Vehicle Occupancy Data Collection Methods (Phase 2)

Final Report

Contract No. BD015-14

August 2007

Prepared for:

Transportation Statistics Office
Florida Department of Transportation

Prepared by:

Lehman Center for Transportation Research
Florida International University

Final Report

Vehicle Occupancy Data Collection Methods (Phase II)

Contract No. BD015-14

Prepared by:

Albert Gan, Ph.D., Associate Professor
Kaiyu Liu, Senior Research Associate
Rax Jung, Ph.D., P.E., Senior Research Associate (formerly)

Lehman Center for Transportation Research
Department of Civil and Environmental Engineering
Florida International University
10555 West Flagler Street, EC 3680
Miami, Florida 33174
Phone: (305) 348-3116
Fax: (305) 348-2802
E-mail: gana@fiu.edu

in cooperation with the

State of Florida Department of Transportation
605 Suwannee Street, MS 30
Tallahassee, FL 32399-0450

August 2007

DISCLAIMER

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of Florida Department of Transportation.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Vehicle Occupancy Data Collection Methods (Phase II)		5. Report Date August 2007 6. Performing Organization Code
7. Author(s) Albert Gan, Kaiyu Liu, and Rax Jung		8. Performing Organization Report No.
9. Performing Organization Name and Address Lehman Center for Transportation Research Florida International University 10555 W. Flagler Street, EC 3680, Miami, FL 33174		10. Work Unit No. (TRAIS) 11. Contract or Grant No. BD015-14
12. Sponsoring Agency Name and Address Office of Research and Development State of Florida Department of Transportation 605 Suwannee Street, MS 30, Tallahassee, FL 32399-0450		13. Type of Report and Period Covered Final Report August 2005 – August 2007 14. Sponsoring Agency Code 99700-3596-119

15. Supplementary Notes

Mr. Gordon Morgan of the Office of Transportation Statistics at the Florida Department of Transportation served as the project manager for this project.

16. Abstract

Vehicle occupancy data are increasingly being used to assess and monitor congestion management strategies. The traditional methods used to collect these data include the roadside windshield method and the carousel method. The cost of applying these methods and the accuracy of the results depend mainly on the sampling procedure applied. As a test case, this study applies the sampling procedures identified in the Phase I study to collect vehicle occupancy data in Miami-Dade County over a one-year period. Statistical methods were applied to analyze the data collected, and the results are reported. An alternative to the traditional methods of collecting vehicle occupancy data is to make use of the vehicle occupancy information in traffic accident records to estimate AVOs. This method is cost effective and may provide better spatial and temporal coverage than the transition methods. However, this method is subject to potential biases resulting from under- and over-involvement of certain population sectors in traffic accidents. This study examined such potential biases and developed adjustment factors as appropriate. An information system developed in the Phase I study to estimate AVOs from the Florida accident database for the state roadway system was updated to include adjustments for the potential biases, as well as to enforce the minimum required sample size. A reasonableness check of the results from the system shows AVO estimates that are highly consistent with expectations. In addition, comparisons of AVOs from accident data with the field estimates show that the two data sources produce relatively consistent results.

17. Key Word	18. Distribution Statement
Vehicle Occupancy, Data Collection Methods, Sampling, Accident Data Applications	

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	128	

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

ACKNOWLEDGEMENTS

This research was funded by the Research and Development Center of the Florida Department of Transportation (FDOT). The authors are grateful to the project manager, Mr. Gordon Morgan, of the FDOT Transportation Statistics Office for his guidance and assistance. The authors are also grateful to Mr. Mark Mandell for his editing of this report and to the following student assistants who helped to collect the vehicle occupancy data used in this study (in alphabetical order): Jie Bian, Lei Cai, Rene Ontivero, Pablo Orozco, Jose Rivera, Tao Wang, Hunter Wei, Wanyang Wu, Cheng Xu, Guan Yuan, Peng Zhu, Xiaoxia Zhu, and Alex Zhu.

TABLE OF CONTENTS

EXECUTIVE SUMMARY

Introduction

As congestion management strategies begin to put more emphasis on person capacity than vehicle capacity, the need for vehicle occupancy data has become more critical. Recognizing the increasing need for vehicle occupancy data, the Florida Department of Transportation (FDOT) undertook a study in 1996 and 1997 that used the roadside windshield method to collect over 2,000 hours of vehicle occupancy data from 21 sites around the state (URS, 1997). Following this data collection and analysis effort, FDOT contracted with the Florida International University (FIU) to conduct a second study in 2004 and 2005 to examine the different methods available to estimate vehicle occupancy. Building on the foundation of these two studies, this Phase II study aims to achieve the following objectives:

1. Apply procedures identified in the Phase I study to collect field data to test and demonstrate the sampling process and the statistical methods used to analyze the data.
2. Identify potential biases in accident data for vehicle occupancy estimation and develop adjustment factors to account for the biases.
3. Develop vehicle occupancy prediction models as a function of local socioeconomic data.
4. Evaluate and refine the field data collection tool developed in Phase I of this study.
5. Evaluate and refine the Florida Accident Vehicle Occupancy Rate Information Estimator (FAVORITE) system, also developed in Phase I of this study.

Sampling Process

A statistical sampling procedure was applied to collect vehicle occupancy data in Miami-Dade County, Florida using both the roadside windshield and carousel methods. A systematically random sampling approach was applied to select the observation locations and dates. Sites were selected for roadways classified as surface streets, freeways, and toll facilities. An unbiased list of 48 sampling sites was, thus, generated to ensure that the observations represent true countywide AVO. The short-count procedure was conducted for 20- or 40-minute intervals per hour from 7:00 a.m. to 6:00 p.m. Data were collected for passenger vehicles, including pick-ups, on selected Tuesdays, Wednesdays, and Thursdays over a one-year span.

Statistical Analysis

A rigorous statistical analysis was performed on the vehicle occupancy data collected. The vehicle occupancy data were analyzed at the level of individual locations, facility types, and the whole county for a.m. peak, midday, p.m. peak, off-peak, and entire daylight hours.

- At the individual location level, the AVOs ranged from 1.0044 for freeway segments during the a.m. peak to 1.4205 for freeway segments during midday.

