportWIMresultfile
     End If
     Exit For
    End If
   Next i

 tb2.Columns.Append "STATE_CODE", adInteger
 tb2.Columns.Append "SHRP_ID", adInteger
 tb2.Columns.Append "LANE_ID", adInteger
 tb2.Columns.Append "DIR_ID", adInteger
 tb2.Columns.Append "YEAR", adInteger
 tb2.Columns.Append "AXLE-GROUP", adInteger
 tb2.Columns.Append "MONTH", adInteger
 tb2.Columns.Append "VEH-CLASS", adInteger
 For j = 0 To 39
  tb2.Columns.Append "AX_CT_" + CStr(j), adDouble
 Next j

  cat.Tables.Append tb2
'   rcdWIM.Close
   rcdwim1.CursorType = adOpenStatic
   rcdwim1.LockType = adLockOptimistic

  rcdwim1.Open tb2.Name, cat.ActiveConnection
  nt = rcdWIM.RecordCount
  rcdWIM.MoveFirst
For i = 0 To nt - 1
 rcdwim1.AddNew
  For j = 0 To rcdWIM.Fields.Count - 1
   rcdwim1.Fields(j).Value = rcdWIM.Fields(j).Value
  Next j
  rcdWIM.MoveNext
Next i
  rcdwim1.Update
  rcdwim1.Close

Set cat = Nothing
```

```
  End Sub
'-----------------------------------------------------------------------------------------------------------
'save monthly normalized axle load distribution to ASCII FILE, Which is directly
'required by the new pavement design

  Sub axleloadtxtsavefile(filename As String)
  Dim i As Integer, j As Integer, k As Integer, axleloaddata() As Variant, ij As Integer
  Dim ss As String
  Open filename For Output As #1

rcdWIM.MoveFirst
For ij = 1 To 2

  For i = 1 To 12
   For j = 1 To 10
  ss = MonthName(i) + "," + CStr(j + 3) + "," + "100" + ","
  For k = 3 To 40
  ss = ss + CStr(rcdWIM.Fields(k + 2).Value) + ","
  Next k
  ss = ss + "0"
  Print #1, ss
 rcdWIM.MoveNext
Next j
Next i
Next ij

  For ij = 3 To 4

  For i = 1 To 12
   For j = 1 To 10
  ss = MonthName(i) + "," + CStr(j + 3) + "," + "100" + ","
  For k = 4 To 34
  ss = ss + CStr(rcdWIM.Fields(k + 2).Value) + ","
  Next k
   Print #1, ss
 rcdWIM.MoveNext
  Next j
Next i
Next ij
Close #1
End Sub

'-----------------------------------------------------------------------------------------------------------

'Compute monthly normalized axle load distribution data
```

```
‘ If multiple sites are selected, average value of the selected sites will be computed
'apomonth: monthly axle passes by class and axle type
'Results will be stored in recordset: rcdWIM

Function axleloadrecordset()

   Dim cat As New ADOX.Catalog, tname As String
   Dim nt As Long, i As Long, nc As Long, cname As String, item As Long
   Dim j As Long, k As Long, l As Long, kl As Long, ii As Long, m As Long, N As Long
   Dim apomonthtotal() As Double, iselected As Long
   Dim apomonth() As Double, iii As Long, ss As Double, aposum() As Double
   Dim nyear As Long, year() As Long, iyear As Long
   Dim col As New Column, rcd As New ADODB.Recordset
   Dim nl As Integer, stateid As Integer, shrpid As Integer, lanetrf As Integer, dirtrf As Integer
   Dim il As Integer, fieldstring As String, fieldstring1 As String
   Dim msg, Style

   ReDim apomonth(12, 4, 10, 40)
    ReDim apomonthtotal(12, 4, 10, 40)
' number of selected data sites
   iselected = 0
'Connect to daily axle passes WIM file

   cat.ActiveConnection = _
     "Provider=Microsoft.Jet.OLEDB.4.0;" & _
     "Data Source=" & PDGINPmain.WIMfile.Text
      Set rcdWIM = New ADODB.Recordset

'initialize rcdWIM recordset

    rcdWIM.Fields.Append "AXLE-GROUP", adInteger
    rcdWIM.Fields.Append "MONTH", adInteger
    rcdWIM.Fields.Append "VEH-CLASS", adInteger
    For j = 0 To 39
     rcdWIM.Fields.Append "AX_CT_" + CStr(j), adDouble
    Next j
      rcdWIM.CursorType = adOpenStatic
      rcdWIM.LockType = adLockOptimistic
      rcdWIM.Open

