CLASSIFICATION OF LONGER COMBINATION VEHICLES USING WEIGH-IN-MOTION DATA

A Thesis

Presented in Partial Fulfillment of the Requirements for the

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ABSTRACT

Although short-term counts and permanent counts of trucks is common practice in most states in general, the classification system used for these vehicles is generally based on the Federal Highway Administration's (FHWA) 13 vehicle classification system. This system does not allow for the identification of longer combination vehicles (LCVs), leading to difficulty in the systematic identification of these vehicles and difficulty in LCV truck sampling.

The objective of this research was to propose a method that would allow systematic LCV truck sampling through the development of discriminant functions based on a classification algorithm developed for LCV and non-LCV truck classification; additionally seasonal factors were to be derived based on the truck classification results. Seasonal factors would then be used for seasonal variation comparison between truck classes and road types. The data consisted of weight in motion (WIM) raw data from Idaho, Utah, and Montana.

This objective was accomplished through the development of an algorithm that systematically classifies raw WIM data into five truck categories, three of which are LCV truck types. The discriminant function was then developed with the truck classification algorithm results. Once the data were classified accordingly, the results were used for seasonal factor development; seasonal variations between road classes and truck types were compared.

Based on the results of this research, it was concluded that raw WIM data can be used for LCV truck identification through the application of a truck characteristics based algorithm and a discriminant function. This research also found that the classification potential of a discriminant function is considerably improved with the inclusion of major axle spacings as a classification variable.

Additionally, based on the seasonal factors developed from the algorithm and discriminant function classified data, it was concluded that triple trailer trucks tend to demonstrate different seasonal patterns in comparison to other LCV and non-LCV truck types when comparing seasonal factor trends. Seasonal variation for LCVs between road types (interstate versus non-interstate highways) was not statistically significant for any of the truck types with the exception of singles during winter months.

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DEDICATION

This work is dedicated to my parents who have guided me and supported me through all efforts throughout my life.

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LIST OF ACRONYMS

AADT	Average Annual Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
ANSI	American National Standards Institute
ATP	Average Truck Percentage
ATR	Automatic Traffic Recorder
CMV	Commercial Motor Vehicle
DOT	Department of Transportation
FBF	Federal Bridge Formula
FHWA	Federal Highway Administration
FMCSA	Federal Motor Carrier Safety Administration
GVWR	Gross Vehicle Weight Rating
HPMS	Highway Performance Monitoring System
ISTEA	Intermodal Surface Transportation Efficiency Act
LCV	Longer Combination Vehicle
MCMIS	Motor Carrier Management Information System
NHTSA	National Highway Traffic Safety Administration
RMD	Rocky Mountain Double
STAA	Surface Transportation Assistance Act
TMG	Traffic Monitoring Guide
TPD	Turnpike Doubles
USDOT	United States Department of Transportation
VMT	Vehicle Miles Traveled
WASHTO	Western Association of State Highway and Transportation Officials
WIM	Weigh-In-Motion

1. INTRODUCTION AND BACKGROUND

1.1 Background

Longer combination vehicles (LCVs) are among the largest vehicles on our nation's highways. Because of their economic efficiency and productivity, they are increasing, both in proportion of vehicles on the road and number of miles they are driven each year. Typically, an LCV is a large truck with two or more cargo spaces (e.g., a tractor with two or more trailers or a straight truck with additional trailing units). The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 defined an LCV as "*any combination of a truck tractor with two or more trailers or semi-trailers which operates on the Interstate System at a gross vehicle weight greater than 80,000 pounds*" (USDOT 1991). The most common types of LCVs currently operating on national highways are: 1) Rocky Mountain doubles; 2) turnpike doubles; 3) intermediate doubles; and 4) triple combination trucks. Longer combination vehicles also include other truck combinations such as tandems using a B-Train configuration, which are known as B-Train trucks.

The safety of LCVs is a contentious issue, with many conflicting claims being made about how safe or unsafe these vehicles are. As a specific sub-class of commercial vehicles, LCVs have proven difficult to study using the data sets and methodologies typically applied to commercial motor vehicle safety such as the Fatality Analysis Reporting System (FARS) and the National Automotive Sampling System/General Estimates System (NASS/GES). The primary reason for the difficulty is the unavailability of LCV-specific crash and vehicle exposure data. As a consequence, there are no truly definitive answers to questions about LCV safety performance. It is not known, for example, whether these vehicles have a better or worse safety record than other types of commercial vehicles using the same roadways.

For the analysis presented in this thesis, LCVs are defined as any combination vehicle with two or more cargo spaces in which at least one of the cargo spaces is longer than 28 feet. This definition of LCV is consistent with that used by the Federal Motor Carrier Safety Administration (FMCSA). Based on this definition, any truck-tractor with only one semi-trailer or any "truck and trailer" are not considered LCVs irrespective of the number or axles of the combination or the gross weight at which it is registered. For truck-tractors with two trailers (a semi and a trailer), at least one of the trailers must be in excess of 28 feet 6 inches long and the combination registered above 80,000 pounds gross weight in order to be an LCV. All triples are LCVs. This applies to both a truck-tractor with a semi-trailer and two trailers and a truck having an integral freight bed or box with two trailers. It should be noted that since the registered weight cannot be obtained from raw data provided by weight-in-motion stations, this document will consider LCVs based on length criteria and not registered weight. The type of power unit (tractor or truck) in a conventional or cabover is irrelevant to the determination of whether or not the combination is an LCV. The following truck combinations are considered LCVs and are presented in Figure 1 and Table 1:

1) Rocky Mountain Double – a truck-tractor, semi-trailer 40 to 48 feet long and a trailer 20 to 32 feet long. Usually it is a seven-axle combination but may have as many as 11 axles.
2) Intermediate Double – a truck-tractor, semi-trailer 30 to 35 feet long and a trailer of the same length. Usually it is a seven-axle combination but may have as many as 11 axles.
3) Turnpike Double – a truck-tractor, semi-trailer 45 to 48 feet long and a trailer of the same length. Usually it is a nine-axle combination.
4) B-Train Double – tractor semi-semi similar to turnpike doubles, except that a platform or stinger is used to connect the semi-trailers. Neither trailer can exceed 48 feet in length.
5) Triple – a truck-tractor, semi-trailer and two trailers. Trailers are generally 28 feet 6 inches in length. Most commonly seen as a seven- or eight-axle combination in line-haul service.
6) Triple – truck and two trailers. The truck is not to exceed 40 feet; trailers normally are not in excess of 28 feet 6 inches and often have ten to eleven axles.
7) Other – Other combinations not described above that have two or more trailers (or semi-trailer) and are registered in excess of 80,000 pounds. An example of equipment falling into this category would be an auto transporter where two stinger-steered trailers are used.

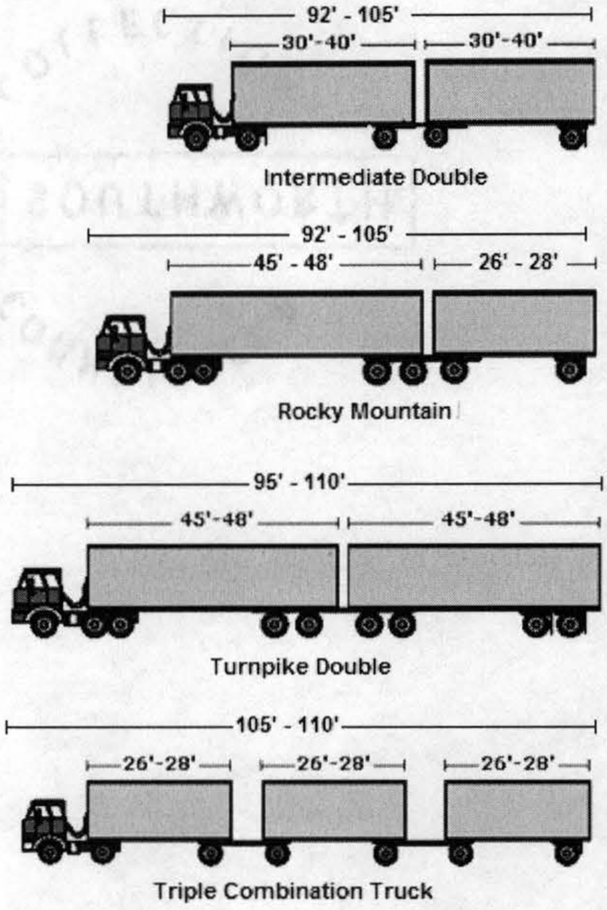

Figure 1: Configuration of Different Types of LCVs.

Table 1: LCV Truck Length Configuration

LCV Truck	First Trailer	Second Trailer	Third Trailer
Intermediate Double*	30-40 ft.	30-40 ft.	
Rocky Mountain Double	40-48 ft.	20-28 ft.	---
Turnpike Double	45-48 ft.	45-48 ft.	---
Triple	26-28 ft.	26-28 ft.	26-28 ft.

*Intermediate doubles are commonly classified as Rocky Mountain doubles.

1.2 Problem Statement and Thesis Objectives

Total vehicle miles of travel (VMT), a primary vehicle exposure measure used in safety research, is gathered from permanent and portable count stations in different segments of the highway. However, all vehicle classification algorithms classify vehicles according to the Federal Highway Administration's (FHWA) 13 vehicle classes that are primarily based on the number of axles rather than the configuration of the truck. These classifications are not detailed enough to differentiate between LCVs and non-LCVs. Accordingly, no estimates of LCVs VMT are currently available, precluding any crash rate analysis for these categories of heavy vehicles.

In this thesis, a new algorithm to identify LCVs using data obtained from Weigh-In-Motion (WIM) stations is developed and presented. The algorithm was developed and tested using vehicle-by-vehicle data to classify vehicles into subcategories based on axle weight and spacing, gross vehicle weight (GVW), vehicle length, and cargo length. The algorithm classifies vehicles into: 1) single unit trucks; 2) non-LCV double combination trucks; 3) LCV double combination trucks; and 4) LCV triple combination trucks. Moreover, the algorithm attempts to identify different types of LCV double combination trucks, such as Rocky Mountain doubles and turnpike doubles. The results of a discriminant analysis to classify vehicles using WIM data are also presented. Finally, the output of the classification algorithm is used to determine seasonal adjustment factors for each truck type. These factors are intended for use in LCV truck sampling where yearly counts are not available. The objectives of the work presented in this thesis are to

1. Develop, test, and validate an algorithm to classify different classes of heavy vehicles, including LCVs; using raw WIM data,
2. Apply discriminant analysis to classify different classes of heavy vehicles using WIM data, and
3. Use the WIM data classification algorithm output to develop seasonal and monthly adjustment factors for different classes of heavy vehicles.

1.3 Organization of Thesis

This thesis is organized into five chapters including this introductory chapter. Chapter 2 describes the development of the WIM data classification algorithm. Chapter 3 introduces the discriminant analysis for WIM data classification. In Chapter 4, the seasonal factors derived from WIM data using the previous two classification methods are presented. Chapter 5 presents conclusions drawn from the analysis results and recommendations for future research.

2. WIM DATA TRUCK CLASSIFICATION ALGORITHM

2.1 Truck Classification: State-of-the-Practice

A study that examines different technologies used for truck classification and methodologies for estimating truck VMT finds that the FHWA's 13 vehicle class classification method (see Appendix A) is the most common classification method used in most states (Benekohal and Girianna 1998). Tube counters were found to be the most common tool used for short-term truck counts. Additionally, the study finds that truck data from short counts were adjusted using continuous general traffic count data and not necessarily continuous truck data. A handful of states in this study did use factors for trucks that varied from those used for general traffic. Benekohal and Girianna also categorize current truck classification technologies into three groups: axle-based, vehicle-length-based, and machine-vision-based. Axle-based classifications are usually done using tube counters along with a vehicle classification algorithm. The disadvantages of tube sensors include the difficulty in installation in segments with high traffic volumes, the large number of unclassified vehicles, and the low durability of tube counters.

Vehicle-length-based systems measure the vehicle length based on vehicle speed and occupancy time. These systems may not provide sufficient details on the vehicle or trailer configuration to classify trucks into specific single or multiple trailer trucks. Machine-vision-based systems use cameras to record vehicles and feed the data to digitizers that distinguish vehicle characteristics based on the recorded frames. Drawbacks to this system are the difficulty in distinguishing vehicles closely spaced together, as well as distinguishing vehicles when the line of sight is blocked by other vehicles. Other classification technologies include inductive loops; pressure sensitive devices placed under the pavement; and non-intrusive technologies that use light beams to detect the presence of a vehicle. Some of these technologies are currently still under research and have been shown to have different levels of accuracy at varying vehicle speeds (Benekohal and Girianna 1998).

WIM scales are dynamic weighing systems that determine weights while vehicles are in motion. They enable vehicles to be weighed with little or no interruption of their travel. WIM scales have been designed to sense the weights of the axles passing over the instrument using piezo sensors, strain gauges, or hydraulic or pneumatic pressure transducers (FHWA 2001). The readings are transmitted to a receiving unit where they are converted to actual weights. WIM data is used in different fields such as pavement studies, highway monitoring and capacity studies, accident rate calculation, analysis of truck transport practices to measure vehicle counts, axle and gross weight, and vehicle classification.

WIM data format and coding instructions have been developed to provide input to national databases maintained by the FHWA. These include the Traffic Volume Trends (TVT) system and the Vehicle Travel Information System (VTRIS). The TVT system is used to process the continuous traffic volume data and produce the monthly Traffic Volume Trends report. The VTRIS is used to process the vehicle classification and truck weight data collected as part of the annual Truck Weight Study (FHWA 2001). Both are database management systems that apply a series of algorithms to process, validate, summarize, and maintain traffic data. The VTRIS approach to obtain vehicle counts for each vehicle class is presented in Figure 2. WIM data records are divided into four types: 1) station description data; 2) traffic volume data; 3) vehicle classification data; and 4) truck weight data. Several fields in the station description record were replaced with fields that are needed to tie traffic data to geographic information systems (GIS), which allow traffic data to be overlaid on the National Highway Planning Network (NHPN) and similar systems.

Algorithms for vehicle classification identified in the FHWA Traffic Monitoring Guide include: 1) human observation either on-site (manual) or video image; 2) vehicle length classification; 3) axle spacing classification; 4) axle spacing and vehicle length classification; and 5) axle spacing, weight, and vehicle length classification (FHWA 2002). Examples of axle spacing classification algorithms include the American Society for Testing and Materials (ASTM) Standard E1572 (ASTM 2000), scheme F algorithm, and scheme F modified algorithm (Elliot, et al. 1997). Scheme F assumptions regarding axle spacing for each of the 13 vehicles classes included in the FHWA vehicle classification system are presented in Table 2.

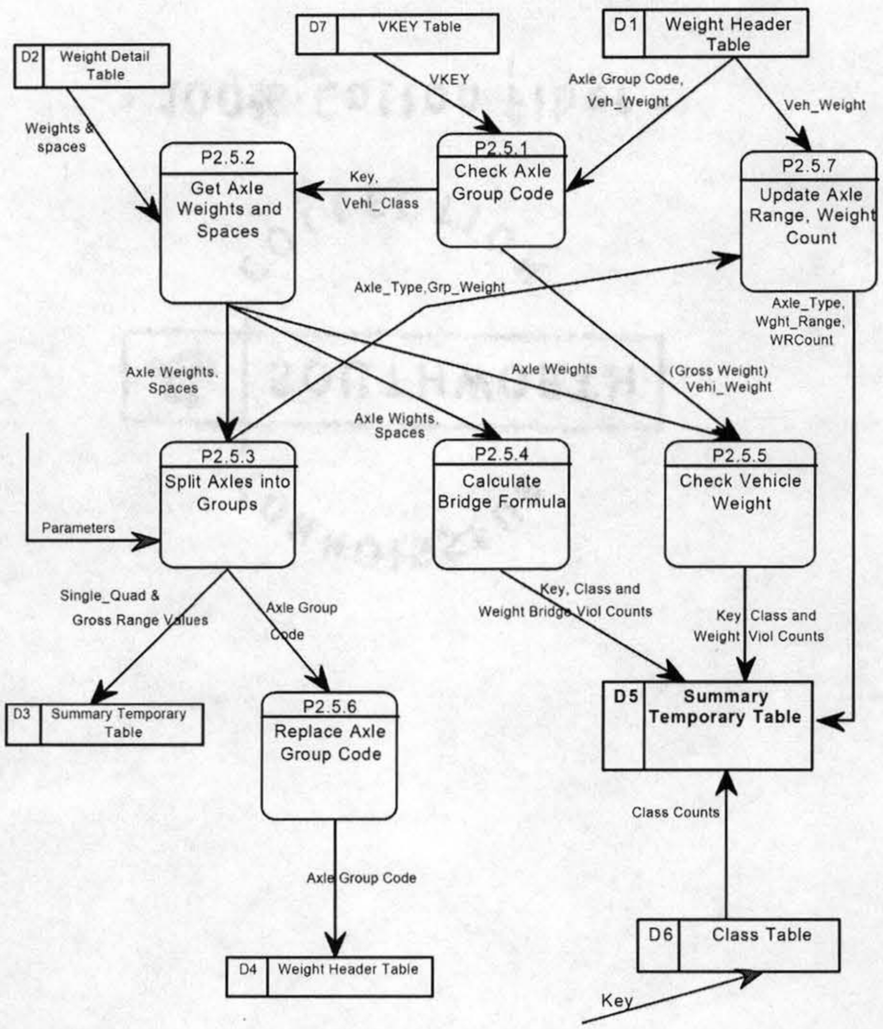

Figure 2: Vehicle Travel Information System (VTRIS) WIM Data Management System (FHWA 2001)

All classification algorithms classify vehicles into the FHWA vehicle classes which are primarily based on the number of axles on each vehicle. These classifications are not detailed enough to differentiate between LCVs and non-LCVs. For example, vehicle classes 11 through 13 in the FHWA system all pertain to multi-trailer trucks with different numbers of axles with no reference to trailer length and/or configurations (Table 2). Multi-trailer trucks include both non-LCVs (freeway doubles) and LCVs (turnpikes doubles, Rocky Mountain doubles, and triples). Additionally the Scheme F algorithm presents some classification problems such as the possibility of misclassifying single unit trucks. One example of this possible misclassification is illustrated by vehicle class 13 in Table 2, the description for these vehicles is identified as any truck with 7 or more axles. There are single unit trucks with seven or more axles that would be incorrectly classified as multi-trailer trucks (Figure 3). Another possible error is identified with class 11 of the Scheme F algorithm, there are single unit trucks that fit this class description (Figure 4) and again would be misclassified as multi-trailer trucks.