- At the facility-type level, AVOs ranged from 1.0969 for freeways during the a.m. peak to 1.2281 for surface streets during the p.m. peak.

- Countywide the AVOs ranged from 1.1287 for the a.m. peak to 1.2199 for the p.m. peak. Regardless of facility type, the p.m. peak and a.m. peak data consistently showed the highest and lowest AVO among different times of day, respectively.

- Countywide AVO and its composite standard deviation for the entirety of daylight hours were 1.1902 and 0.0338, respectively, and the corresponding 95% confidence interval was 1.1902 ± 0.0382. The data analysis showed that, in general, either the midday or off-peak AVO can best represent the AVO of the entire daylight hours.

- Freeways consistently experienced the lowest AVOs among the facility types regardless of the time of day. In contrast, the surface streets consistently experienced the highest AVOs for all but the p.m. peak.

Moving vs. Stopped Vehicles

To determine the potential difference in AVOs between observing moving and stopped vehicles, data were collected at three mid-block locations for moving vehicles and at upstream or downstream intersection stoplines on the same roadway segment for stopped vehicles. The data show that the AVOs collected based on stopped vehicles can be up to 11.8% higher than the AVO collected based on moving vehicles. While the AVO based on stopped vehicles are generally higher, the overall difference, at 1.03%, is both insignificant and inconclusive. It was also seen that the number of vehicles that could be observed while performing AVO counts only on stopped vehicles was much smaller than that of the stopped vehicles' moving counterparts. This suggests that the potentially better accuracy that could be achieved from observing only stopped vehicles might be offset by a lower degree of accuracy from a smaller sample size.

Site-Specific Study

As part of the data collection effort in this study, seven days of occupancy data were collected over a one-week (seven-day) period at a specific location on a major corridor. The results did not show significant differences in AVOs among the weekdays. However, the AVOs for Saturday and Sunday were significantly higher, with Sunday experiencing the highest AVO. To examine potential differences in AVOs along a corridor, data were collected at two additional locations on the same roadway. The results show that the AVOs could vary significantly along a corridor, which suggests a need for collecting data at multiple locations for a corridor study.

Updated Field Data Collection System

To facilitate field data collection, a Pocket PC application tool was developed as part of the Phase I study. The tool replaces the traditional manual data recording and post-processing by allowing the user to make use of the touch-screen interface on a Pocket PC to record the number of occupants. Based on the lessons learned from the data collection effort in this study, the system was improved to allow the user to enter the number of occupants more easily and quickly. This was achieved mainly by increasing the size of touch-screen buttons, recording data at the instant of button tapping, and removing unnecessary option selections.

Factors Affecting Vehicle Occupancies

Parametric and nonparametric statistical tests were applied to examine the contributing factors affecting AVOs in the state of Florida. The following factors were analyzed: year, month, day-of-week, time periods, county, driver's age, driver's gender, driver's race, accident severity, facility type, and weather conditions. Both parametric and non-parametric analyses of variance (ANOVA) were applied, and it was found that AVOs were affected by all of the factors examined to various degrees. Despite continued efforts over the past decades to encourage people to carpool, the data show that the overall AVO in Florida has continued to decline over the years, from a high 1.58 occupants per vehicle in the 1990 down to 1.42 occupants per vehicle in 2005, or a 10% decrease. This study also found that a.m. peaks tend to have the lowest AVO in a day and that weekend AVOs were significantly higher than weekday AVOs. In addition, younger drivers were found to have higher AVOs than older drivers, female drivers tend to have more occupants in their vehicles than male drivers, black and Hispanic Americans tend to have higher AVOs than white Americans, and rural AVOs are significantly higher than urban AVOs.

Potential Biases and Adjustment Factors

As a potential source of vehicle occupancy data, accident data has met with some doubt due to its possible biases. Based on findings from past studies, two possible biases were analyzed and discussed in detail: accident severity and driver's age. By comparing accident vehicle data with field data, however, analysis results showed that although multi-occupant (two and more than two) vehicles occupy higher percentages of severe accidents (injury and fatality) than do single-occupant vehicles, multi-occupant vehicles in the whole accident vehicle population were not overrepresented in the accident database. However, a driver's age bias was found in the accident data. By comparing the year 2000 Miami-Dade County accident data and the 2000 census demographic data, it was found that there is a significant difference between the distribution of the ages of drivers involved in accidents and the ages of the general driving population in the county. A census weighting method was used to adjust for this bias in the AVO estimates. Other potential bias factors may include driver's gender, driver's race, and weather conditions. However, adjustment factors for these potential biases cannot currently be developed because of the lack of driving exposure data associated with their population subgroups.

FAVORITE Information System Updates

FAVORITE is a user-friendly information system capable of estimating average vehicle occupancies from multiple years of accident records for Florida's state roadway system. As part of the continued development of the system, the potential biases resulting from accident severity and driver's age were examined and the corresponding adjustment factors for driver's age were developed and implemented in the system. Also incorporated in the system in this Phase II study was consideration given to the minimum required number of accident records necessary to meet the desired accuracy in the AVO estimates.

Version 2 of the system includes the 1990-2005 accident data that are cross-classified by year, month, day, and hours, making it possible to perform temporal monitoring. The database also includes district, county, roadway section, and area type that can be used for spatial comparisons and monitoring. Comparisons can also be made by vehicle type, facility type, and accident severity. Because the system makes use of a comprehensive, statewide database, it can potentially be a highly cost-effective means of monitoring statewide, regional, and site-specific vehicle occupancy trends.

Evaluation of AVO Estimates from Accident Data

A reasonableness check of the results from the FAVORITE system shows AVO estimates that are consistent with expectations. In addition, comparisons of AVOs from accident data with the field estimates show that the two data sources produce results that are generally consistent. The comparisons also show that the AVO estimates from accident data tend to be slightly higher, most likely because accident records are able to include infants and small children who are often difficult to see during field observation.

AVO Prediction Models

Regression models for the purpose of predicting weekday AVOs were developed in this study using census demographic data integrated with 2002 InfoUSA employment data. Four regression models were developed: a weekday county area level model, a weekday large urban county arterial level model, a medium urban county arterial level model, and a weekday urban freeway model. Essentially, these models expressed the average occupancy rate for arterials and areas as a function of several statistically significant socioeconomic variables.