' tname: name of axle passes data file, nl: number of data site selected

    tname = PDGINPmain.WIMtable.Text
    nl = PDGINPmain.WIMsites.ListItems.Count

    For il = 1 To nl
```

```
    If PDGINPmain.WIMsites.ListItems(il).Selected = True Then
     iselected = iselected + 1
     stateid = PDGINPmain.WIMsites.ListItems(il).Text
     shrpid = PDGINPmain.WIMsites.ListItems(il).SubItems(1)
     lanetrf = PDGINPmain.WIMsites.ListItems(il).SubItems(2)
     dirtrf = PDGINPmain.WIMsites.ListItems(il).SubItems(3)
     iyear = PDGINPmain.WIMsites.ListItems(il).SubItems(4)

      rcd.CursorType = adOpenKeyset
      fieldstring = "STATE_CODE, SHRP_ID, LANE_TRF, DIR_TRF,VEH_CLASS,
AXLE_GROUP, " _
                 & "YEAR, MONTH, DAY, RECORD_STATUS, DAY_OF_WEEK, "

      For j = 1 To 9
       fieldstring1 = fieldstring & "AX_CT_0"
       fieldstring = fieldstring1 & CStr(j)
       fieldstring = fieldstring & ", "
      Next j
      For j = 10 To 39
      fieldstring1 = fieldstring & "AX_CT_"
       fieldstring = fieldstring1 & CStr(j)
      fieldstring = fieldstring & ", "
      Next j
       fieldstring = fieldstring & "AX_CT_40 "

       On Error GoTo errhandler
' SQL statement extracting data for selectd data sites from the ACCESS datafile
      rcd.Open "SELECT " & fieldstring _
         & "FROM " & tname _
         & " WHERE STATE_CODE=" & stateid & " and SHRP_ID=" & CStr(shrpid) & _
          " and LANE_TRF=" & lanetrf & " and DIR_TRF=" & dirtrf & " and YEAR=" & iyear
& _
          " ORDER BY STATE_CODE ASC, SHRP_ID ASC, LANE_TRF ASC, DIR_TRF
ASC,YEAR ASC, MONTH ASC, DAY ASC", cat.ActiveConnection
      nr = rcd.RecordCount
      traffi = rcd.GetRows
      nc = rcd.Fields.Count

      Call month__spectraWIM(iyear, apomonth())

      For i = 1 To 4
      For j = 1 To 12
      For k = 1 To 10
       For kl = 1 To 40
         apomonthtotal(j, i, k, kl) = apomonthtotal(j, i, k, kl) + apomonth(j, i, k, kl)
       Next kl
```

```
      Next k
     Next j
     Next i

  rcd.Close
  End If
 Next il

     For i = 1 To 4
     For j = 1 To 12
     For k = 1 To 10

         rcdWIM.AddNew

         rcdWIM.Fields(0).Value = i
         rcdWIM.Fields(1).Value = j
         rcdWIM.Fields(2).Value = k + 3
         ss = 0
         For kl = 0 To 39
         ss = ss + apomonthtotal(j, i, k, kl + 1)
         Next kl

         For kl = 0 To 39
         If ss > 0 Then
         rcdWIM.Fields(3 + kl).Value = Format(apomonthtotal(j, i, k, kl + 1) * 100 / ss, "##0.00")
         Else
         rcdWIM.Fields(3 + kl).Value = 0
         End If
         Next kl
         rcdWIM.Update

     Next k
     Next j
     Next i
  rcdWIM.MoveFirst
 Set cat = Nothing

' Format the output axle load data table
 Set WIMresult.WIMresultdatagrid.DataSource = rcdWIM

 With WIMresult.WIMresultdatagrid.Columns(0)
   .Visible = True
   .Width = 850
   .Caption = "AXLE-GROUP"
   .DataField = "AXLE-GROUP"
   .Alignment = dbgCenter
```

```
  End With

   With WIMresult.WIMresultdatagrid.Columns(1)
     .Visible = True
     .Width = 850
     .Caption = "MONTH"
     .DataField = "MONTH"
     .Alignment = dbgCenter
  End With

  With WIMresult.WIMresultdatagrid.Columns(2)
     .Visible = True
     .Width = 850
     .Caption = "VEH-CLASS"
     .DataField = "VEH-CLASS"
     .Alignment = dbgCenter
  End With

  For i = 1 To 40
   With WIMresult.WIMresultdatagrid.Columns(i + 2)
     .Visible = True
     .Width = 850
     .Caption = "AX_CT_" + CStr(i)
     .DataField = "AX_CT_" + CStr(i - 1)
     .Alignment = dbgCenter
    End With
  Next i

  WIMresult.Show
  Exit Function
errhandler:

 msg = "cannot find one or more of required fields in the data table," + _
"make sure the data table includes the fields required for the vehicle classification calculation"
Style = vbOK   ' Define buttons.
axleloadrecordset = MsgBox(msg, Style)

 End Function

‘-----------------------------------------------------------------------------------------------------------------
     Sub month__spectraWIM(iyear As Long, apomonth() As Double)

Dim j As Long, m As Long, N As Long, iii As Long, inr As Long, nweekday() As Long
Dim apoyear() As Double, dayofyear As Long, sdmonth As Double, sdyear As Double
Dim tot As Double, apoclass() As Double, numdayofweek As Long, idayofweek As Long,
monthid() As Long, nmonth As Long
```

```
ReDim apomonth(12, 4, 10, 40)

' Compute monthly daily average of axle passes in each load bin for each axle type and each
vehicle class