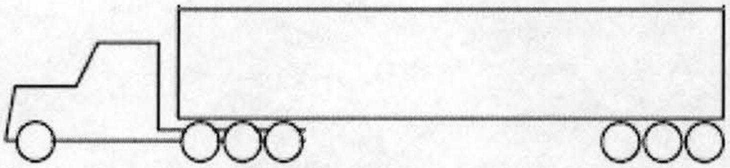

Figure 3: Seven Axle Single Trailer Truck

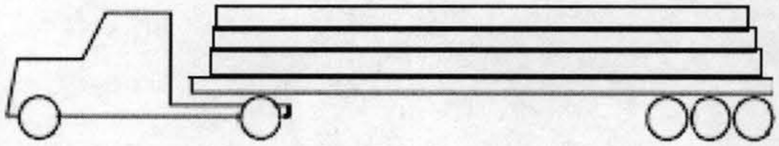

Figure 4: Five Axle Single Trailer Truck

Table 2: Scheme F Assumptions Regarding Axle Spacing for Different Vehicle Classes

			Axle Space In Feet				
Class	FHWA Vehicle Type	No of Axles	Axle 1 to 2	Axle 2 to 3	Axle 3 to 4	Axle 4 to 5	Axle 5 to 6
1	motorcycle	2	0-5.8				
	car	2	5.8-10				
2	car/1 axle trailer	3	0-10	10-18			
	car/2 axle trailer	4	0-10		<3.5		
	pickup	2	10-15				
3	pickup/1 axle trailer	3	10-15	10-18			
	pickup/2 axle trailer	4	10-15		<3.5		
	pickup/3 axle trailer	5	9.9-15			<3.5	
4	bus	2	>20				
	bus	3	>19				
5	single unit truck/dual rear axle	2	15-20				
6	single unit truck	3		<18			
7	single unit truck	4					
	2 axle tractor with 1 axle trailer	3		>18			
8	3 axle tractor with 1 axle trailer	4		<=5	>10		
	2 axle tractor with 2 axle trailer	4		>5	>3.5		
9	3 axle tractor with 2 axle trailer	5					
	2 axle tractor with 3 axle trailer	5		<6.1		3.5-8	
10	any single tractor/trailer comb. with 6 or more axles	6 or more			3.5-5		
11	any tractor/double trailer unit with 5 or less axles	5		>6			
12	tractor/double trailer unit	6					>10
13	any tractor/double trailer unit with 7 or more axles	7 or more					

Source: FHWA (2001)

The algorithm developed for this thesis and presented in this chapter uses WIM vehicle-by-vehicle data to provide a more-detailed vehicle classification based on axle weight and spacing, GVW, vehicle length and length of cargo units. The algorithm classifies vehicles into: 1) single unit trucks (non-LCV); 2) freeway doubles (non-LCVs); 3) Rocky Mountain doubles (LCVs); 4) turnpike doubles (LCVs); and 5) Triples (LCVs).

2.2 Algorithm Development

The length and weight criteria for different classes of heavy vehicles used for the development of this algorithm were obtained from several sources such as the FHWA's Western Uniformity Scenario report (FHWA 2004), and FHWA's Truck Size and Weight Study (FHWA 2000). Additionally, field observations and measurements of different truck types were conducted. A sample of 250 trucks, representing different truck types, was used to obtain the configuration characteristics of different truck types used in the algorithm.

The classification algorithm is initially based on the number of "major spacings" between axle groups in each vehicle based on the criteria shown in Figure 5. The length of 8.4ft was selected as a breakpoint between consecutive axles that would be considered tandem and consecutive axles that would be considered major spacings. The selection of this length was accomplished through iterations with raw WIM data as well as the sources presented earlier in this section. Vehicles were initially classified into one of six groups based on the number of major spacings. Each group has one or more vehicle classes (Table 3). The characteristics of major spacings for each different truck type are presented in Figure 6. This figure shows the number of major axle spacings for each of the initial truck types.

Table 3: Preliminary Truck Classifications Groups

Major Spacing	Possible Truck Classification
1	Single-unit truck
2	Single trailer truck
3	B-train truck, or full truck with 1 trailer
4	Double trailer truck
5	Full truck with 2 trailers
6	Triple

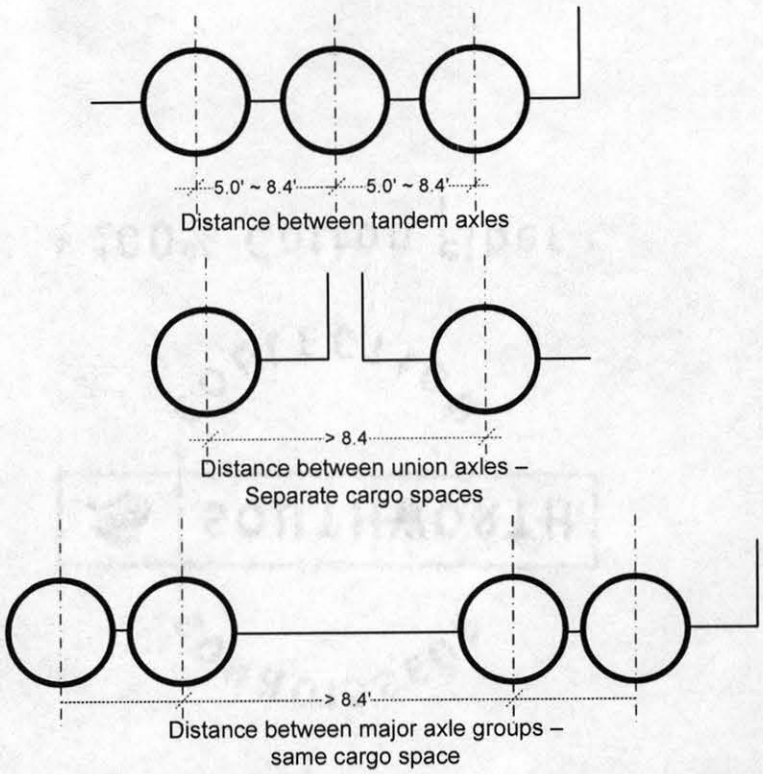

Figure 5: Criteria for Defining the Type of Axle Based on Axle Spacing Length.

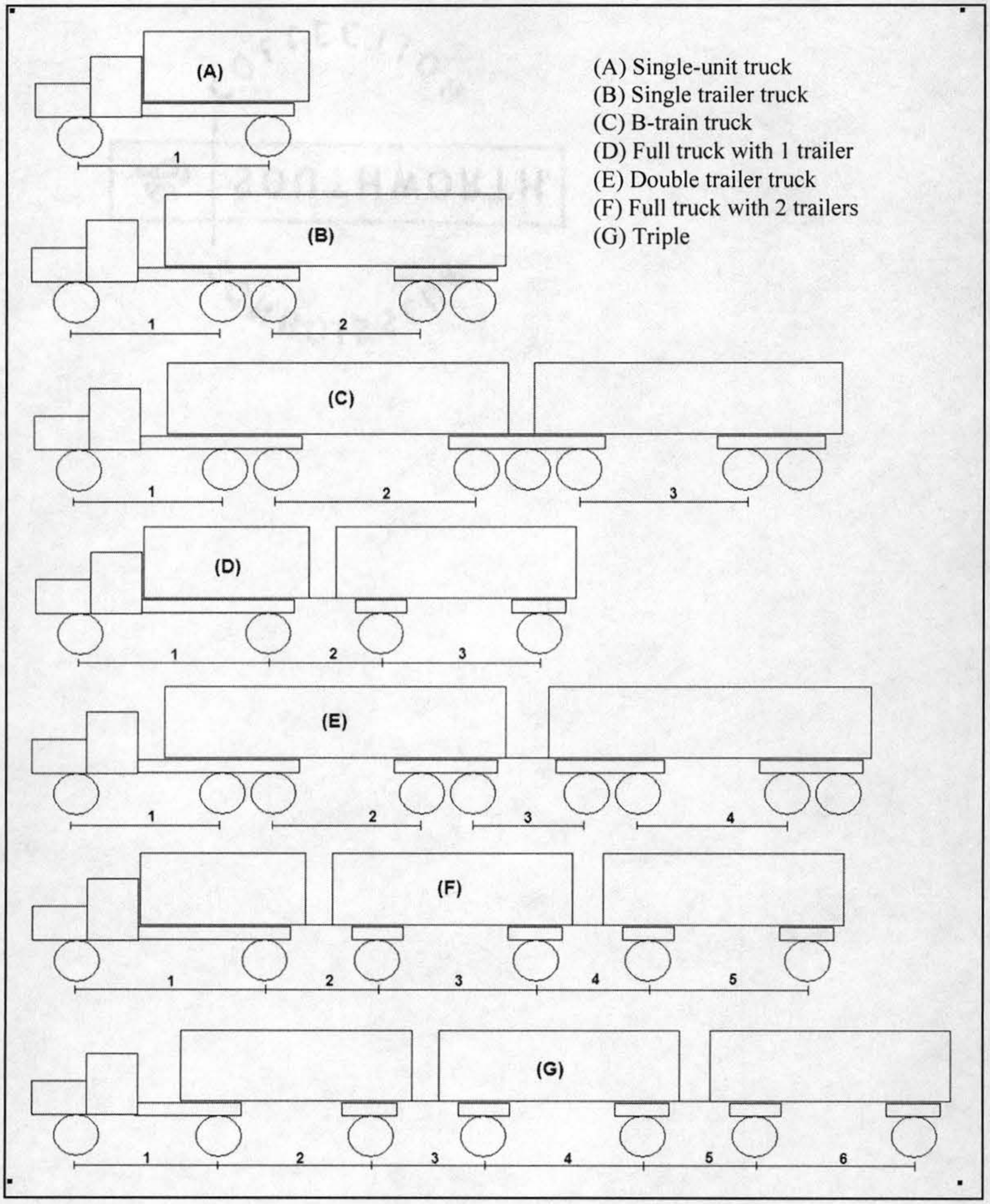

Figure 6: Characteristics of Major Spacings for Different Truck Types.

Trucks with one or two major spacings were classified as either a single-unit truck or a single trailer truck. Similarly, trucks with five or six major spacings were classified as triple combination trucks (a truck pulling two trailers or triple trailer truck). Trucks with three or four major spacings were classified as double combination trucks. These trucks were classified based on the estimated length of trailer 1, trailer 2, and the total cargo length according to the criteria presented in Table 4. It should be noted that intermediate doubles have been combined with Rocky Mountain doubles for final classification.

Table 4: Length Criteria for Classifying Double Trailer Trucks

Trailer 1		Trailer 2		Total Length	Preliminary Truck Classification
26-28 ft	and	26-28 ft	and	< 57 ft	Freeway Double
40-48 ft		20-28 ft		60 – 76 ft	Rocky Mountain Double
30-40 ft		30-40 ft		60 – 80 ft	Intermediate Double
40-48 ft		40-48 ft		> 75 ft	Turnpike Double

The following set of equations were used to determine the length of each trailer (for regular doubles) and the total cargo space (for B-trains and full-truck-plus-trailer), used by the classification algorithm to classify groups C, D, and E in Figure 6:

For Group C (B-train double) with 3 major axle spacings:

$$LMC = Total\_Length - LMS1\,, \tag{1}$$

where

LMC = the length of total cargo space

LMS1 = the length of major space 1, and

Total_Length = the total axle length (distance between the first and last axle of the truck).

For Group D (full truck plus one trailer) with THREE major axle spacings:

$$LMC = Total\_Length - LMS2\,, \tag{2}$$

where

$LMS2$ = the length of major space 2.

The criteria for final classification of B-train doubles and full trucks with one trailer (groups C and D) are presented in Table 5.

Table 5: Classification Criteria for B-train and Full Truck plus One Trailer Doubles

Three Major Spacing Truck Type	Total Cargo Space (LMC)
Freeway Double	45-57 feet
Rocky Mountain	57-68 feet
Turnpike Double	68-80 feet

For Group E (double trailer truck) with four major axle spacings:

$$LMC = Total\_Length - LMS3prev, \tag{3}$$

$$LMC = Total\_Length - LMS1 - LMS3 - TR2, \tag{4}$$

where

$TR2$ = the length of the second trailer,

$LMS3prev$ = the length of all axle spacings previous to and including major space 3,

$TR1$ = the length of the first trailer, and

$LMS3$ = the length of major space 3.

Figure 7 details the WIM data truck classification algorithm in a flowchart.

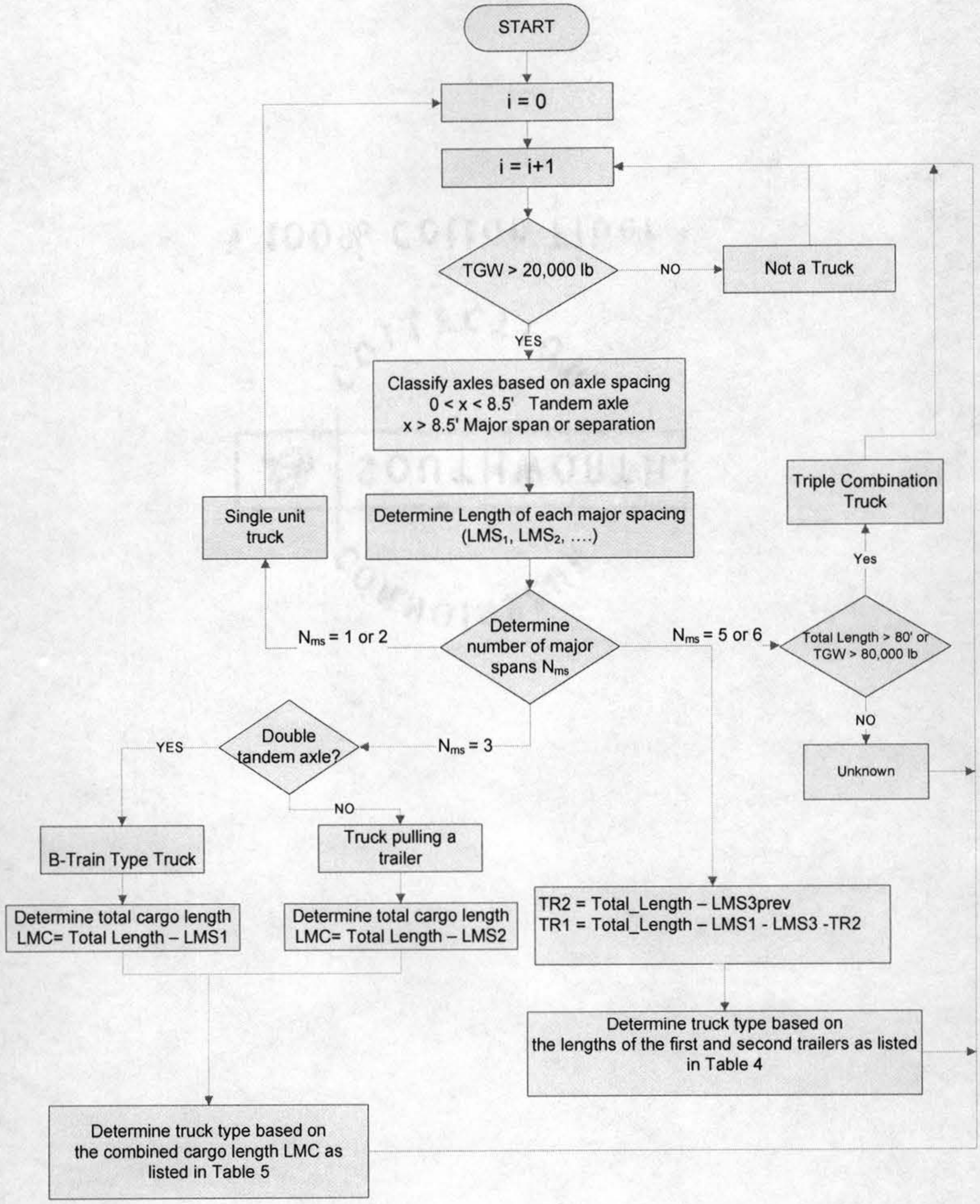

Figure 7: Flow Chart for the WIM Data Truck Classification Algorithm

2.3 Algorithm Validation through Field Observations

To validate the algorithm, vehicle-by-vehicle data were obtained from a WIM station located on I-84 west of Boise, Idaho. Data were collected for a sample of 595 trucks during a four-hour data collection period (3–7 PM). Data were obtained for each truck through manual observations and included truck type; number of axels; and truck weight as reported by the WIM station. To verify the manual observations in the lab, the operations of the WIM station during the data collection period were also recorded by video. The WIM data in Traffic Management Guide (TMG) format were obtained from the station for the same time periods.

The WIM data were analyzed using the WIM data truck classification algorithm. The algorithm outputs were compared against the manually collected data. The results of this comparison are presented in Table 6. The algorithm successfully identified all 34 triple combination vehicles; all 23 non-LCV double combination vehicles; and all 35 LCV double combination vehicles that passed the WIM station during the data collection period. Out of the 503 single trucks, the algorithm correctly identified 501 and reported two as unknowns. While the sample size of the field data used in the validation may not be large or comprehensive enough to provide a final conclusion regarding the validity of the algorithm output, it clearly shows that the algorithm successfully classified different classes of heavy vehicles with a high degree of reliability. More field validation is needed before final conclusions can be made.

To further verify the output, the algorithm was tested using a set of WIM data from stations on road segments where LCVs are not permitted. Data from 7 WIM stations were used in this verification analysis. The results are presented in Table 7. These results show minimal error with only two trucks incorrectly classified as LCV doubles out of a total of 275,000 trucks analyzed. The results help reinforce the classification capacity of the developed algorithm.