For the weekday county area level AVO model, the R^2 value is 0.452, which is considered acceptable. During the model development, a weekday model for the census blockgroup level was also developed. However, the R^2 value for this model is relatively low. Hence, this model was not recommended. The R^2 values for the three recommended arterial models are 0.357 for the large urban county arterial level model, 0.386 for the urban freeway model, and 0.182 for the medium-size urban county arterial level model. These models show that such socioeconomic factors as income, vehicle ownership, and employment play a part in vehicle occupancy forecasting models.

Although the AVO prediction models developed were statistically significant, their R^2 values are not high. The accident vehicle occupancy data do not explicitly represent the context in which accident vehicle trips were made. As more accident vehicle trip information and driver and passenger information become available, an update of the model parameters and predictors may be conducted to produce more accurate predictions. Consequently, one of the main future studies could involve developing a survey data method to obtain the needed data and a procedure for automatically integrating these survey data into the current accident database.

Further Development

This study has shown that accident records provide a viable and reliable data source for estimating AVOs, especially at the statewide and regional levels. As identified in this study, the use of accident records for AVO estimation offers the following advantages over the traditional field data collection methods:

- It is both cost effective and safe as it involves no field observation.
- It does not require any data post-processing, which is tedious and time consuming.
- It covers all time periods, including night hours when field data collection cannot be performed.
- It counts all occupants, including small children, who are difficult for observers to see in the field.
- It is not subject to visibility problems due to tinted vehicle windows.
- It is not subject to data quality problems as a result of field crews experiencing fatigue, providing poor job performance, over- or under-counting, etc.

Accordingly, it is recommended that the Department continues to develop the FAVORITE prototype, which is already a very powerful system considering its rich set of integrated accident records (since the year 1990), its ease of use, and its many capabilities and functionalities, including variable re-classification, variables filtering, data cross-classification, GIS visualization, chart plotting, etc.

While it is not necessary that AVOs derived from accident records be adjusted for potential biases for continuous AVO monitoring, further development may address other potential biases and possibly develop the corresponding adjustment factors for the benefit of applications that require absolute AVO estimates. Although FAVORITE is already freely available through web download, it is recommended that a web version be developed using ArcGIS Server as the software platform to take advantage of the instant accessibility of web applications. Additional functionalities can also be developed, for example, the ability to automatically upload new accident records as they become available.

CHAPTER 1
INTRODUCTION

1.1. Background

Vehicle occupancy data are increasingly being used to assess and monitor congestion management strategies. Unlike counting vehicles, which can be done with machine counters, counting the number of persons in a vehicle remains the task of human observers. As such, vehicle occupancy data are much more costly to collect than are vehicle data themselves. In the face of budget constraints, agencies must apply collection methods that strike a good balance between data accuracy and data acquisition cost. Traditionally, vehicle occupancy data have been collected using the roadside windshield method, in which observer(s) are stationed along the roadside to perform physical counts of vehicles and occupants, and the carousel method, in which observers are positioned in vehicles traveling on multi-lane highways to count occupants in neighboring vehicles.

Recognizing the increasing need for vehicle occupancy data, the Florida Department of Transportation (FDOT) undertook a study in 1996 and 1997 that used the roadside windshield method to collect over 2,000 hours of vehicle occupancy data from 21 sites around the state (URS, 1997). The data were used to analyze variations across different locations, lanes, directions, times of day, days of week, months of year, and seasons of year. Following this data collection and analysis effort, FDOT contracted with the Florida International University (FIU) to conduct a second study in 2004 and 2005 to examine the different methods available to estimate vehicle occupancy (Gan *et al.*, 2005). The project reviewed both existing and potential methods of occupancy data collection; examined issues related to geographic, temporal, and vehicle coverage design of occupancy data; and developed guidelines for performing data collection. Sampling plans for corridor and county studies using different methods were presented. A Pocket PC application designed for the collection of occupancy data in the field to avoid manual data entry was developed as part of the study. Also developed was a user-friendly software system that can calculate occupancy rates from the vehicle occupancy data in traffic accident records.

1.2. Need Statement

The single most important factor affecting the cost of conducting vehicle occupancy data collection is the minimum required sample size. A statistical procedure to better determine the minimum sample size necessary to achieve the desired accuracy in average vehicle occupancy (AVO) estimates is, thus, of critical importance. The 2004–2005 FIU study (i.e., Phase I of this study) identified the statistical sampling techniques necessary to determine the minimum sample size for different vehicle occupancy data collection methods. These techniques are based on sound statistical methods that consider various sources of variation, including time, day, season, and observer, on the accuracy of AVO estimates. There is a need to apply the procedures and techniques identified to test and demonstrate their use. The field data collected would also be used for comparisons with AVOs estimated from accident records.

While the traditional methods of collecting vehicle data have the benefit of allowing for the collection of up-to-date data, as well as the benefit that they can be tailored to more specific application needs, these traditional methods are also much more costly to conduct. Hence, these methods are impractical when regular data collection is needed for the purpose of continuous monitoring. An alternative to using the traditional field collection methods is to make use of the existing occupancy data for vehicles involved in traffic accidents. However, in using accident data to estimate the average occupancy rates, it is important to consider the potential biases resulting from under- and over-involvement of certain population sectors in traffic accidents. It is also important to determine the accuracy that can be achieved given the available number of accidents.

While accident records can be used to study historical trends of occupancy rates, and field data collection methods such as the windshield and carousel methods are used to collect current occupancy rates, there have been no known methods developed to project future occupancy rates. A study is needed to explore the feasibility of developing prediction models that can be used to estimate the expected occupancy rates given projected socioeconomic data. Essentially, the models will express the occupancy rate for a specific category of facility and temporal conditions as a function of several statistically significant socioeconomic variables. Such models should also be of interest to the transportation planning community, given the need to convert person trips into vehicle trips in Florida Standard Urban Transportation Model Structure (FSUTMS), which usually assumes a constant occupancy rate for the entire study area as well as the planning horizon.