ReDim monthid(12)
For N = 1 To 12
  Call numweekdayWIM(iyear, N, nweekday())

     numdayofweek = 0

     For idayofweek = 1 To 7
      If nweekday(idayofweek) <> 0 Then
        numdayofweek = numdayofweek + 1

        For m = 1 To 4
        For j = 4 To 13

            For inr = 0 To nr - 1
             If (traffi(7, inr) = N And traffi(4, inr) = j And traffi(5, inr) = m And traffi(10, inr) =
idayofweek) Then
                For iii = 0 To 39
                  apomonth(N, m, j - 3, iii + 1) = apomonth(N, m, j - 3, iii + 1) + traffi(iii + 11, inr) /
nweekday(idayofweek)
                Next iii
             End If
            Next inr

         Next j
         Next m

      End If
      Next idayofweek

      If numdayofweek <> 0 Then
        For m = 1 To 4
        For j = 4 To 13
            For iii = 0 To 39
              apomonth(N, m, j - 3, iii + 1) = apomonth(N, m, j - 3, iii + 1) / numdayofweek
            Next iii
         Next j
         Next m
        monthid(N) = 1
      Else
        monthid(N) = 0
```

```
    End If

  Next N

' use average of available month's axle load data to represent missing month's axle load data

For m = 1 To 4
  For j = 4 To 13

     nmonth = 0
     ReDim apoclass(40)
     For N = 1 To 12
      If monthid(N) = 1 Then
        nmonth = nmonth + 1
        For iii = 0 To 39
          apoclass(iii) = apoclass(iii) + apomonth(N, m, j - 3, iii + 1)
        Next iii
       End If
      Next N

      For N = 1 To 12
      If monthid(N) = 0 Then
       For iii = 0 To 39
          apomonth(N, m, j - 3, iii + 1) = apoclass(iii) / nmonth
        Next iii
       End If
      Next N

   Next j
  Next m

End Sub

'------------------------------------------------------------------------------------------------------------
' compute number of each day of week in a month that has traffic data in WIM database file

Sub numweekdayWIM(nyear As Long, imonth As Long, nweekday() As Long)
Dim day() As Long, dow() As Long
Dim i As Long, j As Long, ii As Long, dayofmissing() As Long, imissingday As Long


ReDim day(31)
ReDim dow(31)
ReDim dayofmissing(100)

      ReDim nweekday(7)
```

```
 i = 0
For ii = 0 To nr - 1

    If traffi(6, ii) = nyear And traffi(7, ii) = imonth Then
     For j = 0 To i
       If (traffi(8, ii) = day(j)) Then
       Exit For
      End If
     Next j

     If j = i + 1 Then
       i = i + 1
       day(i) = traffi(8, ii)
       dow(i) = traffi(10, ii)

      End If
     End If
 Next ii

 If (i < dayofmonth(imonth, nyear)) Then
   For ii = 1 To i
    nweekday(dow(ii)) = nweekday(dow(ii)) + 1
   Next ii

   imissingday = 0
   For ii = 1 To dayofmonth(imonth, nyear)
      For j = 1 To i
       If (day(j) = ii) Then
        Exit For
       End If
       Next j

      If j = i + 1 Then
        imissingday = imissingday + 1
        dayofmissing(imissingday) = ii
       End If
    Next ii
 Else
  Call numdayweekpmonth(imonth, nyear, nweekday())
  End If
End Sub

'-------------------------------------------------------------------------------------------------------------

' Export monthly normalized axle load distribution data into files
Public Function exportWIMresultfile() As String
```

```
Dim fs, a, mes As String
Dim aex As Boolean
Dim appAccess As New Access.Application
Dim aw As EXCEl.Application
' open save file window
On Error GoTo errhandler
    With PDGINPmain.dlgDialog
        .DialogTitle = "exporting axle load distribution file"
        .Filter = "((*.alf)|*.alf|*.MDB)|*.mdb"
         .DefaultExt = "alf"
        .filename = "*.alf"
        .CancelError = True
        .ShowSave
    End With
'get file name
    exportWIMresultfile = PDGINPmain.dlgDialog.filename

    Set fs = CreateObject("Scripting.FileSystemObject")
    aex = fs.FileExists(exportWIMresultfile)
    If aex = False Then
      If PDGINPmain.dlgDialog.FilterIndex = 2 Then
        appAccess.NewCurrentDatabase exportWIMresultfile
        appAccess.CloseCurrentDatabase
        Call axleload(exportWIMresultfile)
'      ElseIf PDGINPmain.dlgDialog.FilterIndex = 2 Then
'      aw (exportWIMresultfile)

      Else
'    Set a = fs.CreateTextFile(exportWIMresultfile, True)
        Call axleloadtxtsavefile(exportWIMresultfile)
      End If
    Else
       If PDGINPmain.dlgDialog.FilterIndex = 2 Then
        Call axleload(exportWIMresultfile)
       Else
         If messages = "Yes" Then
          Call axleloadtxtsavefile(exportWIMresultfile)
         Else
          Resume
         End If
       End If
     End If

errhandler:
End Function
```