Table 6: Results of Field Data Validation of Algorithm Output (Number of Trucks)

	Single	Freeway Double	Rocky Mountain Double	Turnpike Double	Triple	Percent Error
Hour 1						
Observed	135	4	3	1	6	0%
From Algorithm	135	4	3	1	6	
Hour 2						
Observed	118	6	9	0	7	0%
From Algorithm	118	6	9	0	7	
Hour 3						
Observed	155	5	11	2	9	Less than 1 %
From Algorithm	156	5	11	2	9	
Hour 4						
Observed	95	8	5	4	12	Less than 2 %
From Algorithm	97	8	5	4	12	

Table 7: Results of Algorithm Verification Using Data from Seven WIM Stations Not Allowing LCVs (Number of Trucks)

	Non-LCV		LCV		
Utah WIM Station	Single	Freeway Double	Rocky Mountain Double	Turnpike Double	Triple
30001	56886	1926	0	2	0
30005	50572	1199	0	0	0
430007	56610	788	0	0	0
450003	21399	444	0	0	0
450007	15493	499	0	0	0
530001	39064	853	0	0	0
530005	27921	1314	0	0	0

2.4 Average Length and Standard Deviations for Major Axle Spacings of Doubles

Average length and standard deviations for major axle spacings of different truck types are presented in Table 8. The axle spacing data were obtained from WIM data for a sample of 23,000 trucks randomly chosen from all WIM stations in Utah. The trucks were selected randomly from over 6 million trucks in order to obtain a representative sample.

Table 8: Major Axle Spacings Average Lengths and Standard Deviations by Truck Class

Truck Class	Major Spacings (values in feet)											
	1		2		3		4		5		6	
	Avg.	σ	Avg.	σ	Avg.	σ	Avg.	σ	Avg.	σ	Avg.	σ
Singles	17.1	2.4	30.9	4.4								
Freeway Doubles	15.5	2.8	20.4	2.0	11.5	4.7	21.8	3.6				
Rocky Mountain Doubles	16.7	2.7	28.0	3.1	12.8	2.6	18.3	2.9				
Turnpike Doubles	11.3	1.0	30.3	3.3	11.6	2.5	30.8	3.0				
Triples	12.8	0.9	21.3	0.6	9.4	0.3	22.2	0.4	9.4	0.3	22.2	0.4

Most major spacing lengths are fairly consistent for all vehicles with standard deviations below four feet. The high standard deviation of 4.7 ft observed for freeway doubles major spacing 3 is due to the fact that this spacing is a union between the two trailers and may vary considerably. The other high value of 4.4 ft observed for the trailer section of singles can also be explained by the large variety of trailer lengths observed for single trailer trucks.

2.5 Chapter Conclusion

The development, testing, and validation of an algorithm to classify different classes of heavy vehicles using WIM data are presented in this chapter. Results of the algorithm testing and validation show that the algorithm has a significant classification power and that it successfully classifies and identifies different types of heavy vehicle classes, including LCVs. Output from the algorithm could be used as a base to estimate relative truck exposure measures (such as VMT) for different truck types. This will allow for a comparative crash rate analysis for different classes of heavy vehicles, including different types of LCVs. The output of the algorithm can be improved through more extensive calibration using a large sample of hand counted field data.

Additional data showing the classification of trucks with existing algorithms and a comparison to the algorithm developed in this thesis may provide a more general conclusion on the classification potential of this algorithm. Based on the classification criteria of the algorithm presented in this thesis, in comparison to the scheme F algorithm, all single unit trucks would be correctly classified, whereas with the scheme F algorithm some singles, particularly those mentioned in this section, would be incorrectly classified as multi trailer truck. Additionally the scheme F algorithm does not allow for a detailed classification of LCVs.

3. DISCRIMINANT ANALYSIS

3.1 Introduction

The purpose of the discriminant analysis was to develop discriminant functions that could be used to classify different classes of heavy vehicles using WIM data. The vehicle classification data used to develop and train the discriminant functions were obtained from the output of the WIM data classification algorithm presented in Chapter 2 of this thesis. In essence, the classification potential of the WIM data classification algorithm was translated into discriminant functions that classify heavy vehicles based on axle-weight and axle-spacing characteristics available from the WIM data.

3.2 Discriminant Analysis: An Overview

Discriminant analysis can be used to train a series of discriminant functions with known (previously classified) data in order to apply these functions to unknown data for classification. The classification is based on a series of predictor variables that are combined to produce a canonical root similar to multiple regression. The difference is that in discriminant analysis, the combination of the discriminating variables is organized in a way that produces the greatest difference between the means of the dependent variables. The general form of the discriminant function is given by (Johnson & Wichern, 2002):

$$L = b_1 x_1 + b_2 x_2 + b_n x_n + C ,$$

where

b = discriminant coefficients,

x = discriminating variables,

C = constant.

The number of discriminant functions is equal to one less than the number of classes used for the analysis, in the case of this study, since five final truck classes are being used, four discriminant functions will be generated.

The eigenvalues reflect the ratio of importance of each discriminant variable, the first eigen value is the most important and will account for the largest percentage of the classification power. The following values will be consecutively less until 100 percent of the classification power is described by all discriminant functions. The number of discriminant functions that are important for group classification is based on an overall 100 percent by all discriminant functions. If the first two discriminant functions describe 98 percent of the classification, the following two functions may be omitted since their combined classification power is only 2 percent.

Discriminant scores can be obtained from the application of the discriminant functions to cases in the data set. These scores help explain the classification characteristics of each discriminant function. This means that one discriminant function may do a good job of discriminating between groups one and two (provides discriminant scores that are very different for each of these groups) but may not discriminate between groups two and three as readily. On the other hand another discriminant function may discriminate better between groups two and three but not as well between groups one and two.

Prior probabilities may also be used in a discriminant analysis to improve the classification power of the discriminant functions. Prior probabilities are usually included in the analysis when there is previous knowledge of how the groups would most likely be classified. In the analysis conducted for this thesis no prior probabilities were used since previous knowledge about the percent distribution of LCVs was unavailable due to a lack of previous studies dealing with these vehicles. Other methods may also be used to improve the final classification into groups of discriminant functions. One of these methods uses a cost of misclassification, where misclassifying data into a specific class is more costly than misclassifying the data into another class. With this parameter the discriminant function applies a weight criterion that avoids misclassifying data into the more "expensive" category or group.

The validation of discriminant functions is typically conducted through comparison to known data or through crossvalidation. Crossvalidation takes data previously classified, then applies the discriminant function, and ultimately compares the final classification between the discriminant function and the real classification. Another method consists of a hold-out analysis in which part of a data set is randomly selected and used for calibration of the discriminant functions and the rest is used to test the data set. This method was used in this thesis to obtain the classification comparison between the algorithm and the discriminant functions as will be explained ahead. A data set containing 700,000 trucks was selected for the development of the discriminant function. Seventy percent of the trucks were used for the development and calibration of the discriminant functions while 30 percent were used to verify the classification in relation to the algorithm classification.

Parametric discriminant analysis may be applied when within-class values have a normal distribution. Parametric discriminant analysis generates a linear or a quadratic discriminant function depending on whether the covariances among the variables are assumed to be similar or not. If the covariances are assumed similar, a pooled covariance matrix may be used, and a linear discriminant function is generated by the analysis. If the covariances are assumed to be different, a quadratic discriminant function is generated. For the analysis presented in this thesis the covariances were assumed to be similar.

Vehicle classification criterion for the discriminant analysis was calculated using the pooled covariance matrix, the distance to each individual class was calculated using a squared distance criterion or Mahalanobis distance, given by the Equation. (Johnson & Wichern, 2002):

$$d_t^2(X) = (X - m_t)' COV^{-1} (X - m_t), \tag{5}$$

where

t = classification group,

X = vector that contains all variable values,

m_t = vector containing variable means for each group,

COV = pooled covariance matrix.

The discriminant function for each vehicle class is calculated using the following formulas:

$$C = -0.5 m_t ' COV^{-1} m_t \text{,} \tag{6}$$

$$Coeff = COV^{-1} m_t \text{,} \tag{7}$$

where

C = constant,

$Coeff$ = coefficient vector.

There have been considerable applications of discriminant analysis in different areas of transportation research. Coleman and Taylor (1996) applied discriminant analysis to predict the effectiveness of several proposed speed zones in reducing crashes. The discriminant function developed in this study was based on variables such as driveway frequency, 85th percentile speed, and signalization. The objective of the analysis was to determine whether a variation of the speed limit on a road segment is effective or ineffective in reducing crash rates. In essence the discriminant function was used to classify candidate sites into either effective or ineffective speed zones based on quantifiable values of the variables. Variables selected for the discriminant functions were those which could contribute most to the classification of speed zones. The initial number of 200 variables were systematically reduced through correlation analysis, cross-tabulation, and through the value of Wilk's lambda, an indicator that ranges from zero to one with one indicating a discriminant function that has the highest classification power.

The study identifies predictor variables that can be used to develop a discriminant function. The variables, arranged in order of predictive power, include: 1) driveway frequency, 2) signalization, 3) skewness index of speed distribution, and 4) the 85th percentile speed. The development of a discriminant function with these variables was found to be a good predictor of speed zoning effectiveness in candidate zones.

In another study, Cobbs, et al. (2002) evaluated the safety performance of different vehicles. Vehicles were classified into one of five safety performance groups: excellent; good; acceptable; marginal; and poor. The study identifies a series of vehicle characteristics that were used as predictor variables for an initial principal components analysis (PCA) and ultimately the discriminant function. The discriminant function was used to classify new vehicles based on individual vehicle's characteristics. An initial PCA on the predictor variables was conducted to identify variables to be included in the discriminant function. The primary purpose of the PCA was to eliminate correlation between the variables. The study used a quadratic function rather than linear function due to the statistical difference among the covariance matrices of the variables included in the function.

Variables used in the study include vehicle characteristics such as dimensions; weight, engine size; wheel base; center of gravity location; and price. The safety performance associated with each vehicle included in the study was obtained from the results of crash tests and using a safety performance index ranging from one to five, with five being the vehicle with the highest safety performance. The initial PCA reduced the number of variables from seventeen to nine; the result was a set of eight variables that could adequately describe 94.8 percent of the variance of the original 17 variables. The PCA is done through a correlation analysis where variables that describe similar variances or are "parallel" are combined into a single more robust variable minimizing the total number of variables. The second step was the development of a quadratic discriminant function using the eight principal components (variables). The safety performance of vehicles was used as the classification or grouping criterion. Once the discriminant function was developed, new vehicles were classified into one of the five safety performance categories. Vehicles in all safety performance categories with the exception of one (acceptable rating which was 83.3% correctly classified) were classified with 100% accuracy. The total number of vehicles correctly classified was 94.6%.

Yamanda, et al. (2001) applied discriminant analysis to determine existing surface conditions on pavement surfaces on a real time basis based on still digital images. Road surface conditions were classified into five groups: dry, wet, slushy, icy and snowy. The variables used to develop the discriminant function were based on a series of image quantifiable properties that were digitally extracted from photos of the roadway surface. Examples of these variables include: coarseness; gray level; texture uniformity; and image contrast. The Mahalanobis generalized distance was applied during the classification process to determine the correct classification of any given photo into one of the five road surface conditions.

3.3 Discriminant Analysis

3.3.1 Analysis Approach

Data used in the discriminant analysis were obtained from the state of Utah 2003 WIM data, this data consisted of all trucks including LCVs and non-LCVs. Vehicles were classified using the WIM data classification algorithm presented in the previous chapter. The output of the classification algorithm provided the vehicle classification data used to develop and train the discriminant function. They also provide benchmark true data to which the outputs of the discriminant analysis are compared against. Two sets of data are randomly extracted from the WIM data. The first set is used to develop and train the discriminant functions. The second set of data is used to test and validate the output of the discriminant analysis. Both data sets include data for a total of 700,000 vehicles. Four different analyses are conducted using different sets of independent variables and classification approach:

1) *Discriminant analysis using variables obtained directly from the WIM data:* Discriminant functions were developed using variables obtained directly from the raw WIM data. The variables included: length between each pair of axles (11 variables), total vehicle length, weight of different axles (12 variables), and number of axles. These variables described the specific characteristics of each vehicle type and are reported in the raw WIM data.

2) *Sequential Discriminant analysis using variables obtained directly from the WIM data:* Discriminant functions were developed using the same set of variables obtained directly from the WIM data. However, the classification was done through a sequential approach. Vehicles were classified first into different groups based on the number of axles on each vehicle. Discriminant functions were developed for each axle-group of vehicles. The resulting classifications were then aggregated together to provide the final classification for all vehicles.

3) *Discriminant analysis using variables generated from the WIM data:* Discriminant functions were developed using variables generated from the WIM

data using the WIM data classification algorithm in addition to those obtained directly from the WIM data. These generated variables consist of major spacings between axles.

4) *Sequential Discriminant analysis using variables generated from the WIM data*: Similar to the previous analysis, the discriminant functions were developed using variables generated from the WIM data using the WIM data classification algorithm. However, the classification was done through a sequential approach. Vehicles were classified first into different groups based on the number axles. Discriminant functions were developed for each group of vehicles. The resulting classifications were then aggregated together to provide the final classification for all vehicles.

The purpose of using a sequential analysis was to eliminate blanks in data sets when vehicles with different numbers of axles are combined. If a vehicle with four axles is analyzed concurrently with a vehicle with five axles, the fifth axle entry for the four axle vehicle would be a zero and adversely affect the discriminant function by considering zero an actual axle length.

Five different vehicle groups were classified in this analysis: 1) single unit trucks; 2) freeway doubles (FWD); 3) turnpike doubles (TP); 4) Rocky Mountain doubles (RMD); and 5) triple combination trucks. Because only five groups are classified, the maximum number of discriminant functions that can be used is limited to four.

3.3.2 Variables Description

Twenty five variables, directly obtained from the WIM data, and eight variables derived from the WIM data were used in the analysis. The variables include: length between each pair of axles (11 variables), total vehicle length, number of axles, weight of different axles (12 variables), actual length of major axle spacings (7 variables), and the number of major axle spacings. Table 9 lists all the 33 variables considered for the analysis. Other variables included in the raw WIM data (see Appendices B and C) were not included as they do not describe any vehicle characteristics.

Table 9: Variables Obtained Directly from the WIM Data and Generated Variables

Source	Variable Number	Variable
Obtained Directly from WIM Data	1	Spacing between axles A and B
	2	Spacing between axles B and C
	3	Spacing between axles C and D
	4	Spacing between axles D and E
	5	Spacing between axles E and F
	6	Spacing between axles F and G
	7	Spacing between axles G and H
	8	Spacing between axles H and I
	9	Spacing between axles I and J
	10	Spacing between axles J and K
	11	Spacing between axles K and L
	12	Total length (front axle to rear axle)
	13	Axle A Weight
	14	Axle B Weight
	15	Axle C Weight
	16	Axle D Weight
	17	Axle E Weight
	18	Axle F Weight
	19	Axle G Weight
	20	Axle H Weight
	21	Axle I Weight
	22	Axle J Weight
	23	Axle K Weight
	24	Axle L Weight
	25	Number of Axles
Generated Using the WIM Data	26	Major Spacing 1
	27	Major Spacing 2
	28	Major Spacing 3
	29	Major Spacing 4
	30	Major Spacing 5
	31	Major Spacing 6
	32	Major Spacing 7
	33	Number of Major Spacings

3.3.3 Variable Inclusion in Discriminant Functions: Direct versus Step-Wise

There are two methods for independent variables' inclusion in the discriminant functions: direct and stepwise methods. In the direct method, all variables are forced into the discriminant analysis and the discriminant functions are developed using all input variables. In the stepwise method, variables are selected one by one based on their discriminating power. In the analysis presented in this thesis, the direct method was used. This method was selected because all independent variables that are used describe the vehicles' lengths and weight configurations; thus, each of them could have a significant discriminating power to classify different classes of heavy vehicles.

3.3.4 Correlation among Independent Variables

Correlations among different variables are examined to identify highly correlated variables. The correlation matrices for the variables are presented in Appendix D. The correlation matrices show, in general, a low degree of correlation existing among most variables. Accordingly, none of the variables initially selected for the analysis were eliminated.

3.3.5 Discriminant Analysis Results

3.3.5.1 Discriminant Analysis Using Variables Obtained Directly from the WIM Data

Statistical Package for Social Science (SPSS) was used as a tool for the discriminant analysis presented in this thesis. Table 10 illustrates the discriminant function classification coefficients for the discriminant functions developed using variables obtained directly from the WIM data (25 independent variables). The table shows the constant and coefficients assigned to each variable for each of the five vehicle classes classified. Only one variable (total vehicle length) was excluded as it failed the tolerance test (the total length of the vehicle is already explained by some of the other variables and therefore does not add any classification power to the analysis); accordingly, it was eliminated from the analysis. For singles, freeway doubles, and triple combination trucks, the number of axles is the variable that has the highest coefficient, and thus high discriminating power. Variables that describe spacing between the last group of axles (axles I, J, K, and L) have larger coefficients than variables describing other axles. Moreover, the values of the coefficients for the axle spacing variable are much higher than those for axle weights. These results are reasonable since the algorithm used to classify trucks initially applied axle spacings as the main classification criteria and therefore it would be expected that axle spacings would have a larger coefficients than axle weights for example.

Table 10: Classification Coefficients (Directly Obtained Variables Analysis)

Variables	Vehicle Classification				
	Single	FWD	RM	TP	Triple
ABspacing	2.12	1.62	1.99	1.28	1.38
BCspacing	2.23	2.75	2.38	2.67	3.03
CDspacing	-0.60	-0.34	-0.15	0.22	0.02
DEspacing	-2.17	-0.91	-1.46	-0.93	0.10
EFspacing	-2.96	-1.08	-0.73	-1.29	-0.18
FGspacing	-4.56	-3.53	0.05	0.67	1.68
GHspacing	-5.67	-4.79	-1.97	5.74	-0.96
HIspacing	-9.42	-7.62	-4.78	-0.38	-5.60
IJspacing	-10.17	-9.73	-6.33	-19.30	-9.92
JKspacing	-27.22	-20.36	-31.09	-19.76	-24.19
KLspacing	49.96	38.79	48.93	-73.84	23.99
Axles	58.03	54.99	47.44	41.07	44.99
axlAweight	0.14	0.13	0.12	0.14	0.13
axlBweight	0.07	0.14	0.07	0.09	0.15
axlCweight	0.18	0.18	0.21	0.20	0.16
axlDweight	0.07	0.02	0.03	0.00	0.04
axlEweight	-0.21	-0.19	-0.17	-0.14	-0.15
axlFweight	-0.56	-0.70	-0.61	-0.35	-0.73
axlGweight	-0.06	-0.15	-0.30	-0.48	-0.49
axlHweight	-0.41	-0.46	-0.73	-1.31	-0.81
axlIweight	-0.10	-0.05	-0.10	0.02	-0.03
axlJweight	0.19	0.17	0.34	0.35	0.41
axlKweight	1.20	1.20	1.87	4.13	2.05
(Constant)	-160.30	-169.30	-167.40	-221.75	-197.05

Table 11 illustrates the eigenvalues for each of the four canonical functions generated for the directly-obtained-variables analysis. This table shows that the first function describes 77 percent of the variance between the final groups. The second, third and fourth variables account for much lower variance values but still significantly contribute to the overall classification.