1.3. Objectives

Building on the foundation of the 1996–1997 URS study, as well as Phase I of this study, this Phase II study was conducted with the aim of achieving the following objectives:

1. Apply procedures identified in the Phase I study to collect field data to test and demonstrate the sampling process and the statistical methods used to analyze the data.
2. Identify potential biases in accident data for vehicle occupancy estimation and develop adjustment factors to account for the biases.
3. Develop vehicle occupancy prediction models as a function of local socioeconomic data.
4. Evaluate and refine the field data collection tool developed in Phase I of this study.
5. Evaluate and refine the Florida Accident Vehicle Occupancy Rate Information Estimator (FAVORITE) system, also developed in Phase I of this study.

1.4. Report Organization

The rest of this report is organized as follows. Chapter 2 describes the process of determining the minimum sample size and the sample locations for the data collection conducted in this study. Chapter 3 presents the statistical analysis results from the data collected. Chapter 4 describes an improved version of a Pocket PC application originally developed in the Phase I study for field collection of vehicle occupancy data. Chapter 5 presents the results from an analysis using the vehicle occupancy data from accident records to identify factors that have an impact on AVOs. Chapter 6 focuses on the adjustment factors to account for potential biases stemming from using accident records to estimate AVOs. Chapter 7 provides an updated description of an AVO information system developed as part of the Phase I study. Chapter 8 evaluates the AVOs extracted from accident records based on both reasonableness checks and comparisons with field data. Chapter 9 presents several statistical models that were developed to predict AVOs given socioeconomic information. Finally, Chapter 10 summarizes the study and provides conclusions from this study and recommendations for further study.

CHAPTER 2
FIELD DATA COLLECTION DESIGN AND DEPLOYMENT

2.1. Introduction

In the Phase I study, the existing procedures for conducting a vehicle occupancy study were reviewed and summarized. The procedural guidelines based on a statistical sampling technique were established for the manual counting methods. This Phase II study demonstrates the entire process of determining the sample size, selecting the survey locations, performing the actual data collection, and applying rigorous statistical methods to analyze the field collected data. This chapter presents the sampling process. The analysis results are presented in the next chapter. The data collected are also used in this study to compare with those extracted from traffic accident records in Chapter 9.

2.2. Data Collection Locations and Methods

To establish a statistically sound baseline from which future vehicle occupancy evaluations can be performed, an initial area-wide study was conducted. Miami-Dade County was selected as the study area for field data collection. For this study, the target collection population was divided into strata by roadway facility, including surface streets, freeways, and toll facilities. Observations were made from 7:00 a.m. to 6:00 p.m.

It was initially determined that the roadside windshield method would be used for the entire data collection effort. However, it was later determined that this method would have presented safety concerns were the survey crew stationed on high-speed freeways. It was also determined that, where toll facilities are concerned, the observers would have the option of locating themselves near toll plazas; thus, the windshield method could be used in these instances.

To conserve manpower resources, a systematic short-count procedure was applied. Observations were made of multiple lanes at a time for a fixed interval during each hour. This involved scheduled shifts from direction to direction. One observer for each observation session was preliminarily assigned. To examine the feasibility of this arrangement, a field data collection test was conducted on one of the selected segments for surface streets. The heavy traffic during peak periods not only placed an intensive workload on the observer, but also increased the chances of the observer recording data incorrectly. The observers worked in two-person teams, and each observer collected data for one travel direction. Observations were made of multiple lanes in each direction for 20- or 40-minute intervals during each hour. A 20-minute interval was reserved for reviewing the counts taken and for rest. Observations were made from 7:00 a.m. to 6:00 p.m. Data were collected only for passenger vehicles (including pick-up trucks) using a modified version of the Pocket PC application developed as part of the Phase I study. (See Section 5 for details.) Data were collected on Tuesdays, Wednesdays, and Thursdays only.

A separate, site-specific study using the windshield method was also performed to investigate the day-to-day variation in AVO on Flagler Street, a major arterial in Miami-Dade County. Data were collected for a total of seven days, from 2:00 p.m. to 6:00 p.m. This timeframe covers two off-peak (2:00 – 4:00 p.m.) and two peak (4:00 – 6:00 p.m.) hours.

2.3. Minimum Sample Size

The first step in the vehicle occupancy data collection effort was to determine the minimum sample sizes required to achieve the desired accuracy in AVO estimates. Ferlis (1981) was the first to develop a sampling scheme for determining the minimum sample size for vehicle occupancy data collection. Ferlis' method considers the following primary sources of variation to account for the impact of spatial and temporal factors on AVO estimates:

- The variation across link-days within a season (σ_L)
- The variation from day to day within a season (σ_D)
- The variation from season to season (σ_S)
- The variation from time interval to time interval during a day as a result of short-counts (σ_W)

A link-day is defined as one observation session made on a particular link on a particular day over a specified time period. Sources of variations other than the above have also been suggested by other researchers. Ulberg and McCormack (1988) examined potential sources of error and concluded that observer counting variations (σ_O) should also be included.

In 1997, the Florida Department of Transportation (FDOT) conducted a study to collect vehicle occupancy data from 21 individual sites throughout the state of Florida (URS, 1997). The sites were selected for roadways ranging from two-lane rural routes to four- and six-lane urban arterial routes, including interstate highways. Occupancy data were collected for two directions from 17 conventional sites for 12 hours during daylight on five consecutive weekdays. Based on these data, variations in the occupancy data of private vehicles due to different locations, time periods during a day resulting from the use of short-counts, and the day of the week were established. Four seasonal sites were used as observation points twice each month over a one-year period to determine the monthly and seasonal variation in vehicle occupancy. Table 2-1 summarizes the variations reported in the three studies described above.

Table 2-1. Sources of Variation in Average Occupancy.