Table 11: Eigen values for Canonical Functions (Directly Obtained Variables Analysis)

Function	Eigenvalue	% of Variance	Cumulative %
1	4.12	77.65	77.65
2	0.66	12.47	90.13
3	0.39	7.41	97.53
4	0.13	2.47	100.00

Table 13 shows the canonical discriminant function coefficients for the directly-obtained-variables analysis. A set pattern between the discriminant function coefficients and the variables is not immediately apparent; however, the first canonical function has larger coefficients for the axle spacing variables than for the weight variables in general, this could lead to the conclusion that this is a weight discriminant function. Additionally this same function has the largest coefficient for the number of axles indicating that it explains the number of axles variable the best. Discriminant functions three and four show higher coefficients for axles JK spacing that the other functions, this indicates that these variables describe the trailers of trucks more readily than the other two discriminant functions since the JK spacing is usually located in the trailer portion of a truck.

Table 12: Standardized Canonical Discriminant Function Coefficients

	Function			
	1	**2**	**3**	**4**
AB spacing	-0.16	-0.04	-0.38	-0.02
BC spacing	0.22	0.23	0.50	0.02
CD spacing	0.50	-0.05	0.16	0.06
DE spacing	0.49	0.44	0.71	-0.02
EF spacing	0.65	0.49	0.17	0.73
FG spacing	1.21	0.17	-0.45	-0.73
GH spacing	0.89	-0.88	0.27	-0.42
HI spacing	0.75	-0.43	0.00	0.45
IJ spacing	0.01	0.31	-0.37	0.26
JK spacing	0.02	0.00	0.39	0.11
KL spacing	-0.07	0.16	-0.16	0.06
axles	-0.88	0.18	0.12	0.23
axlAweight	-0.01	-0.02	0.04	-0.06
axlBweight	0.07	0.15	0.30	0.09
axlCweight	0.03	-0.04	-0.13	0.15
axlDweight	-0.11	-0.02	-0.11	-0.28
axlEweight	0.12	-0.02	0.03	-0.03
axlFweight	-0.07	-0.48	-0.12	-0.19
axlGweight	-0.32	0.00	-0.07	0.28
axlHweight	-0.30	0.28	-0.05	0.17
axlIweight	0.03	-0.02	0.12	-0.01
axlJweight	0.08	0.00	-0.07	-0.14
axlKweight	0.17	-0.27	0.07	-0.15

The effectiveness of the discriminant functions can be measured by observing the territorial map for different canonical functions. Figure 8 shows canonical Functions 1 and 2 for the discriminant analysis developed using variables obtained directly from the WIM data. The graph shows that Function 1 has the greatest power separating singles (1) and double freeways (2) from other vehicle types since the centroids of these two classes (identified by the asterix) are furthest apart in the X coordinate from all other vehicles. Canonical Function 2 separates turnpikes (4) from triples (5). Rocky Mountains (3) appear to be the least defined group based on these two canonical functions since the centroid for these vehicles is close to other variables in the X and Y coordinates. Similar observations can also be made from Figure 9, which illustrates the discriminant scores for all canonical function combinations.

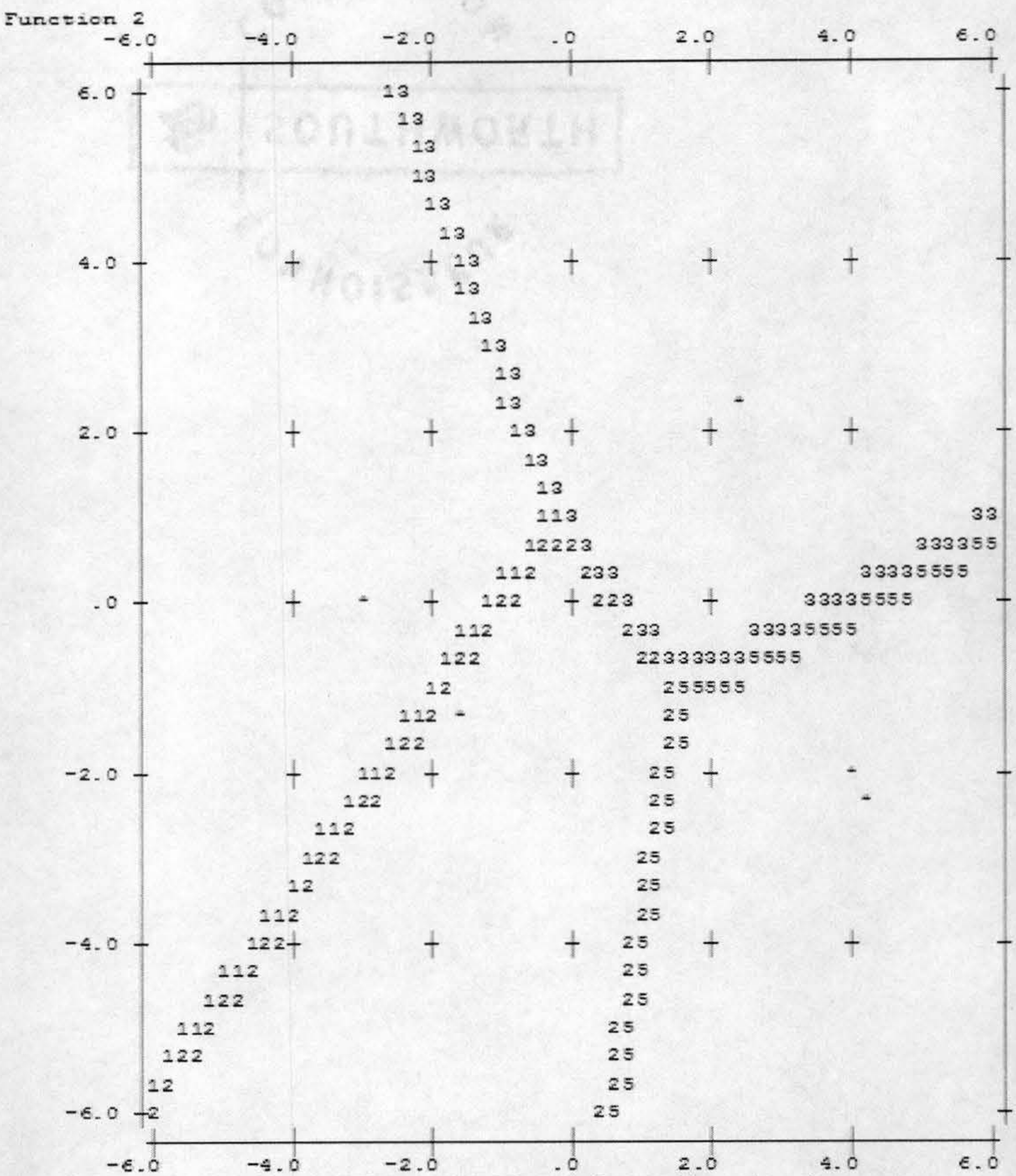

Figure 8: Territorial Map for Function 1 and Function 2

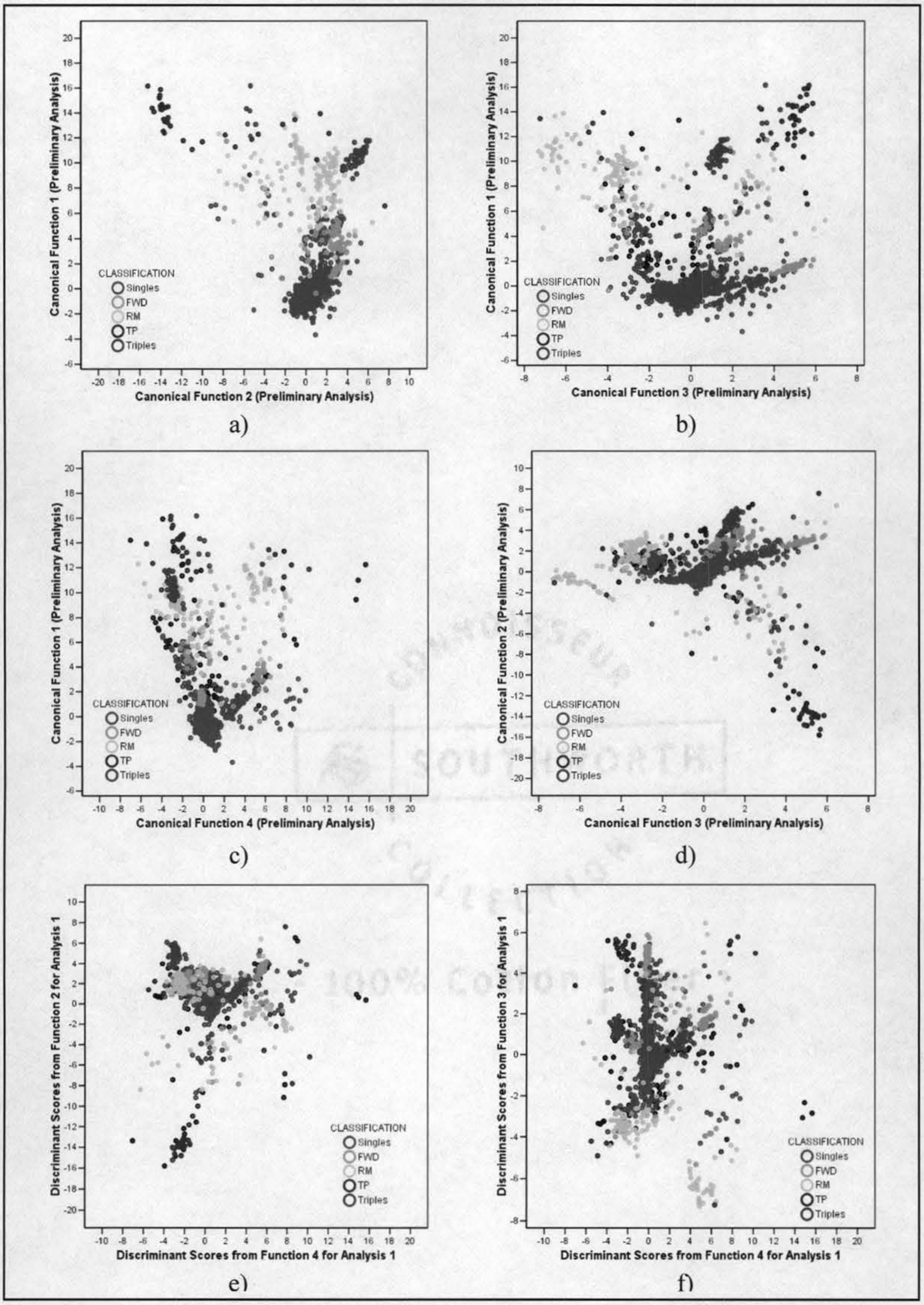

Figure 9: Discriminant Scores for Preliminary Analysis

Table 13 shows the percent of data correctly classified by the discriminant functions developed for the preliminary analysis using variables obtained directly from WIM data. This table shows a comparison between the algorithm and the discriminant function, the values show the percentage of trucks that were classified by the discriminant function into the correct class. FWD represents freeway doubles, RM represents Rocky Mountain doubles, and TP represents turnpike doubles. The table shows a fairly robust classification for singles and triples with 95.83 and 89.92 percent being classified correctly, respectively. The percentage is lower for doubles with turnpike doubles being the least correctly classified vehicles. Although Table 13 shows that the discriminant function

Table 13: Percent of Data Correctly Classified (Directly Obtained Variables Analysis)

	Discriminant Function Classification Results					
Vehicle Class (true classifications from algorithm)	**Single**	**FWD**	**RM**	**TP**	**Triple**	**Total**
Single	**96.6**	2.7	0.6	0.1	0.0	100.0
FWD	3.9	**83.1**	8.5	4.2	0.4	100.0
RM	1.1	8.1	**80.5**	8.9	1.3	100.0
TP	0.0	4.4	12.6	**73.2**	9.9	100.0
Triple	0.0	0.0	0.0	10.4	**89.6**	100.0

3.3.5.2 Sequential Discriminant Analysis using Variables Obtained Directly from the WIM Data

In order to improve the results obtained in Table 13, the previous analysis was repeated by grouping vehicles based on number of axles. Once the classification was concluded by number-of-axle groups, the results were aggregated to obtain the final vehicle classification. Figure 11 illustrates the territorial map for the analysis of five axle vehicles as an example. Canonical Function 1 has good discriminating power between singles (1) and other vehicles, but not between rocky mountain doubles and freeway doubles. Canonical Function 2, on the other hand, discriminates more accurately between Rocky Mountain doubles and the other vehicles.

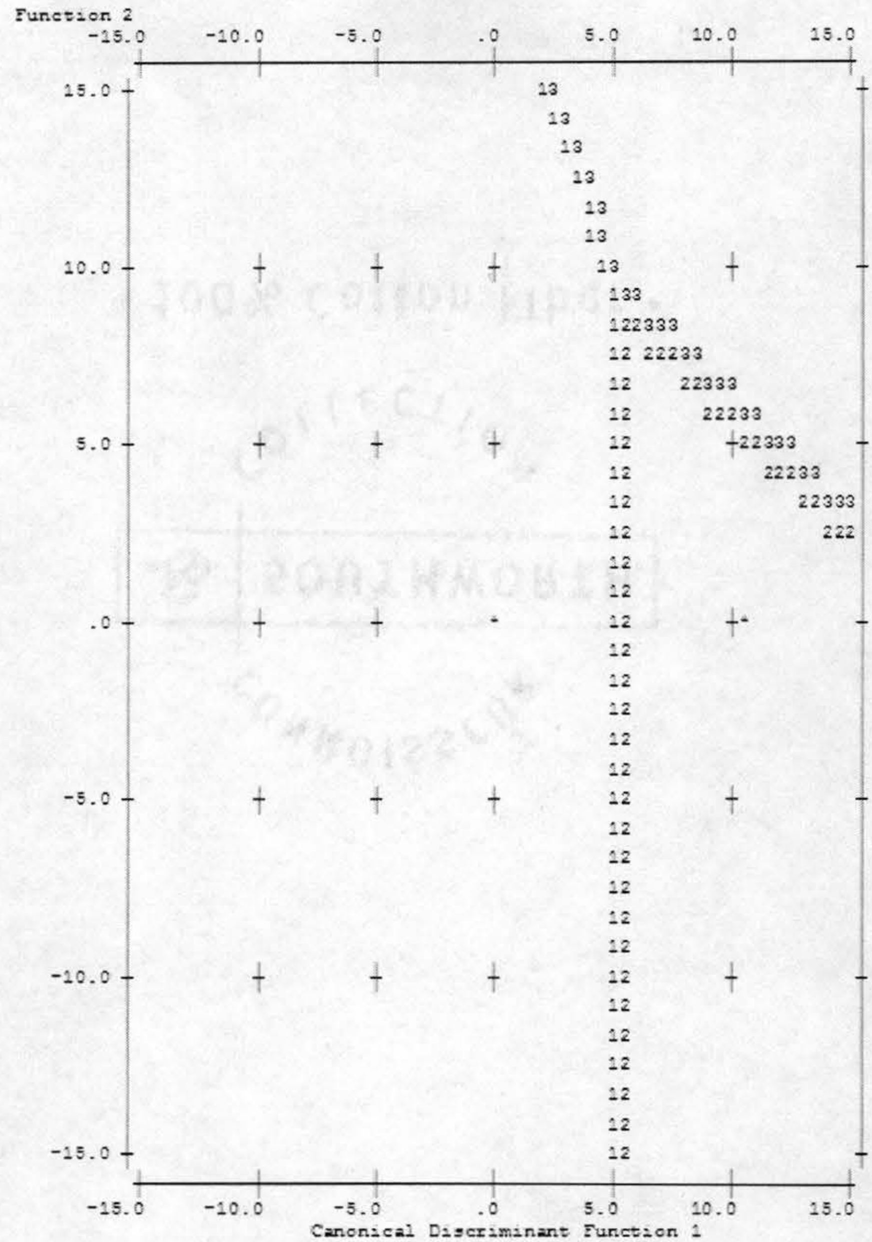

Figure 10: Territorial Map for Grouped Variable Preliminary Analysis (5 axles)

Table 14 shows the results obtained from the classification of vehicles by number-of-axle groups. A considerable improvement is observed for most vehicle classes. Triple combination vehicles, in particular, with the new sequential classification approach have 100 percent correct classifications. Singles have also experienced an improved classification potential with 97.77 percent being correctly classified. The classification for Rocky Mountain doubles has also increased by nearly 11 percent. Turnpikes are the exception with only a slight increase of 0.2 percent. The classification of turnpike doubles by the discriminant function appears to show no improvement, a possible cause for this is the fact that the sequential analysis groups vehicles with similar numbers of axles and therefore Rocky Mountain doubles and turnpike doubles would generally be grouped into one category (since these vehicles typically have similar characteristics and numbers of axles) causing the discriminant function to confuse these trucks more readily than other trucks.

Table 14: Percent of Data Correctly Classified
(Sequential - Directly Obtained Variables Analysis)

	Discriminant Function Classification Results					
Vehicle Class (true classifications from algorithm)	**Single**	**FWD**	**RM**	**TP**	**Triple**	**Total**
Single	**97.8**	2.0	0.2	0.0	0.0	100.0
FWD	4.3	**91.2**	3.3	0.4	0.7	100.0
RM	1.1	5.6	**91.2**	1.5	0.6	100.0
TP	0.0	5.2	16.8	**73.4**	4.6	100.0
Triple	0.0	0.0	0.0	0.0	**100.0**	100.0

3.3.5.3 Discriminant Analysis using Variables Generated from WIM Data

To further improve the classification potential using a discriminant analysis, major spacings were included as additional variables for discriminant function development. These variables were generated because of their high classification potential, considering that most types of vehicles can be preliminarily identified with accuracy based on the number of major axle spacings (as is described in the WIM data classification algorithm development section).

Table 15 shows the classification function coefficients. Similar to the previous analysis, the generated variables analysis shows greater coefficient values for the axle spacings than for the axle weight variables. A substantial difference is observed in the coefficients for the generated variables shown in italics, some of these variables have much higher coefficients than the axle spacing variables that originate from the WIM data. In this analysis the total length variable, axel L weight, and major spacing 7, failed the tolerance test and, accordingly were eliminated from the analysis.

The effectiveness of the discriminant functions again can be measured by observing the territorial map for the canonical functions. Figure 11 shows the territorial map for Canonical Functions 1 and 2 for the generated variables discriminant analysis. The territorial map shows that Canonical Function 1 has the greatest power separating triples from other vehicles. It should be noted that in general these two canonical functions do not provide very good discriminatory power for all other vehicles since the territorial centroids are together. Most of the discriminatory power comes from the other canonical functions not graphed here, as shown by the discriminant scores in Figure 12.

Table 15: Classification Coefficients (Generated Variables Analysis)

Variable	Single	FWD	RM	TP	Triple
ABdist_feet	24.80	7.73	7.52	-4.45	60.16
BCdist_feet	0.88	2.72	0.73	1.67	3.90
CDdist_feet	-2.02	-0.49	-1.95	-0.92	0.00
DEdist_feet	-3.23	-2.19	-3.40	-2.58	0.72
EFdist_feet	-1.78	-0.89	-0.94	-1.92	1.86
FGdist_feet	-2.86	-3.65	0.22	0.08	5.18
GHdist_feet	-3.39	-4.70	-1.80	4.82	-6.75
HIdist_feet	-17.11	-4.52	-3.12	7.90	-35.02
IJdist_feet	-16.59	-5.21	-4.56	-11.21	-44.55
JKdist_feet	-47.88	-26.26	-40.89	-19.30	-111.07
KLdist_feet	129.67	114.13	124.27	-12.64	400.89
axlAweight	0.16	0.16	0.15	0.17	0.16
axlBweight	0.02	0.02	0.01	0.04	1.63
axlCweight	0.26	0.34	0.33	0.30	-1.69
axlDweight	0.06	0.00	0.01	-0.01	0.68
axlEweight	-0.21	-0.21	-0.20	-0.18	-0.65
axlFweight	-0.57	-0.60	-0.55	-0.26	-1.37
axlGweight	-0.39	-0.35	-0.59	-0.69	-1.48
axlHweight	-0.72	-0.53	-0.92	-1.35	-1.00
axlIweight	-0.05	-0.08	-0.15	-0.07	0.56
axlJweight	0.41	0.17	0.45	0.33	0.68
axlKweight	1.91	1.81	2.71	4.88	5.06
MAJ1	-24.21	-7.64	-7.29	4.24	-62.41
MAJ2	2.04	0.30	2.32	1.39	-0.61
MAJ3	-14.14	-12.99	-12.52	-10.14	-46.17
MAJ4	-10.90	2.04	0.77	8.65	-33.47
MAJ5	-6.12	-13.04	-3.29	18.41	1645.79
MAJ6	24.01	15.62	9.88	-12.35	3208.80
MJR_LNGTHS	189.90	183.00	184.00	150.60	549.67
Axles	55.24	55.53	50.34	45.35	82.68

Table 16 illustrates the results obtained from the analysis with the inclusion of the additional major spacing variables. The classification results for singles have increased a small amount to nearly 100 percent correct classification as shown in Table 16. In general the classification results for all trucks are better for the generated variable analysis than for the original directly obtained variable analysis. Again the classification of turnpike doubles is still low with 22% of these trucks being incorrectly classified as Rocky Mountain doubles. The generated variables represent major spacings and both Rocky Mountain doubles and turnpike doubles typically have the same number of major spacings which may explain the incorrect classification of turnpike doubles.

Table 16: Percent of Data Correctly Classified (Generated Variables Analysis)

	Discriminant Function Classification Results					
Vehicle Class (true classification from algorithm)	**Single**	**FWD**	**RM**	**TP**	**Triple**	**Total**
Single	**99.9**	0.1	0.0	0.0	0.0	100.0
FWD	0.1	**85.2**	11.9	2.8	0.0	100.0
RM	0.0	7.1	**90.2**	2.6	0.0	100.0
TP	0.0	4.2	22.0	**73.8**	0.0	100.0
Triple	0.0	0.0	0.0	0.0	**100.0**	100.0

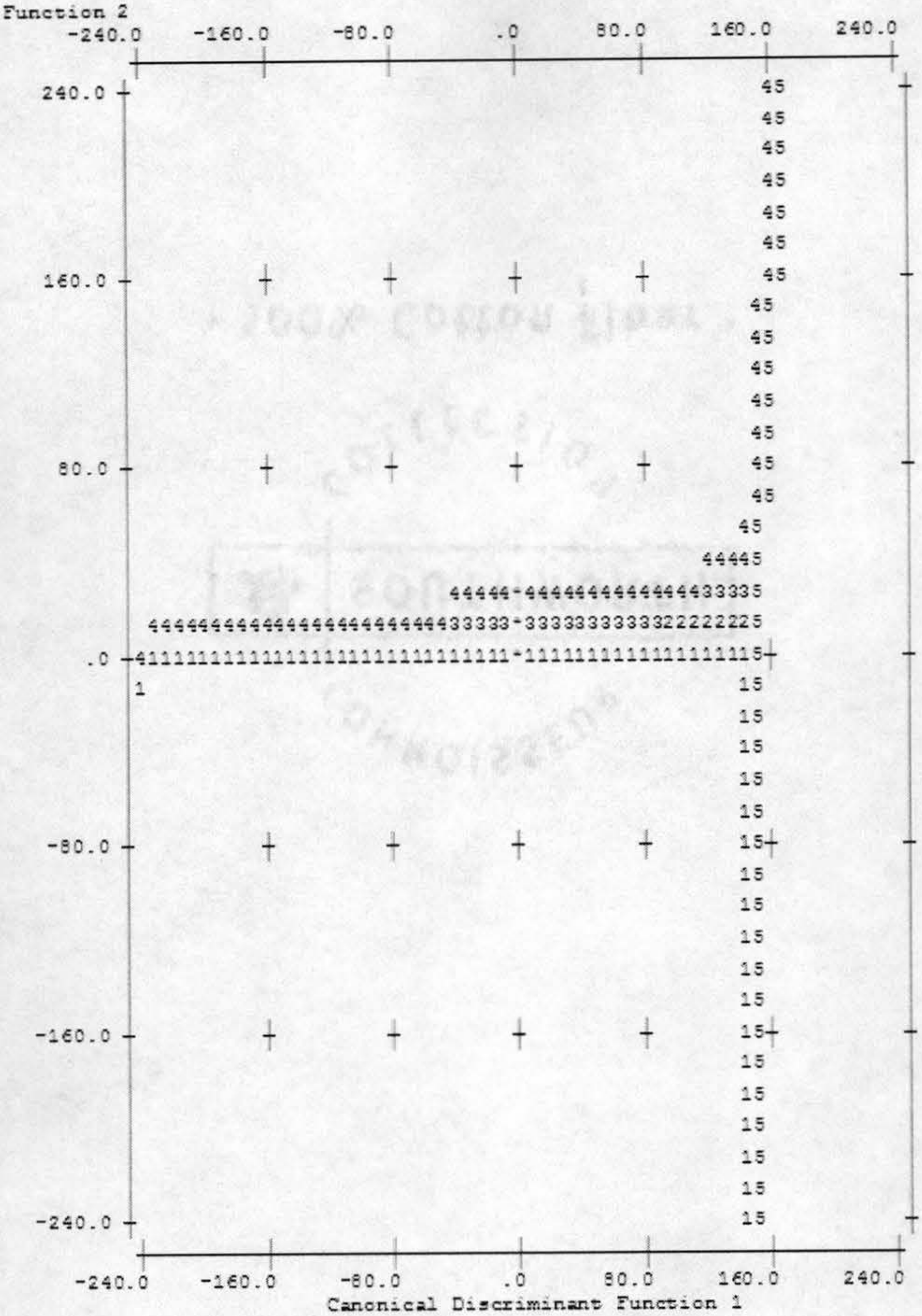

Figure 11: Territorial Map for Generated Variable Analysis

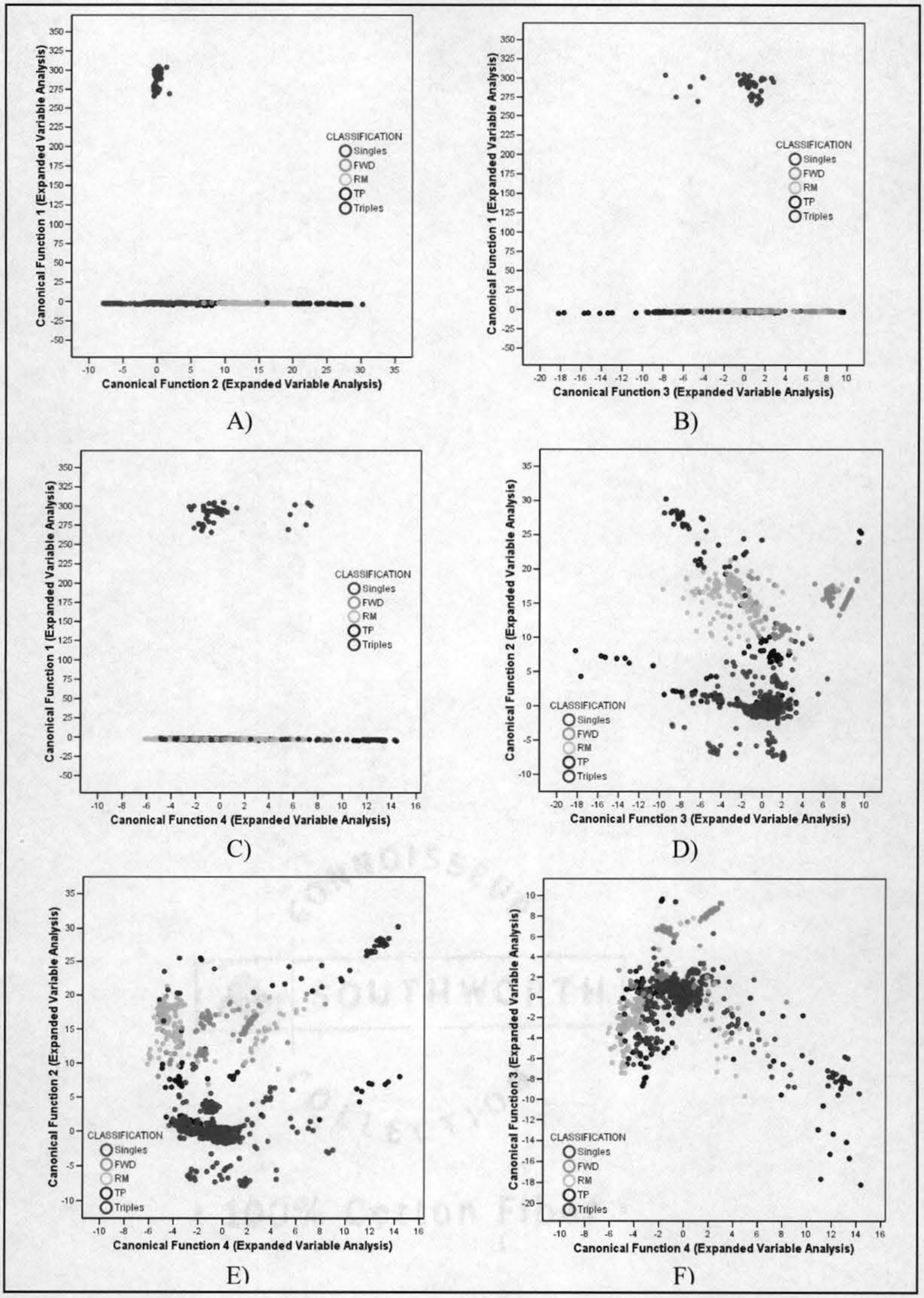

Figure 12: Discriminant Scores for Generated Variables Analysis

3.3.5.4 Sequential Discriminant Analysis Using Variables Generated from WIM Data

Similar to the analysis conducted for the sequential analysis with variables obtained directly from the WIM data, the sequential generated variable analysis consisted of the development of individual discriminant functions for vehicles with 3, 4, 5, 6, 7 and 8 or more axles. Once the classification was completed for each axle group, the classification results for all axle groups were aggregated and compared to the results of the WIM data classification algorithm.

Figure 13 shows the territorial map for this analysis for the five axle group as an example. This map shows that canonical function 1 distinguishes singles from the other types of vehicles. Canonical Function 2 is not as powerful of a discriminant as Canonical Function 1 because most centroids are grouped together in the Y direction.

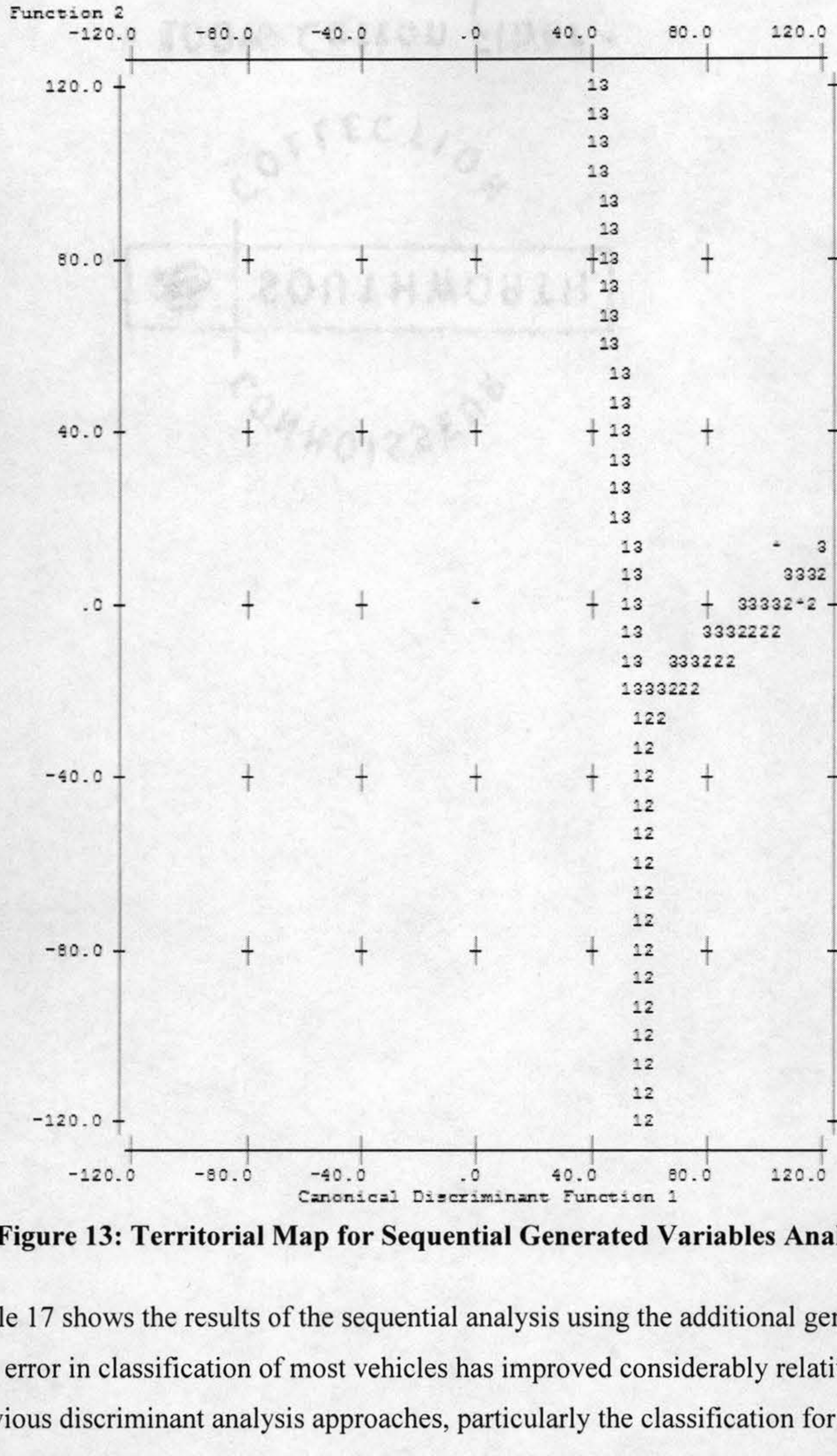

Figure 13: Territorial Map for Sequential Generated Variables Analysis (5 axles)

Table 17 shows the results of the sequential analysis using the additional generated variables. The error in classification of most vehicles has improved considerably relative to the previous discriminant analysis approaches, particularly the classification for all doubles. This analysis is comparable to the sequential analysis using only variables obtained directly from the WIM data (Table 14) and shows a significant 9 percent improvement for turnpike doubles, and about a 5 percent improvement for Rocky Mountain and freeway doubles. Turnpike doubles remain the least correctly classified vehicles due to the overlapping characteristics that exist between these vehicles and other double trailer classes.

Table 17: Percent of Data Correctly Classified (Sequential - Generated Variable Analysis)

	Discriminant Function Classification Results					
Vehicle Class (true classification from algorithm)	**Single**	**FWD**	**RM**	**TP**	**Triple**	**Total**
Single	**99.9**	0.0	0.0	0.0	0.0	100.0
FWD	0.0	**96.6**	3.4	0.1	0.0	100.0
RM	0.0	4.0	**95.4**	0.6	0.0	100.0
TP	0.0	6.5	11.3	**82.2**	0.0	100.0
Triple	0.0	0.0	0.0	0.0	**100.0**	100.0

3.4 Chapter Conclusions

The use of a sequential analysis in which the number of axles is homogeneous for all vehicles in each analysis group can provide a significantly greater classification accuracy of nearly 10 percent as shown by a comparison between Table 14 and 14. This improvement in accuracy is due to the elimination of "blanks" in the data set inherent when vehicles with different numbers of axles are mixed. As explained earlier, if a four-axle vehicle is mixed with a three-axle vehicle, the fourth axle entry for the three-axle vehicle will be blank or zero; the classification function may interpret the zero as an actual value and incorrectly skew the discriminant classification function. The results presented in this chapter provide a discriminant classification method that identifies LCVs in particular based on the results of the algorithm presented in the previous chapter.