Geographic Scope	Standard Variation	Ferlis (1981)	Ulberg and McCormack (1988)	Data from URS Study (1997)
Area-wide	σ_L	0.063		0.076
	σ_S	0.015		0.068
	σ_W	0.017		0.008
	σ_O		0.006	
Site-specific or Corridor	σ_D	0.015		0.028
	σ_S	0.015		0.068
	σ_W	0.017		0.008
	σ_O		0.006	

Before the minimum sample size can be computed, a composite standard deviation of AVO must be computed, as follows:

$$\sigma = \left(\sigma_L{}^2 + \sigma_S{}^2 + \sigma_W{}^2 + \sigma_O{}^2\right)^{1/2}$$

where σ is the composite standard deviation of AVO. To estimate the number of sampling units on the basis of spatial and temporal variation and with the precision required, the sampling scheme developed by Ferlis (1981) was used. Because the standard deviation for different terms were difficult to estimate before an initial study was conducted, the values derived from the data collected by URS (1997) were used to estimate the composite standard deviation for each stratum, as follows:

$$\begin{aligned}\sigma &= \left(\sigma_L{}^2 + \sigma_S{}^2 + \sigma_W{}^2 + \sigma_O{}^2\right)^{1/2} \\ &= \left(0.076^2 + 0.068^2 + 0.008^2 + 0.006^2\right)^{1/2} \\ &= 0.102\end{aligned}$$

After the composite standard deviation was estimated, the sample sizes required to estimate the AVO within a desired tolerance and confidence level could be determined. The minimum sample sizes required to attain a 95% confidence level within a precision level of ±0.03 for the area-wide studies were calculated as follows:

$$N = \left(\frac{Z \times \sigma}{T}\right)^2 = \left(\frac{1.96 \times 0.102}{0.03}\right)^2 = 44$$

where

N = the number of link-days to be sampled,
Z = the normal variant for the specific level of confidence, and
T = the desired tolerance.

Thus, a minimum sample size of 44 was required for the area-wide study, respectively, for each time-of-day stratum. To facilitate the arrangement of data collection tasks, the sample size was increased to 48. The 48 observation locations were further divided into 24 sites on surface streets, 12 sites on freeways, and 12 sites at toll facilities.

2.4. Sampling Procedure

After the minimum sample size was determined, the observational locations and days were randomly selected from a list of link-days to generate an unbiased estimate of AVO. The random sampling technique was applied to specific highway links, and dates were used to allocate the required observation sample size. The 2005 highway network travel demand model for Miami-Dade County, Florida was used to identify detailed roadway segments within the study area. The loaded highway network file provided a link data list for determining the links to be observed. The centroid connectors used in the travel demand model were simplified roadways used to simulate the local streets in the actual network system. Therefore, these centroid connectors were excluded in the sampling. To avoid potential bias resulting from failure to select high-volume segments, and to take into account the variations in link length, the links were selected systematically with a probability proportional to the vehicle miles traveled (VMT) of each link.

2.4.1 Area-Wide Study

2.4.1.1. Observation Links

To select surface streets that cover the entire study area, the following sampling procedure, originally developed by Levine and Wachs (1998), was applied:

Step 1: The VMT of each link for surface streets was derived by multiplying the daily assigned traffic volume times the length of a link. The VMT of each census tract for the year 2000 was calculated by summing the VMT of links within the boundary. The list of census tracts was sorted by the associated VMT in descending order.

Step 2: The VMT of census tracts were summed to yield the total VMT of surface streets. The cumulative VMT for all census tracts was computed by starting at the first census tract in the list, then continuing the cumulating process until the last census tract. Hence, at the end of the process, the cumulative VMT was equal to the total VMT of surface streets.

Step 3: A census tract sampling interval, *i*, was computed by dividing the total VMT by 24. A random number, *s*, between 1 and *i* was generated to enable selection of the first study census tract with the cumulative VMT containing *s* within its range. The second study census tract was selected based on a census tract with a range of cumulative VMT containing the sum of *i* and *s*. This process was continued by adding *i* to the preceding sum and selecting the census tract in which the number falls. This was continued until the required 24 census tracts were selected. Table 2-2 shows the selected census tracts.

Step 4: For each census tract, the list of links for surface streets was sorted by the VMT in descending order. The cumulative VMT for links within individual census tracts was calculated. The process was continued until the cumulative VMT of the last link, which was equal to the VMT of the census tract.

Step 5: A random number, *s*, between 1 and the VMT of the census tract was generated to select the site on the link with a cumulative VMT containing *s* within its range. Only one observation link for each individual census tract was selected. This continued until the required 24 sites were selected. Table 2-3 shows the initial selected observation links for surface streets with the name and the intersecting roadways defining the segment.

Unlike the sampling procedure used for surface streets, the selection of observation links for freeways and toll facilities required no pre-selected census tracts. However, the procedure for all other steps was identical to that for surface streets. The following steps were used to select a separate sample of observation segments for freeways and toll facilities individually:

Table 2-2. Selected Census Tracts.

Index	2000 Census Tract ID	VMT of Census Tract	Cumulative VMT
1	116	62,011,250	127,608,960
2	34	36,026,539	215,687,868
3	53	30,466,220	338,938,324
4	238	23,626,254	451,039,554
5	317	21,447,763	587,109,397
6	45	18,904,282	703,982,159
7	309	17,258,771	829,195,504
8	52	14,324,647	955,374,782
9	247	13,341,555	1,079,793,708
10	288	12,282,711	1,196,259,820
11	307	11,827,236	1,328,375,839
12	192	10,775,412	1,451,771,927
13	314	10,351,534	1,578,863,974
14	97	9,686,882	1,699,194,824
15	220	8,918,037	1,819,949,727
16	91	8,318,416	1,948,803,102
17	241	7,412,503	2,073,493,804
18	356	6,913,882	2,195,423,063
19	283	6,322,036	2,320,981,958
20	22	5,933,706	2,444,087,863
21	76	5,383,240	2,568,082,788
22	8	4,577,273	2,691,965,526
23	134	3,789,331	2,814,363,372
24	269	2,315,709	2,938,188,294

Table 2-3. Initial Selected Observation Roadway Segments for Surface Streets.