4. SEASONAL FACTOR DEVELOPMENT

In this thesis, seasonal factors and monthly factors were developed for Montana, using truck classification results obtained from the classification algorithm for 2002 and 2003. The objective of this analysis was to conduct a preliminary analysis into LCV truck behavior and to provide an example of the application of algorithm outputs. The development of seasonal factors for LCV trucks has not been done previously; the seasonal factors presented in this thesis have the purpose of providing an indication of the LCV truck volume variations across LCV truck types as well as LCV truck volume variation differences between interstate and non-interstate highways. Given these seasonal factors short term counts can be extrapolated through the application of the seasonal factors to estimate annual average daily traffic. This information in turn can be used for vehicle miles traveled estimations for their application in crash data analysis, traffic estimates, and commercial activity estimates among others. Seasonal factors may also be used to estimate traffic during seasons when counts are difficult to obtain due to weather conditions. Counts can be carried during summer months, and winter traffic volumes may be estimated through the application of winter seasonal factors.

Benekohal, et al. (2000) reported that the 19 states included in their study used seasonal adjustment factors to adjust monthly data to yearly data. The adjustment factors were derived from continuous truck count stations. Their study defines groups for which different adjustment factors such as road class, day of the week, and geographic areas, are calculated. Iowa, for example, divides its roadways into eight different road classes and develops adjustment factors for each one. These factors are then applied to short term counts taken on highways with the corresponding road class. The authors reported that most truck data are factored using continuous general traffic counts as opposed to truck counts. Additionally, their study suggests the need for the determination of optimal truck sample size and a procedure to factor truck data.

French, et al. (2002) developed a set of factors for traffic and truck variation. These factors include: 1) an axle correction factor for tube counters, 2) a factor to determine design hourly volume from peak hourly volume, 3) a factor to determine truck percentage in average daily traffic from truck percentage in peak hour traffic, and 4) a factor to determine truck percentage in average daily traffic from manual classifications taken at different hours throughout the day. The study used raw traffic data for 1995 and 1996 from permanent count stations for factor development. For the first factor (axle correction factor for tube counters), raw permanent count station data for every day of the year was initially cleared of errors manually and compared to tube counts on the same roadway. The axle correction factor was determined using the following formula:

$$Factor = \frac{actual\_veh\_count}{tube\_veh\_count}, \tag{8}$$

The denominator in Eq. (8) is the number of axles counted by the tube counter divided by two. The axle correction factors for tube counters were aggregated by day of the week, month, and quarter. An analysis of variance was then used to determine roadway functional class groups for the factors calculated. The research team determined that when factors were developed for each day of the week, regardless of the month, the differences among factors for each roadway class were statistically significant. There were no statistically significant differences in roadway class factors for any time grouping analyzed when Fridays, Saturdays, and Sundays were eliminated from the analysis. The study concluded by reevaluating the original roadway functional class groupings and arriving at final groups each of which were assigned with a calculated tube counter correction factor, French, et al. (2002).

The seasonal factors were developed based on a multiplicative seasonal decomposition analysis. A statistical analysis was conducted to determine significant variations in seasonal truck traffic variations between the five classified truck types (singles, freeway doubles, Rocky Mountain doubles, turnpike doubles, and triples). Additionally statistical analyses were conducted to determine seasonal variation differences for vehicles operating on interstate versus non-interstate highways; this analysis was also divided by truck type. A similar analysis was conducted for the monthly factors; a comparison was made between seasonal variations across the state by month for each truck type.

The seasonal variation analysis consisted of the development of factors for each of 4 seasons as shown in Table 18.

Table 18: Seasonal Factor Groups

Season	Months of Data
1	December – February
2	March – May
3	July – August
4	September – November

4.1 Montana

Table 19 illustrates the seasonal factors obtained for Montana classified by the 4 seasons and 5 vehicle classes used for this analysis. A t-test was conducted between the seasonal factors to determine differences in seasonal factor trends by truck type and road type. Table 20 shows the comparison between seasonal variations across the state by truck type, and Table 21 shows the comparison of seasonal variations between interstate and non-interstate highways, also by truck type.

4.1.1 Seasonal Factor Variation Comparison by Vehicle Class

The comparison between seasonal factor variations by truck type yields little or no variation between all truck types except triples. This would indicate that seasonal patterns can be expected to be independent of the truck type. Triples however do show a statistically significant variation in seasonal factor for all four seasons when compared to singles and freeway doubles. The statistically significant difference is also observed for three seasons when compared to Rocky Mountain doubles and turnpike doubles. Table 20 illustrates these results by presenting the t-test values, the significant results, at the 2.5 percent significance level, are highlighted.

4.1.2 Seasonal Factor Variation Comparison by Road Type

The road type comparison also yielded no significant variations in truck traffic behavior when comparing interstate to non-interstate routes. This may be attributed to the fact that most non-interstate routes on which data were collected for this project are principal arterials classified into the same functional class as interstate highways. For this reason little variation would be expected since truck traffic on principal arterials in general may be similar. Table 21 shows the results of the t-test comparing interstate to non-interstate seasonal factor averages for each season. The only significant value (at the 2.5 percent significance level) was found to be for singles during season four (winter). There was insufficient data to conduct a comparative analysis for triples.

Table 19: Montana Seasonal Factors by Station and Vehicle Class

Station	Road Type	Single Unit				FWD				RM				TP				Triple			
		Season				Season				Season				Season				Season			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
104	int.	0.85	0.98	1.09	1.08	1.04	1.02	0.98	0.95	0.84	1.01	1.13	1.02	0.93	1.07	1.03	0.97	0.32	0.85	1.63	1.20
102	non int.	0.95	0.90	1.04	1.12	1.06	1.24	0.89	0.81	1.01	1.03	0.98	0.99								
105	non int.	0.89	1.02	1.00	1.10	0.81	1.00	1.13	1.05	0.94	1.00	1.11	0.96	0.87	1.06	1.21	0.85				
111	non int.	1.06	0.85	0.89	1.21	1.02	0.93	1.23	0.82	1.06	0.73	1.64	0.57								
112	int.	0.78	0.88	1.26	1.08	0.83	0.90	1.12	1.15	0.63	0.82	1.30	1.25	0.47	0.79	1.57	1.17				
113	non int.	0.89	1.01	0.96	1.14	0.87	0.98	1.06	1.10	0.96	1.00	1.03	1.02								
114	non int.	0.88	0.98	1.06	1.08	0.89	1.04	1.11	0.95	0.87	0.91	1.16	1.05								
116	non int.	0.79	0.98	1.07	1.16	0.47	0.96	1.43	1.14	0.73	1.01	1.16	1.10	0.79	0.90	1.40	0.91				
118	non int.	0.74	1.02	1.14	1.11	0.86	0.87	1.22	1.06	0.87	0.93	1.13	1.08	1.12	0.82	1.00	1.05				
119		0.84	1.01	1.09	1.06	1.22	1.02	0.78	0.98	1.37	0.84	0.66	1.13	0.92	0.92	0.98	1.17	0.41	0.88	1.42	1.29
120	int.	0.84	0.99	1.08	1.08	1.17	1.00	0.89	0.94	0.86	0.97	1.08	1.09	0.88	0.94	1.07	1.11	0.26	0.72	1.71	1.32
121	int.	0.86	1.05	1.06	1.03	1.03	1.17	0.89	0.90	0.92	1.06	1.05	0.96	0.78	1.41	0.86	0.96	0.24	1.01	1.59	1.17
122	int.	0.92	1.08	1.03	0.97	1.24	1.11	0.72	0.93	0.92	1.07	1.02	0.99	1.00	0.98	1.12	0.90	0.40	0.95	1.39	1.26
124	int.	0.83	0.99	1.11	1.07	1.06	1.06	0.96	0.92	0.95	1.01	1.09	0.95	1.00	1.05	0.98	0.97	0.20	0.81	1.74	1.26
125	int.	0.94	1.06	1.04	0.97	1.02	0.96	0.93	1.09	0.70	1.01	1.14	1.14	0.45	0.96	1.51	1.08				
127	non int.	0.97	0.84	1.05	1.15																
202	int.	0.92	1.12	1.05	0.91	1.39	1.05	0.70	0.86	0.99	1.02	0.92	1.07	1.00	1.00	0.98	1.02	0.45	0.95	1.45	1.15
203	int.	0.88	0.98	1.09	1.05	1.10	1.00	0.96	0.94	1.07	0.88	1.04	1.01	0.87	0.94	1.06	1.13	0.31	0.83	1.62	1.25

Table 20: Statistical Significance of Seasonal Factor Comparison by Vehicle Class in Montana (P values)

	T-Test Analysis Values			
	Season 1	Season 2	Season 3	Season 4
Singles and Freeway Doubles	0.023	0.261	0.217	0.002
Singles and Rocky Mountain Doubles	0.322	0.360	0.484	0.161
Singles and Turnpike Doubles	0.597	0.959	0.195	0.104
Singles and Triples	0.000	0.004	0.000	0.000
Freeway Doubles and Rocky Mountain Doubles	0.217	0.072	0.155	0.283
Freeway Doubles and Turnpike Doubles	0.052	0.502	0.084	0.243
Freeway Doubles and Triples	0.000	0.001	0.000	0.000
Rocky Mountain Doubles and Turnpike Doubles	0.297	0.527	0.606	0.999
Rocky Mountain Doubles and Triples	0.000	0.048	0.000	0.000
Turnpike Doubles and Triples	0.000	0.076	0.000	0.000

Table 21: Seasonal Factor Comparison by Road Type, Interstate to Non-Interstate for Montana (P values)

	T-Test Analysis Values			
	Season 1	Season 2	Season 3	Season 4
Singles	0.484	0.090	0.090	0.001
Freeway Doubles	0.048	0.594	0.027	0.651
Rocky Mountain Doubles	0.224	0.266	0.814	0.350
Turnpike Doubles	0.399	0.345	0.909	0.557
Triples	---	---	---	---

4.1.3 Monthly Factor Comparison by Vehicle Class

Table 22 thru Table 26 present the monthly factors for each of the five vehicle classes. These factors were developed using 2003 WIM data; the stations analyzed for each vehicle type were selected based on data availability.

Table 27 presents the comparison of seasonal factor variations among the 5 vehicle classes. Similar to the seasonal analysis, little monthly variation exists among all trucks except triples. Triples show a significant difference in monthly factor from all other vehicles for most months of the year. The exceptions are for April and May during which no difference was found in monthly factors between triples and any other truck class. Additionally, during July and August seasonal factors do not show significant variation between triples and Rocky Mountain doubles; and during June, September, and November there is no significant difference in monthly factors between triples and turnpike doubles.

Table 22: Monthly Factors for Singles

Station	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
104	0.86	0.81	0.96	1.00	1.04	1.07	1.10	1.15	1.09	1.11	0.95	0.88
105	0.92	0.85	0.89	1.03	1.11	0.97	1.03	1.12	1.14	1.22	0.86	0.87
106	0.70	0.69	0.83	0.92	1.04	1.28	1.36	1.29	0.94	1.37	0.88	0.70
110	0.94	0.82	0.93	1.05	1.13	0.95	1.07	0.95	0.98	1.30	1.02	0.87
112	0.81	0.71	0.76	0.83	0.85	1.32	1.52	1.59	1.03	1.15	0.72	0.72
113	0.96	0.87	0.98	1.09	1.15	0.97	0.75	0.83	1.04	1.37	1.09	0.90
114	0.95	0.82	0.95	1.00	1.04	0.99	1.06	1.05	1.04	1.24	0.98	0.88
115	0.88	0.91	0.48	1.16	1.17	1.23	1.18	1.32	1.25	1.33	0.10	0.99
116	0.88	0.70	0.90	1.10	0.80	1.03	1.13	1.18	1.06	1.32	0.94	0.96
118	0.91	0.77	0.88	1.23	0.89	1.22	1.28	1.27	1.24	1.23	0.88	0.20
119	0.86	0.81	0.98	1.00	1.07	1.13	1.09	1.11	1.08	1.09	0.94	0.85
120	0.94	0.91	1.08	1.10	0.70	0.74	0.96	1.19	1.20	1.26	0.95	0.95
124	0.86	0.82	1.00	1.03	1.07	1.11	1.12	1.19	1.12	1.13	0.69	0.86
202	0.95	0.97	1.07	1.22	0.79	1.03	1.13	1.02	0.99	1.07	0.99	0.77
203	0.89	0.83	0.98	0.97	1.03	1.08	1.06	1.13	1.07	1.10	0.97	0.90

Table 25: Monthly Factors for Turnpike Doubles

Station	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
104	0.99	1.26	1.31	1.25	1.07	1.17	0.89	0.93	1.01	1.26	0.47	0.38
113	0.85	1.19	1.47	0.96	1.53	1.58	0.68	0.45	1.02	0.62	1.19	0.45
119	0.66	0.86	1.41	0.97	1.03	1.03	0.41	1.45	1.83	1.28	0.31	0.76
124	0.82	0.81	0.81	1.40	1.21	1.40	0.90	1.00	1.04	1.02	0.71	0.89

Table 26: Monthly Factors for Triples

Station	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
103	0.75	0.62	0.78	0.92	0.60	0.98	0.99	1.12	1.83	1.82	0.87	0.72
104	0.28	0.20	0.40	0.75	1.33	1.59	1.75	1.68	1.79	1.68	0.34	0.20
112	0.10	0.10	0.36	0.83	0.93	2.04	2.19	2.32	1.44	1.42	0.21	0.05
119	0.32	0.15	0.40	0.76	1.40	1.72	1.04	1.49	2.13	2.02	0.42	0.14
120	0.27	0.16	0.42	0.67	0.52	1.13	1.64	1.95	2.37	2.30	0.46	0.11
121	0.22	0.21	0.60	1.23	0.97	1.57	2.33	1.13	1.24	2.24	0.21	0.06
122	0.38	0.40	0.75	1.21	0.96	1.69	1.17	1.42	1.68	1.59	0.49	0.27
124	0.19	0.08	0.28	0.76	1.29	1.75	1.85	1.88	1.94	1.83	0.12	0.03
125	0.18	0.08	0.45	1.34	1.40	1.95	1.85	1.78	1.15	1.42	0.30	0.10
202	0.34	0.42	0.66	1.19	0.95	1.40	1.55	1.58	1.60	1.56	0.52	0.24
203	0.34	0.21	0.45	0.76	1.22	1.53	1.58	1.61	1.86	1.71	0.53	0.21

Table 27: Statistical Significance of Monthly Factor Comparison by Vehicle Class in Montana (P values)

	T-Test Analysis Values											
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Singles and Freeway Doubles	0.099	0.170	0.911	0.041	0.529	0.071	0.988	0.735	0.269	0.639	0.825	0.636
Singles and Rocky Mountain Doubles	0.076	0.405	0.044	0.624	0.630	0.988	0.434	0.358	0.526	0.654	0.967	0.342
Singles and Turnpike Doubles	0.239	0.006	0.004	0.215	0.030	0.034	0.001	0.144	0.204	0.070	0.215	0.094
Singles and Triples	0.000	0.000	0.000	0.163	0.513	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Freeway Doubles and Rocky Mountain Doubles	0.788	0.883	0.117	0.051	0.433	0.027	0.338	0.536	0.843	0.506	0.702	0.964
Freeway Doubles and Turnpike Doubles	0.958	0.041	0.090	0.566	0.407	0.025	0.032	0.384	0.928	0.199	0.345	0.339
Freeway Doubles and Triples	0.000	0.000	0.001	0.035	0.990	0.000	0.010	0.003	0.008	0.000	0.000	0.000
Rocky Mountain Doubles and Turnpike Doubles	0.812	0.014	0.004	0.201	0.135	0.720	0.053	0.329	0.782	0.273	0.346	0.246
Rocky Mountain Doubles and Triples	0.000	0.000	0.019	0.989	0.392	0.022	0.176	0.065	0.002	0.004	0.000	0.000
Turnpike Doubles and Triples	0.000	0.000	0.000	0.179	0.366	0.133	0.002	0.008	0.038	0.001	0.104	0.004

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 WIM Classification Algorithm

The detailed classification of LCVs can be achieved through analytical methods that use truck characteristics currently available from WIM station data.

The error associated with the classification of LCVs can be considerably reduced for single unit trucks and triple trailer trucks. A nearly 100 percent correct classification can be achieved for these two types of vehicles. Much of the classification potential for these vehicles stems from the major axle spacing criteria (as supported by the discriminant function coefficients), since single unit trucks almost without exception tend to have 2 major axle spacings and triples 6 major axle spacings as shown in Figure 14.

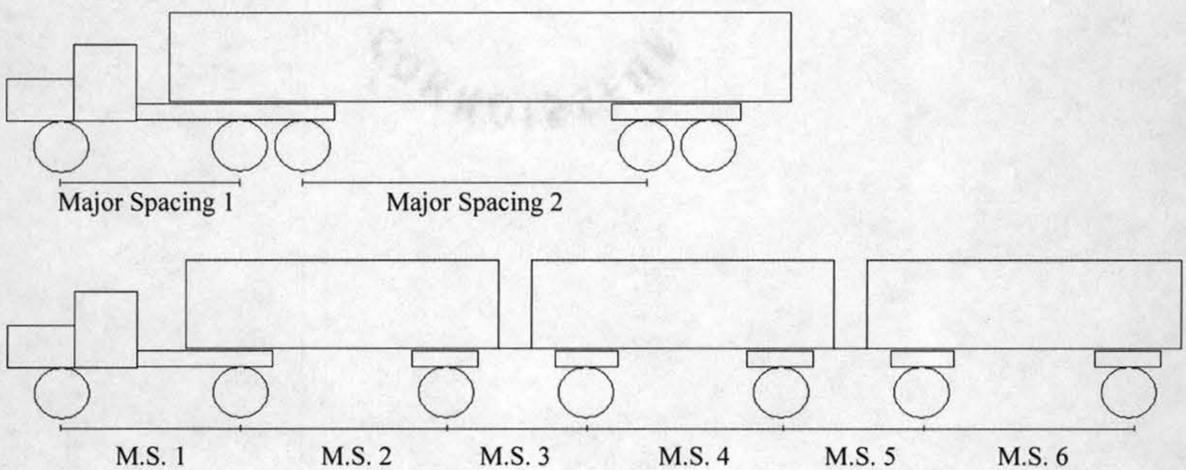

Figure 14: Major Spacings of Singles and Triples

The distinction between the 3 types of double trailer trucks (freeway doubles, rocky mountain doubles, and turnpike doubles) is much more complex since these vehicles tend to have overlapping characteristics and the definition of each of these vehicles is not standardized across all states. The classifications for these vehicles using the WIM classification algorithm presented in this thesis may produce classifications between 80 and 90 percent correct, although improvements to the algorithm may considerably improve this correct classification percentage.

Improvements to the LCV truck classification can be made through field recollection of a larger sample of trucks. Variety is almost as important as quantity since a very large number of non-standard vehicle configurations exist on the roads and may skew results if their configurations are not identified by the algorithm. Double trailers are the most difficult to distinguish for the reasons previously mentioned, the classification of these vehicles could be further improved by identifying more details in the truck axle spacings and axle weights that could help improve accuracy.

One example of an additional classification parameter for future consideration in the classification of doubles is whether the second and third axles are tandem or not. Typically Rocky Mountain doubles and turnpike doubles tend to have the second and third axles in tandem, freeways generally do not (Figure 15). The analyst could determine the percentage of vehicles that follow this assumption and use this information to further improve the classification potential of the algorithm and discriminant function.

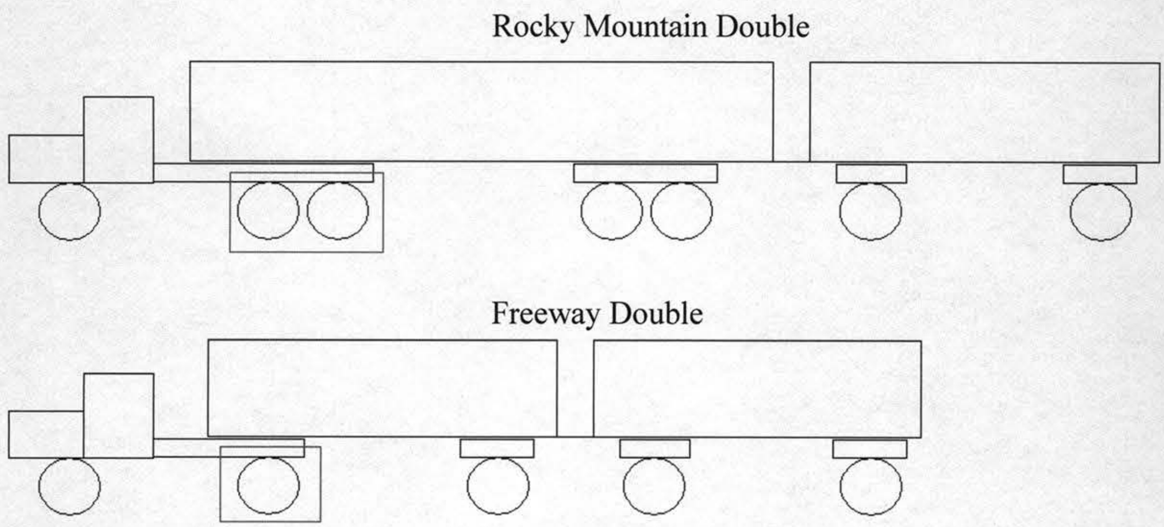

Figure 15: Characteristics of Second and Third Axles

Additionally, state specific algorithms could be developed to take into account the definition of LCVs in each state. Prior probabilities can also be used as the classification of LCV doubles improves and truck patterns are identified by LCV truck class. Slight variations exist in the classification criteria used in each state; these variations may cause classification errors when the analysis is conducted without considering the state from which the data were obtained.

5.2 Discriminant Analysis

The classification can also be accomplished, supported and tested through the application of a discriminant analysis that is based on variables available from WIM stations, and variables easily generated from raw WIM station data, namely, major spacings.

Major spacings provide a robust classification variable for a discriminant analysis; this is supported by the large coefficients observed for major spacing variables in the discriminant analysis results. The major spacing variables were found to be even more robust than simple axle length variables. This is due in part to the large variation that exists in the axle configurations of trucks.

Figure 16 attempts to illustrate the advantage of using major axle spacings (M.S. in the figure) for the classification of trucks using discriminant analysis. Given two trucks belonging to the same truck class, as shown in Figure 16, the axle configurations are different for the truck tractor. This makes axle spacing BC from truck 1 not comparable to axle spacing BC of truck 2, the significant difference in length will weaken axle spacing BC as a classification variable. Major spacings on the other hand remain constant regardless of the number of axles. Figure 16 also illustrates that major spacing 1 and major spacing 2 for both trucks are fairly comparable regardless of the fact that truck 1 has a tandem axle in the truck tractor. This makes major spacings a more robust classification parameter than simple axle spacings; an additional advantage is that major spacings are easily obtainable from raw WIM data as was presented in the algorithm development section of this thesis.

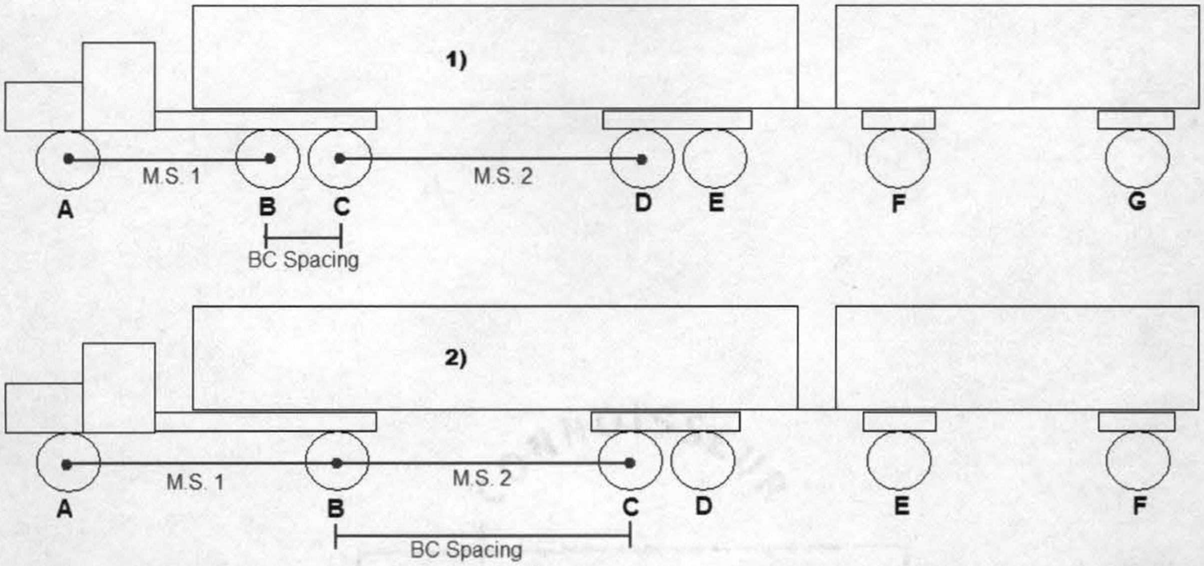

Figure 16: Advantage of "Major Axle Spacings" Criterion for Truck Classification

A future recommendation for the discriminant analysis would be to develop a quadratic discriminant function and analyze whether or not this type of analysis provides better results given the variability in axle spacings across truck types. Qualitative variables could also be applied to the analysis if truck class specific characteristics are identified through more research and data collection such as the existence of a tandem axle in the truck tractor.

5.3 Seasonal Factors

The seasonal factor analysis for Montana illustrates the existence of little variation between factors across truck classes with the exception of triples. In general, the conclusion that truck volumes vary in parallel throughout the year can be made based on the results obtained in this thesis. Triples, however, do show a significantly different pattern with proportionately much lower volumes during winter months than other vehicles.

For future research, a more detailed seasonal factor analysis can be conducted by classifying more years of WIM data. It should be noted that WIM data is currently not stored or collected during all hours of every day of the year, for example Idaho WIM data requested two months after it was collected from Boise WIM station 03 was already deleted, and consequently the development of seasonal factors for the truck classes presented in this thesis requires diligent data collection efforts.

APPENDIX A: FHWA VEHICLE CLASSIFICATION

1. ***Motorcycles*** (Optional) -- All two or three-wheeled motorized vehicles. Typical vehicles in this category have saddle type seats and are steered by handlebars rather than steering wheels. This category includes motorcycles, motor scooters, mopeds, motor-powered bicycles, and three-wheel motorcycles. This vehicle type may be reported at the option of the State.
2. ***Passenger Cars*** -- All sedans, coupes, and station wagons manufactured primarily for the purpose of carrying passengers and including those passenger cars pulling recreational or other light trailers.
3. ***Other Two-Axle, Four-Tire Single Unit Vehicles*** -- All two-axle, four-tire, vehicles, other than passenger cars. Included in this classification are pickups, panels, vans, and other vehicles such as campers, motor homes, ambulances, hearses, carryalls, and minibuses. Other two-axle, four-tire single-unit vehicles pulling recreational or other light trailers are included in this classification. *Because automatic vehicle classifiers have difficulty distinguishing class 3 from class 2, these two classes may be combined into class 2.*
4. ***Buses*** -- All vehicles manufactured as traditional passenger-carrying buses with two axles and six tires or three or more axles. This category includes only traditional buses (including school buses) functioning as passenger-carrying vehicles. Modified buses should be considered to be a truck and should be appropriately classified.

NOTE: In reporting information on trucks the following criteria should be used:

a. Truck tractor units traveling without a trailer will be considered single-unit trucks.
b. A truck tractor unit pulling other such units in a "saddle mount" configuration will be considered one single-unit truck and will be defined only by the axles on the pulling unit.
c. Vehicles are defined by the number of axles in contact with the road. Therefore, "floating" axles are counted only when in the down position.
d. The term "trailer" includes both semi- and full trailers.

5. ***Two-Axle, Six-Tire, Single-Unit Trucks*** -- All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., with two axles and dual rear wheels.
6. ***Three-Axle Single-Unit Trucks*** -- All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., with three axles.
7. ***Four or More Axle Single-Unit Trucks*** -- All trucks on a single frame with four or more axles.
8. ***Four or Fewer Axle Single-Trailer Trucks*** -- All vehicles with four or fewer axles consisting of two units, one of which is a tractor or straight truck power unit.
9. ***Five-Axle Single-Trailer Trucks*** -- All five-axle vehicles consisting of two units, one of which is a tractor or straight truck power unit.
10. ***Six or More Axle Single-Trailer Trucks*** -- All vehicles with six or more axles consisting of two units, one of which is a tractor or straight truck power unit.
11. ***Five or fewer Axle Multi-Trailer Trucks*** -- All vehicles with five or fewer axles consisting of three or more units, one of which is a tractor or straight truck power unit.
12. ***Six-Axle Multi-Trailer Trucks*** -- All six-axle vehicles consisting of three or more units, one of which is a tractor or straight truck power unit.
13. ***Seven or More Axle Multi-Trailer Trucks*** -- All vehicles with seven or more axles consisting of three or more units, one of which is a tractor or straight truck power unit.

APPENDIX B: SAMPLE RAW WIM DATA

The data below characterizes raw WIM data in TMG format typically obtained from WIM stations. Each row is a vehicle entry and each column contains a series of vehicle-specific data. The meaning of each column of data is presented in an excerpt from the TMG guide in Appendix C.

```
W08000001710201010009101 362 5 52 34 79 13 78 96 87 12 67
W08000001710201010009106 336 5 46 34 71 13 71 96 74 12 73
W08000001710201010009109 362 5 65 49 65 13 75 93 81 12 76
W08000001710201010009101 371 5 68 51 73 13 75 94 83 12 73
W08000001710201010009100 314 5 40 37 69 13 71 90 64 13 70
W08000001710201010009098 336 5 53 34 68 13 73 96 81 12 61
W08000001710201010109098 259 5 35 39 59 13 63 96 53 12 50
W08000001710201010109103 247 5 26 34 54 13 63 90 44 12 59
W08000001710201010109103 360 5 51 33 78 13 77 83 82 12 72
W08000001710201010109111 360 5 46 36 80 13 79 89 75 12 80
W08000001710201010109105 356 5 55 34 71 13 75 95 75 12 78
W08000001710201010109103 353 5 46 34 75 13 85 89 77 12 71
W08000001710201010209105 344 5 51 34 70 13 75 96 76 12 73
W08000001710201010209109 364 5 52 39 77 13 79 95 69 12 86
W08000001710201010309105 315 5 44 33 63 13 69 95 71 12 68
W08000001710201010309103 331 5 51 37 68 13 71 97 66 12 75
W08000001710201010409103 318 5 42 34 67 13 68 95 78 12 63
W08000001710201010409111 358 5 62 49 73 13 72 94 80 12 71
W08000001710201010409101 362 5 63 52 71 13 75 94 79 12 74
W08000001710201010409111 327 5 54 35 64 13 66 97 80 12 62
W08000001710201010509113 327 5 55 34 65 13 67 96 69 12 70
W08000001710201010509105 345 5 53 34 71 13 73 95 73 12 75
W08000001710201010509113 301 5 35 37 65 13 67 90 69 12 65
W08000001710201010609105 334 5 47 34 70 13 71 96 83 12 63
W08000001710201010609116 346 5 56 34 72 13 72 97 74 12 73
W08000001710201010609108 302 5 41 34 59 13 64 97 72 12 66
W08000001710201010609105 290 5 42 36 68 13 70 88 50 12 60
W08000001710201010709108 311 5 42 34 67 13 74 89 68 12 59
W08000001710201010709100 313 5 50 33 72 13 71 94 65 12 56
W08000001710201010709106 357 5 54 38 78 13 74 94 80 12 72
W08000001710201010809113 349 5 39 37 75 13 74 98 75 12 85
W08000001710201010809111 331 5 39 36 73 13 76 89 70 12 73
W08000001710201010810108 336 6 54 52 62 13 63 97 44 14 50 15 62
W08000001710201010809108 341 5 54 52 67 13 73 94 79 12 67
W08000001710201010809105 361 5 60 48 78 13 79 93 75 12 68
W08000001710201010809106 314 5 50 34 64 13 65 84 71 13 64
W08000001710201010809111 348 5 53 34 73 13 75 95 75 12 72
W08000001710201010909105 316 5 45 34 68 13 68 95 76 12 59
W08000001710201010909113 327 5 42 37 68 13 74 90 72 13 69
W08000001710201010909105 348 5 48 34 73 13 83 96 82 12 62
W08000001710201010909106 350 5 47 33 77 13 80 89 64 12 82
W08000001710201010909109 353 5 49 38 73 13 75 81 81 12 75
```

APPENDIX C: TRAFFIC MONITORING GUIDE (TMG) WEIGHT FILE FORMAT DESCRIPTION

The following table presents description of each column for vehicle raw WIM data in TMG format. The column labeled "Field" represents the number of the entry, the column labeled "Columns" represents the initial and ending column number of a particular entry, column numbers are not included in the raw WIM data but are simply counted starting from the left. The column labeled "Length" represents the length of each entry, for example the year of data has a length of two because the raw data presents the year in two data columns such as "03" for year 2003. The final column presents a brief description of each entry.

Field	Columns	Length	Description
1	1	1	Record Type
2	2-3	2	FIPS State Code
3	4-9	6	Station ID
4	10	1	Direction of Travel Code
5	11	1	Lane of Travel
6	13-Dec	2	Year of Data
7	14-15	2	Month of Data
8	16-17	2	Day of Data
9	18-19	2	Hour of Data
10	20-21	2	Vehicle Class
11	22-24	3	Open
12	25-28	4	Total Weight of Vehicle
13	29-30	2	Number of Axles
14	31-33	3	A-axle Weight
15	34-36	3	A-B Axle Spacing
16	37-39	3	B-axle Weight
17	40-42	3	B-C Axle Spacing
18	43-45	3	C-axle Weight
19	46-48	3	C-D Axle Spacing
20	49-51	3	D-axle Weight
21	52-54	3	D-E Axle Spacing
22	55-57	3	E-axle Weight
23	58-60	3	E-F Axle Spacing
24	61-63	3	F-axle Weight
25	64-66	3	F-G Axle Spacing
26	67-69	3	G-axle Weight
27	70-72	3	G-H Axle Spacing

Field	Columns	Length	Description
28	73-75	3	H-axle Weight
29	76-78	3	H-I Axle Spacing
30	79-81	3	I-axle Weight
31	82-84	3	I-J Axle Spacing
32	85-87	3	J-axle Weight
33	88-90	3	J-K Axle Spacing
34	91-93	3	K-axle Weight
35	94-96	3	K-L Axle Spacing
36	97-99	3	L-axle Weight
37	100-102	3	L-M Axle Spacing
38	103-105	3	M-axle Weight

Source: Table 6-5-1, TMG (4)

Note: The number of axles determines the number of axle weight and spacing fields.