Index	2000 Census Tract ID	VMT of Link	Cumulative VMT	Survey Roadway	Intersecting Roadways
1	116	2,451,215	15,564,751	NW 72nd Ave	NW 36th St and NW 31st St
2	34	1,758,335	9,871,708	NW 116th Wy	NW South River Dr and NW 100th Rd
3	53	547,043	22,348,886	Douglas Rd Et	Langley Rd and Alibaba Ave
4	238	2,035,348	9,620,386	S Dixie Hwy	SW 24th Ave and SW 22nd Ave
5	317	1,409,933	8,436,814	SW 184th St	SW 132nd Ave and SW 127th Ave
6	45	2,097,026	4,903,971	NW 57th Ave	NW 165th Te and NW 159th St
7	309	162,347	15,996,785	SW 152nd St	SW 152nd Ave and SW 148th Ct
8	52	403,650	12,292,283	NW 151st St	NW 27th Ave and NW 24th Ave
9	247	798,748	8,449,012	SW 37th Ave	SW 28th St and Bird Rd
10	288	760,557	4,687,975	SW 88th St	SW 79th Ave and SW 77th Ave
11	307	855,533	1,790,774	SW 112th St	SW 97th Ave and SW 94th Ave
12	192	1,089,431	4,510,872	NW 37th Ave	NW 3rd St and W Flagler St
13	314	1,906,076	1,906,076	Old Cutler Rd	SW 157th Te and SW 168th St
14	97	1,377,801	2,881,456	NW 17th Ave	NW 103rd St and NW 95th St
15	220	520,646	5,974,915	Granada Bd.	SW 8th St and Venetia Te.
16	91	973,995	1,970,545	NW 103rd St	NW 35th Ave and NW 32nd Ave
17	241	348,888	5,708,308	SW 82nd Ave	SW 24th St and SW 28th St
18	356	906,727	2,047,242	S Dixie Hwy	SW 380th St and SW 384th St
19	283	842,322	3,132,449	SW 127th Ave	SW 76th St and SW 80th St
20	22	617,677	3,390,562	NE 190th St	NE 29th Ave and Country Club Dr
21	76	490,107	3,642,763	NE 2nd Ave	NE 117th St and NE 114th St
22	8	2,516,968	2,516,968	NW 215th St	Florida TP and NW 7th Ave
23	134	626,499	2,331,331	N Miami Ave	NE 57th St and NE 54th St
24	269	2,064,756	2,064,756	SW 117th Ave	SW 64th St and SW 72nd St

Step 1: The VMT of each link for freeways (or toll facilities) was calculated by multiplying the daily assigned traffic volume times the link length. The list of all links for freeways (or toll facilities) was sorted by the VMT in descending order.

Step 2: The VMT of links were summed to yield the total VMT of freeways (or toll facilities). The cumulative VMT for all freeways (or toll facilities) was computed by starting at the first link in the list, then continuing the cumulating process until the last link. Hence, at the end of the process, the cumulative VMT was equal to the total VMT of freeways (or toll facilities).

Step 3: A link sampling interval, i, was computed by dividing the total VMT by 12. A random number, s, between 1 and i was generated to select the first observation link with the cumulative VMT containing s within its range. The second observation site was selected on a link with a range of cumulative VMT containing a value of sum of i and s. This process was continued by adding i to the preceding sum and selecting the link in which the number falls. This was continued until the required 12 links were selected. The selected observation links for freeways and toll facilities are shown in Tables 2-4 and 2-5, respectively, with the name and the crossing roadways defining the segment.

2.4.1.2. Sampling Dates

After the observation links were decided on, a list that includes every possible date on which the sample could be randomly selected was generated. The dates within a year for each site were then selected randomly. To spread out the data collection effort evenly throughout the study period, measurements were performed once per week and four days per month: one day for freeways, one day for toll facilities, and two days for surface streets. The sampling dates were selected by applying the following steps:

Step 1: Starting on February 1, 2006, each day within a one-year period was given a unique and sequential index number starting at 1 and continuing to 365. Data were to be collected on Tuesdays through Thursdays, excluding holidays. A list of 157 eligible dates was produced.

Step 2: A three-digit number was randomly generated to help select an observation date. If the generated number matched one of the index numbers of eligible dates, the date was selected and assigned to one of the selected links in the same order that the links are selected. If the number did not match any date on the date list, this number was skipped and another random number generated to identify the date to be sampled. This process was continued until each of the 48 links was assigned a particular date.

Table 2-6 shows the selected days for AVO data collection. Note that, due to weather conditions and crew schedule availability, a small number of these dates were changed to the next available dates. These changes should have no impact on the randomness of the dates.

Table 2-4. Selected Observational Roadway Segments for Freeways.

Index	VMT of Link	Cumulative VMT	Survey Roadway	Crossing Roadways
1	27,288,396	27,288,396	Julia Tuttle CY	Biscayne Bd and N Bay Rd
2	8,250,034	123,725,533	SR 826 EX	W 63rd St and W 52nd St
3	6,636,021	231,722,839	SR 826 EX	NW 17th St and NW 15th St
4	5,274,199	337,042,790	SR 826 EX	NW 48th St and NW 43rd St
5	4,171,200	449,141,036	SR 836 EX	NW 36th Ave and NW 31st Ave.
6	3,525,410	559,691,533	SR 826 EX	NW 12th St and NW 7th St
7	3,036,671	668,447,516	SR 826 EX	SW 75th St and SW 85th St
8	2,383,575	779,800,622	SR 836 EX	NW 57th Ave and Perimeter Rd.
9	1,727,152	888,436,067	SR 826 EX	NW 41st St and NW 36th St
10	1,240,752	998,881,030	SR 836 EX	NW 111th Pl. and NW 107th Ave(Ramps)
11	743,043	1,109,365,864	SR 826 EX	NW 35th Te and NW 34th St (Ramps)
12	337,380	1,219,183,811	I-95	NW 5th Ct and SR 836 EX

Table 2-5. Selected Observation Roadway Segments for Toll Facilities.

Index	VMT of Link	Cumulative VMT	Survey Roadway	Crossing Roadways
1	10,133,384	10,133,384	SR 821 EX	SW 154th St and SW 180th St
2	6,136,620	40,326,778	SR 821 ET	SW 134th St and Louis St
3	4,528,216	70,466,324	SR 821 HY	SW 24th St and SW 35th Te
4	4,061,296	99,793,945	SR 874 EX	SW 56th St and SW 66th St
5	3,523,740	129,234,209	Florida TP	NW 183rd St and NW 170th St
6	3,138,764	159,415,536	Florida TP	NW 202nd St and W 194th St
7	2,771,604	191,594,494	SR 821 ET	SW 106th Ave and SW 112th Te
8	2,128,500	223,118,110	SR 874 EX	SW 117th St and SW 120th St
9	1,681,785	253,067,775	Florida TP	NW 194th St and NW 186th St
10	1,325,888	284,259,600	Opa Locka EX	NW 135th St and NW128th St
11	790,860	314,110,208	Florida TP	NW 186th Te and NW 183rd St
12	367,271	345,077,658	Florida TP	Near NW 27th Ave

Table 2-6. Selected Dates.

Index	Selected Date	Index	Selected Date
022	Wednesday, February 22, 2006	189	Tuesday, August 08, 2006
028	Tuesday, February 28, 2006	198	Thursday, August 17, 2006
035	Tuesday, March 07, 2006	203	Tuesday, August 22, 2006
044	Thursday, March 16, 2006	219	Thursday, September 07, 2006
050	Wednesday, March 22, 2006	226	Thursday, September 14, 2006
057	Wednesday, March 29, 2006	231	Tuesday, September 19, 2006
065	Thursday, April 06, 2006	238	Tuesday, September 26, 2006
071	Wednesday, April 12, 2006	245	Tuesday, October 03, 2006
077	Tuesday, April 18, 2006	253	Wednesday, October 11, 2006
084	Tuesday, April 25, 2006	259	Tuesday, October 17, 2006
092	Wednesday, May 03, 2006	266	Tuesday, October 24, 2006
100	Thursday, May 11, 2006	274	Wednesday, November 01, 2006
105	Tuesday, May 16, 2006	281	Wednesday, November 08, 2006
112	Tuesday, May 23, 2006	288	Wednesday, November 15, 2006
121	Thursday, June 01, 2006	303	Thursday, November 30, 2006
128	Thursday, June 08, 2006	310	Thursday, December 07, 2006
142	Thursday, June 22, 2006	317	Thursday, December 14, 2006
148	Wednesday, June 28, 2006	322	Tuesday, December 19, 2006
155	Wednesday, July 05, 2006	330	Wednesday, December 27, 2006
163	Thursday, July 13, 2006	338	Thursday, January 04, 2007
170	Thursday, July 20, 2006	343	Tuesday, January 09, 2007
177	Thursday, July 27, 2006	357	Tuesday, January 23, 2007
183	Wednesday, August 02, 2006	365	Wednesday, January 31, 2007

2.4.2. Site-Specific Study

For the site-specific study, local knowledge was applied in defining the roadway segments to be selected. A section of a typical six-lane major arterial, Flagler Street, which carried an average annual daily traffic (AADT) of 56,500 in 2006, was selected. The data collection was performed between 2:00 p.m. and 6:00 p.m. from April 2 to April 8, 2007 for the entire seven-day week for one location near SW/NW 90th Ave. To assess the potential difference in AVOs along the corridor, two additional locations upstream and downstream of the SW/NW 90th Ave. location (i.e., near NW/SW 108th Ave. and NW/SW 82nd Ave.), were collected over the same hours, but for only one day, on April 4, 2007. Figure 2-1 shows the map locations of the three study sites along the Flagler Street corridor.