APPENDIX D: DISCRIMINANT ANALYSIS CORRELATION TABLES

Table D- 1: Correlation among Variables – Analysis Using Variables Directly Obtained from Discriminant Function

	ABdist_feet	BCdist_feet	CDdist_feet	DEdist_feet	EFdist_feet	FGdist_feet	GHdist_feet	HIdist_feet	IJdist_feet	JKdist_feet	KLdist_feet	Total Length
ABspacing	1.00	-0.02	0.56	0.12	-0.12	-0.19	-0.07	-0.03	-0.02	0.01	0.00	0.76
BCspacing	-0.02	1.00	-0.59	-0.08	-0.11	-0.01	-0.09	-0.05	-0.04	-0.03	0.00	-0.09
CDspacing	0.56	-0.59	1.00	-0.01	-0.12	-0.15	-0.04	-0.09	-0.09	-0.03	-0.01	0.67
DEspacing	0.12	-0.08	-0.01	1.00	0.01	0.09	-0.03	-0.05	-0.02	-0.04	0.00	0.36
EFspacing	-0.12	-0.11	-0.12	0.01	1.00	0.23	0.21	-0.14	-0.16	-0.09	-0.01	0.13
FGspacing	-0.19	-0.01	-0.15	0.09	0.23	1.00	-0.16	0.08	0.10	0.04	-0.01	0.12
GHspacing	-0.07	-0.09	-0.04	-0.03	0.21	-0.16	1.00	0.08	-0.01	-0.06	0.09	0.08
HIspacing	-0.03	-0.05	-0.09	-0.05	-0.14	0.08	0.08	1.00	0.81	0.35	0.00	0.04
IJspacing	-0.02	-0.04	-0.09	-0.02	-0.16	0.10	-0.01	0.81	1.00	0.48	0.05	0.03
JKspacing	0.01	-0.03	-0.03	-0.04	-0.09	0.04	-0.06	0.35	0.48	1.00	0.34	0.01
KLspacing	0.00	0.00	-0.01	0.00	-0.01	-0.01	0.09	0.00	0.05	0.34	1.00	0.01
Total Length	0.76	-0.09	0.67	0.36	0.13	0.12	0.08	0.04	0.03	0.01	0.01	1.00
Axles	-0.12	-0.44	0.10	0.27	0.41	0.46	0.33	0.47	0.41	0.21	0.03	0.28
axlAweight	0.09	-0.17	0.15	0.05	0.01	-0.01	-0.01	0.01	0.03	0.01	0.00	0.09
axlBweight	0.06	0.01	0.05	-0.02	-0.10	0.01	-0.06	0.00	0.00	-0.01	0.00	0.02
axlCweight	0.06	-0.21	0.16	0.14	-0.06	0.03	-0.03	0.01	0.02	0.00	0.01	0.09
axlDweight	0.03	-0.28	0.20	0.19	0.01	0.00	-0.01	-0.02	-0.01	-0.02	0.01	0.11
axlEweight	0.03	-0.42	0.29	0.21	0.02	0.01	0.00	-0.01	0.00	-0.02	0.01	0.14
axlFweight	-0.14	-0.07	-0.20	0.26	0.61	0.49	0.11	0.04	0.04	0.00	0.02	0.14
axlGweight	-0.17	-0.04	-0.21	0.22	0.33	0.65	0.18	0.17	0.14	0.05	0.03	0.13
axlHweight	-0.10	-0.08	-0.14	0.04	0.14	0.20	0.48	0.53	0.44	0.14	0.05	0.08
axlIweight	-0.04	-0.04	-0.07	-0.02	0.01	0.05	0.22	0.49	0.38	0.08	0.05	0.04
axlJweight	-0.02	-0.02	-0.07	-0.02	-0.10	0.07	0.00	0.61	0.61	0.21	0.07	0.02
axlKweight	0.01	-0.02	-0.03	-0.02	-0.07	0.04	-0.06	0.27	0.49	0.84	0.29	0.01

Table D- 1: Correlation among Variables – Analysis Using Variables Directly Obtained from Discriminant Function (Continued)

	Axles	axlAweight	axlBweight	axlCweight	axlDweight	axlEweight	axlFweight	axlGweight	axlHweight	axlIweight	axlJweight	axlKweight
ABspacing	-0.12	0.09	0.06	0.06	0.03	0.03	-0.14	-0.17	-0.10	-0.04	-0.02	0.01
BCspacing	-0.44	-0.17	0.01	-0.21	-0.28	-0.42	-0.07	-0.04	-0.08	-0.04	-0.02	-0.02
CDspacing	0.10	0.15	0.05	0.16	0.20	0.29	-0.20	-0.21	-0.14	-0.07	-0.07	-0.03
DEspacing	0.27	0.05	-0.02	0.14	0.19	0.21	0.26	0.22	0.04	-0.02	-0.02	-0.02
EFspacing	0.41	0.01	-0.10	-0.06	0.01	0.02	0.61	0.33	0.14	0.01	-0.10	-0.07
FGspacing	0.46	-0.01	0.01	0.03	0.00	0.01	0.49	0.65	0.20	0.05	0.07	0.04
GHspacing	0.33	-0.01	-0.06	-0.03	-0.01	0.00	0.11	0.18	0.48	0.22	0.00	-0.06
HIspacing	0.47	0.01	0.00	0.01	-0.02	-0.01	0.04	0.17	0.53	0.49	0.61	0.27
IJspacing	0.41	0.03	0.00	0.02	-0.01	0.00	0.04	0.14	0.44	0.38	0.61	0.49
JKspacing	0.21	0.01	-0.01	0.00	-0.02	-0.02	0.00	0.05	0.14	0.08	0.21	0.84
KLspacing	0.03	0.00	0.00	0.01	0.01	0.01	0.02	0.03	0.05	0.05	0.07	0.29
Total Length	0.28	0.09	0.02	0.09	0.11	0.14	0.14	0.13	0.08	0.04	0.02	0.01
Axles	1.00	0.07	-0.04	0.10	0.16	0.25	0.56	0.57	0.57	0.34	0.29	0.17
axlAweight	0.07	1.00	0.30	0.32	0.25	0.24	0.06	0.03	0.03	0.02	0.03	0.03
axlBweight	-0.04	0.30	1.00	0.81	0.69	0.62	0.03	0.06	0.02	0.02	0.05	0.01
axlCweight	0.10	0.32	0.81	1.00	0.80	0.74	0.14	0.14	0.07	0.04	0.05	0.02
axlDweight	0.16	0.25	0.69	0.80	1.00	0.87	0.12	0.12	0.06	0.03	0.02	0.00
axlEweight	0.25	0.24	0.62	0.74	0.87	1.00	0.12	0.11	0.06	0.04	0.03	0.00
axlFweight	0.56	0.06	0.03	0.14	0.12	0.12	1.00	0.68	0.33	0.13	0.09	0.03
axlGweight	0.57	0.03	0.06	0.14	0.12	0.11	0.68	1.00	0.51	0.25	0.20	0.09
axlHweight	0.57	0.03	0.02	0.07	0.06	0.06	0.33	0.51	1.00	0.50	0.45	0.19
axlIweight	0.34	0.02	0.02	0.04	0.03	0.04	0.13	0.25	0.50	1.00	0.38	0.12
axlJweight	0.29	0.03	0.05	0.05	0.02	0.03	0.09	0.20	0.45	0.38	1.00	0.26
axlKweight	0.17	0.03	0.01	0.02	0.00	0.00	0.03	0.09	0.19	0.12	0.26	1.00

Table D- 2: Correlation among Variables – Generated Variables Analysis

	ABspacing	BCspacing	CDspacing	DEspacing	EFspacing	FGspacing	GHspacing	HIspacing	IJspacing	JKspacing	KLspacing
ABspacing	1.00	-0.02	0.56	0.12	-0.12	-0.19	-0.07	-0.03	-0.02	0.01	0.00
BCspacing	-0.02	1.00	-0.59	-0.08	-0.11	-0.01	-0.09	-0.05	-0.04	-0.03	0.00
CDspacing	0.56	-0.59	1.00	-0.01	-0.12	-0.15	-0.04	-0.09	-0.09	-0.03	-0.01
DEspacing	0.12	-0.08	-0.01	1.00	0.01	0.09	-0.03	-0.05	-0.02	-0.04	0.00
EFspacing	-0.12	-0.11	-0.12	0.01	1.00	0.23	0.21	-0.14	-0.16	-0.09	-0.01
FGspacing	-0.19	-0.01	-0.15	0.09	0.23	1.00	-0.16	0.08	0.10	0.04	-0.01
GHspacing	-0.07	-0.09	-0.04	-0.03	0.21	-0.16	1.00	0.08	-0.01	-0.06	0.09
HIspacing	-0.03	-0.05	-0.09	-0.05	-0.14	0.08	0.08	1.00	0.81	0.35	0.00
IJspacing	-0.02	-0.04	-0.09	-0.02	-0.16	0.10	-0.01	0.81	1.00	0.48	0.05
JKspacing	0.01	-0.03	-0.03	-0.04	-0.09	0.04	-0.06	0.35	0.48	1.00	0.34
KLspacing	0.00	0.00	-0.01	0.00	-0.01	-0.01	0.09	0.00	0.05	0.34	1.00
Total Length	0.76	-0.09	0.67	0.36	0.13	0.12	0.08	0.04	0.03	0.01	0.01
axlAweight	0.09	-0.17	0.15	0.05	0.01	-0.01	-0.01	0.01	0.03	0.01	0.00
axlBweight	0.06	0.01	0.05	-0.02	-0.10	0.01	-0.06	0.00	0.00	-0.01	0.00
axlCweight	0.06	-0.21	0.16	0.14	-0.06	0.03	-0.03	0.01	0.02	0.00	0.01
axlDweight	0.03	-0.28	0.20	0.19	0.01	0.00	-0.01	-0.02	-0.01	-0.02	0.01
axlEweight	0.03	-0.42	0.29	0.21	0.02	0.01	0.00	-0.01	0.00	-0.02	0.01
axlFweight	-0.14	-0.07	-0.20	0.26	0.61	0.49	0.11	0.04	0.04	0.00	0.02
axlGweight	-0.17	-0.04	-0.21	0.22	0.33	0.65	0.18	0.17	0.14	0.05	0.03
axlHweight	-0.10	-0.08	-0.14	0.04	0.14	0.20	0.48	0.53	0.44	0.14	0.05
axlIweight	-0.04	-0.04	-0.07	-0.02	0.01	0.05	0.22	0.49	0.38	0.08	0.05
axlJweight	-0.02	-0.02	-0.07	-0.02	-0.10	0.07	0.00	0.61	0.61	0.21	0.07
axlKweight	0.01	-0.02	-0.03	-0.02	-0.07	0.04	-0.06	0.27	0.49	0.84	0.29
MAJ1	0.97	-0.04	0.55	0.06	-0.18	-0.29	-0.11	-0.04	-0.03	0.01	0.00
MAJ2	0.68	-0.02	0.76	0.10	-0.14	-0.18	-0.06	-0.13	-0.12	-0.05	-0.01
MAJ3	0.02	0.05	-0.11	0.45	0.33	0.37	0.13	0.08	0.07	0.02	0.03
MAJ4	-0.10	0.09	-0.03	0.14	0.31	0.19	0.12	-0.69	-0.64	-0.38	-0.03
MAJ5	0.00	0.01	0.00	0.03	0.01	0.01	-0.03	-0.01	0.00	-0.01	0.00
MAJ6	0.01	-0.01	0.01	0.00	0.03	0.00	0.07	0.00	0.00	0.00	0.00
MAJ7	.	.	.	.	.	.	.	.	.	.	.
Major Lengths	0.16	0.02	-0.02	0.46	0.23	0.25	0.07	0.02	0.02	0.00	0.00
Axles	-0.12	-0.44	0.10	0.27	0.41	0.46	0.33	0.47	0.41	0.21	0.03

Table D- 2: Correlation among Variables – Generated Variables Analysis (Continued)

	Total Length	axlAweight	axlBweight	axlCweight	axlDweight	axlEweight	axlFweight	axlGweight	axlHweight	axlIweight
ABspacing	0.76	0.09	0.06	0.06	0.03	0.03	-0.14	-0.17	-0.10	-0.04
BCspacing	-0.09	-0.17	0.01	-0.21	-0.28	-0.42	-0.07	-0.04	-0.08	-0.04
CDspacing	0.67	0.15	0.05	0.16	0.20	0.29	-0.20	-0.21	-0.14	-0.07
DEspacing	0.36	0.05	-0.02	0.14	0.19	0.21	0.26	0.22	0.04	-0.02
EFspacing	0.13	0.01	-0.10	-0.06	0.01	0.02	0.61	0.33	0.14	0.01
FGspacing	0.12	-0.01	0.01	0.03	0.00	0.01	0.49	0.65	0.20	0.05
GHspacing	0.08	-0.01	-0.06	-0.03	-0.01	0.00	0.11	0.18	0.48	0.22
HIspacing	0.04	0.01	0.00	0.01	-0.02	-0.01	0.04	0.17	0.53	0.49
IJspacing	0.03	0.03	0.00	0.02	-0.01	0.00	0.04	0.14	0.44	0.38
JKspacing	0.01	0.01	-0.01	0.00	-0.02	-0.02	0.00	0.05	0.14	0.08
KLspacing	0.01	0.00	0.00	0.01	0.01	0.01	0.02	0.03	0.05	0.05
Total Length	1.00	0.09	0.02	0.09	0.11	0.14	0.14	0.13	0.08	0.04
axlAweight	0.09	1.00	0.30	0.32	0.25	0.24	0.06	0.03	0.03	0.02
axlBweight	0.02	0.30	1.00	0.81	0.69	0.62	0.03	0.06	0.02	0.02
axlCweight	0.09	0.32	0.81	1.00	0.80	0.74	0.14	0.14	0.07	0.04
axlDweight	0.11	0.25	0.69	0.80	1.00	0.87	0.12	0.12	0.06	0.03
axlEweight	0.14	0.24	0.62	0.74	0.87	1.00	0.12	0.11	0.06	0.04
axlFweight	0.14	0.06	0.03	0.14	0.12	0.12	1.00	0.68	0.33	0.13
axlGweight	0.13	0.03	0.06	0.14	0.12	0.11	0.68	1.00	0.51	0.25
axlHweight	0.08	0.03	0.02	0.07	0.06	0.06	0.33	0.51	1.00	0.50
axlIweight	0.04	0.02	0.02	0.04	0.03	0.04	0.13	0.25	0.50	1.00
axlJweight	0.02	0.03	0.05	0.05	0.02	0.03	0.09	0.20	0.45	0.38
axlKweight	0.01	0.03	0.01	0.02	0.00	0.00	0.03	0.09	0.19	0.12
MAJ1	0.66	0.09	0.05	0.06	0.03	0.03	-0.21	-0.25	-0.14	-0.06
MAJ2	0.80	0.07	0.03	0.08	0.08	0.10	-0.17	-0.16	-0.13	-0.07
MAJ3	0.31	-0.01	0.00	-0.01	0.02	0.02	0.30	0.30	0.17	0.07
MAJ4	0.06	-0.03	0.00	-0.02	0.02	0.01	0.15	0.09	-0.26	-0.29
MAJ5	0.02	0.02	0.01	0.10	0.02	0.02	0.03	0.01	-0.01	-0.01
MAJ6	0.03	0.00	-0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.00
MAJ7	.	.	.	.	.	.	.	.	.	.
Major Lengths	0.35	0.00	0.01	0.00	0.04	0.04	0.21	0.21	0.10	0.03
Axles	0.28	0.07	-0.04	0.10	0.16	0.25	0.56	0.57	0.57	0.34

Table D- 2: Correlation among Variables – Generated Variables Analysis (Continued)

	axlJweight	axlKweight	MAJ1	MAJ2	MAJ3	MAJ4	MAJ5	MAJ6	MAJ7	Major Lengths	Axles
ABspacing	-0.02	0.01	0.97	0.68	0.02	-0.10	0.00	0.01	.	0.16	-0.12
BCspacing	-0.02	-0.02	-0.04	-0.02	0.05	0.09	0.01	-0.01	.	0.02	-0.44
CDspacing	-0.07	-0.03	0.55	0.76	-0.11	-0.03	0.00	0.01	.	-0.02	0.10
DEspacing	-0.02	-0.02	0.06	0.10	0.45	0.14	0.03	0.00	.	0.46	0.27
EFspacing	-0.10	-0.07	-0.18	-0.14	0.33	0.31	0.01	0.03	.	0.23	0.41
FGspacing	0.07	0.04	-0.29	-0.18	0.37	0.19	0.01	0.00	.	0.25	0.46
GHspacing	0.00	-0.06	-0.11	-0.06	0.13	0.12	-0.03	0.07	.	0.07	0.33
HIspacing	0.61	0.27	-0.04	-0.13	0.08	-0.69	-0.01	0.00	.	0.02	0.47
IJspacing	0.61	0.49	-0.03	-0.12	0.07	-0.64	0.00	0.00	.	0.02	0.41
JKspacing	0.21	0.84	0.01	-0.05	0.02	-0.38	-0.01	0.00	.	0.00	0.21
KLspacing	0.07	0.29	0.00	-0.01	0.03	-0.03	0.00	0.00	.	0.00	0.03
Total Length	0.02	0.01	0.66	0.80	0.31	0.06	0.02	0.03	.	0.35	0.28
axlAweight	0.03	0.03	0.09	0.07	-0.01	-0.03	0.02	0.00	.	0.00	0.07
axlBweight	0.05	0.01	0.05	0.03	0.00	0.00	0.01	-0.01	.	0.01	-0.04
axlCweight	0.05	0.02	0.06	0.08	-0.01	-0.02	0.10	0.01	.	0.00	0.10
axlDweight	0.02	0.00	0.03	0.08	0.02	0.02	0.02	0.01	.	0.04	0.16
axlEweight	0.03	0.00	0.03	0.10	0.02	0.01	0.02	0.01	.	0.04	0.25
axlFweight	0.09	0.03	-0.21	-0.17	0.30	0.15	0.03	0.02	.	0.21	0.56
axlGweight	0.20	0.09	-0.25	-0.16	0.30	0.09	0.01	0.02	.	0.21	0.57
axlHweight	0.45	0.19	-0.14	-0.13	0.17	-0.26	-0.01	0.02	.	0.10	0.57
axlIweight	0.38	0.12	-0.06	-0.07	0.07	-0.29	-0.01	0.00	.	0.03	0.34
axlJweight	1.00	0.26	-0.04	-0.09	0.05	-0.42	0.00	0.00	.	0.01	0.29
axlKweight	0.26	1.00	0.01	-0.04	0.02	-0.31	0.00	0.00	.	0.00	0.17
MAJ1	-0.04	0.01	1.00	0.67	-0.09	-0.19	0.00	0.01	.	0.10	-0.20
MAJ2	-0.09	-0.04	0.67	1.00	-0.17	0.00	0.00	0.01	.	-0.06	-0.10
MAJ3	0.05	0.02	-0.09	-0.17	1.00	0.08	0.01	0.01	.	0.88	0.33
MAJ4	-0.42	-0.31	-0.19	0.00	0.08	1.00	0.02	0.03	.	0.15	-0.15
MAJ5	0.00	0.00	0.00	0.00	0.01	0.02	1.00	0.44	.	0.00	-0.01
MAJ6	0.00	0.00	0.01	0.01	0.01	0.03	0.44	1.00	.	0.00	0.01
MAJ7	.	.	.	.	.	.	.	.	.	.	.
Major Lengths	0.01	0.00	0.10	-0.06	0.88	0.15	0.00	0.00	.	1.00	0.23
Axles	0.29	0.17	-0.20	-0.10	0.33	-0.15	-0.01	0.01	.	0.23	1.00

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