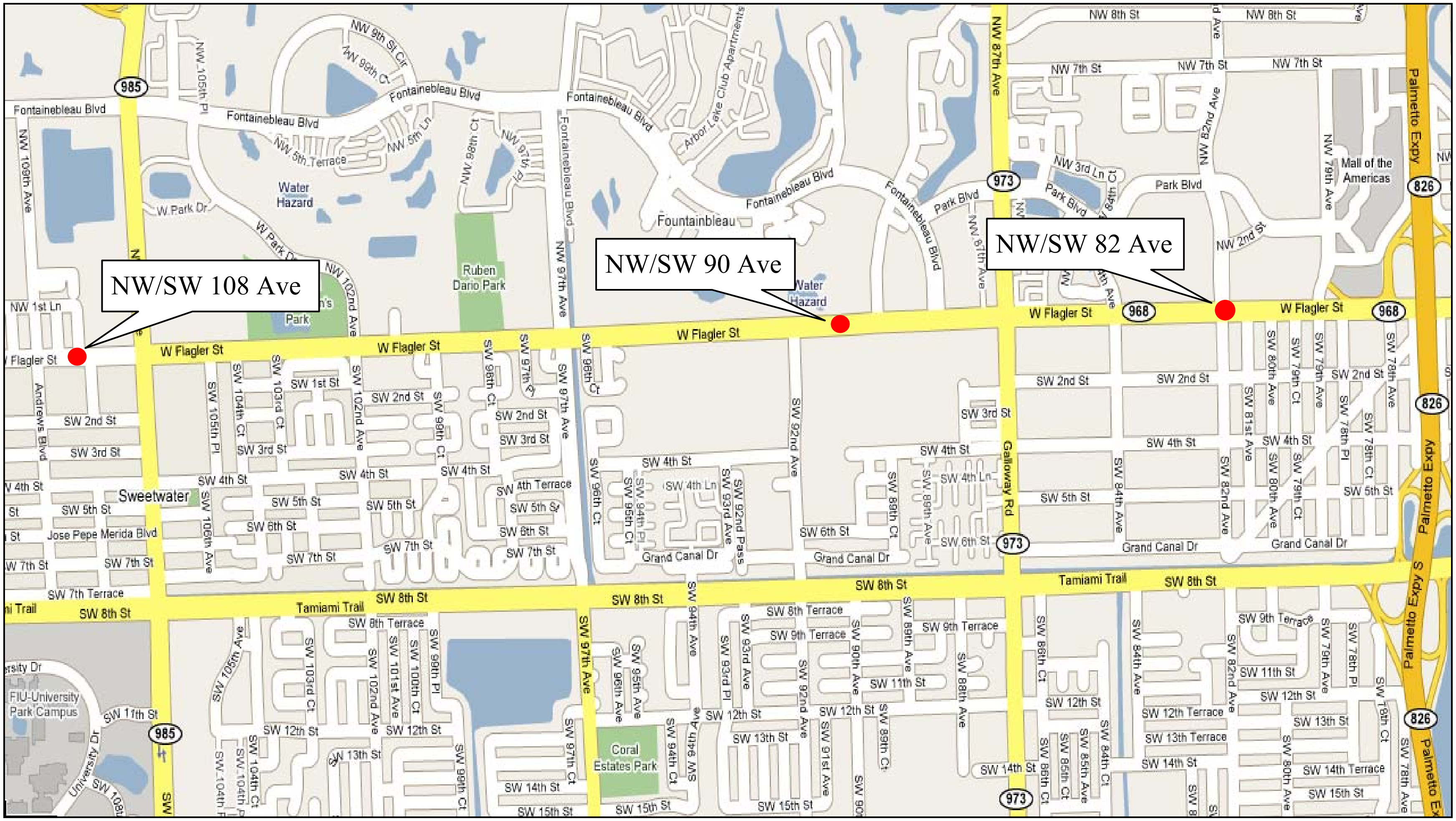


Figure 2-1. Locations for Site-Specific Corridor Study.

2.5. Selecting Counting Locations

To find an appropriate location at which to conduct a count, a field check of each selected roadway segment was made before the observations began. Locations that can facilitate observation activities and that provide adequate protection for the observers were selected. Six selected roadway segments for the surface street survey were eliminated from the first field check. These locations either had no parking facilities or restrooms available, or were in areas with high crime rates. Alternative zones with cumulative VMT closest to the eliminated ones were, hence, selected. A second field check on the newly selected roadway segments was conducted to ensure that the sites were appropriate. A simple survey that included the number of lanes in the roadway, available parking locations, shelter, restroom, and landmarks for identifying the observation location was prepared for each selected link. Table 2-7 shows the final list of selected links for surface streets.

2.6. Work Plan

To conserve manpower resources, a systematic short-count procedure was applied. Observations were made of multiple lanes at a time for a fixed interval during each hour. This involved scheduled shifts from direction to direction. One observer for each observation session was preliminarily assigned. To examine the feasibility of this arrangement, a field data collection test was conducted on one of the selected segments for surface streets. The heavy traffic during peak periods not only placed an intensive workload on the observer, but also increased the chances of the observer recording data incorrectly. The observers worked in two-person teams, and each observer collected data for one travel direction. Observations were made of multiple lanes in each direction for 20- or 40-minute intervals during each hour. A 20-minute interval was reserved for reviewing the counts taken and for rest. Observations were made from 7:00 a.m. to 6:00 p.m. Data were collected only for passenger vehicles (including pick-up trucks) and, as mentioned earlier, were collected on Tuesdays, Wednesdays, and Thursdays only.

The required field crews were decided on and scheduled in accordance with the observation sessions derived from the sampling plan. A work schedule indicating the observation locations and sampling dates with observers' names was prepared monthly. Generally, six crew members were available for scheduling. Before each assigned observation session, the crew members were provided with a sketch of the location obtained from the field check. The information was used to help the observers identify the counting site easily and properly.

2.7. Personnel Training

To ensure that the counts were conducted in a consistent and reliable manner, training on the data collection procedure was provided for the crews. The training was oriented to provide the observers with information such as vehicle types to be counted, usage and maintenance of a Pocket PC field data collection tool, and proper reaction to potential problems during observation. The crews were also told to record data for as many eligible vehicles as they could observe. However, guessing the number of occupants when the observers could not see well into a vehicle was forbidden.

Table 2-7. Final Selected Observation Roadway Segments for Surface Streets.

Index	2000 Census Tract ID	VMT of Link	Cumulative VMT	Survey Roadway	Intersecting Roadways
1	116	2,451,215	15,564,751	NW 72nd Ave	NW 36th St and NW 31st St
2	34	1,758,335	9,871,708	NW 116th Wy	NW South River Dr and NW 100th Rd
3	125	2,183,591	2,183,591	NW 58th St	NW 87th Ave and NW 97th Ave
4	238	2,035,348	9,620,386	S Dixie Hwy	SW 24th Ave and SW 22nd Ave
5	317	1,409,933	8,436,814	SW 184th St	SW 132nd Ave and SW 127th Ave
6	114	353,941	14,969,257	W 29th St	W 8th Ave and W 11th Ave
7	309	162,347	15,996,785	SW 152nd St	SW 152nd Ave and SW 148th Ct
8	41	509,791	13,468,798	Biscayne Bd	NE 143rd St and NE 146th St
9	247	798,748	8,449,012	SW 37th Ave	SW 28th St and Bird Rd
10	288	760,557	4,687,975	SW 88th St	SW 79th Ave and SW 77th Ave
11	307	855,533	1,790,774	SW 112th St	SW 97th Ave and SW 94th Ave
12	192	1,089,431	4,510,872	NW 37th Ave	NW 3rd St and W Flagler St
13	314	1,906,076	1,906,076	Old Cutler Rd	SW 157th Te and SW 168th St
14	167	371,549	3,926,085	NW 20th St	NW 10th Ave and NW 11th Ave
15	220	520,646	5,974,915	Granada Bd	SW 8th St and Venetia Te
16	89	701,012	3,247,735	NE 2nd Ave	NE 95th St and NE 90th St
17	241	348,888	5,708,308	SW 82nd Ave	SW 24th St and SW 28th St
18	356	906,727	2,047,242	S Dixie Hwy	SW 380th St and SW 384th St
19	283	842,322	3,132,449	SW 127th Ave	SW 76th St and SW 80th St
20	22	617,677	3,390,562	NE 190th St	NE 29th Ave and Country Club Dr
21	76	490,107	3,642,763	NE 2nd Ave	NE 117th St and NE 114th St
22	8	2,516,968	2,516,968	NW 215th St	Florida TP and NW 7th Ave
23	101	226,901	3,543,434	W 37th St	W 14th Ave and W 16th Ave
24	269	2,064,756	2,064,756	SW 117th Ave	SW 64th St and SW 72nd St

CHAPTER 3
FIELD OCCUPANCY DATA ANALYSIS

3.1. Introduction

After the data collection plan was established and crew training was conducted, data were collected using the aforementioned Pocket PC application specifically developed for field vehicle occupancy data collection. The application greatly simplified the process of data recording in the field and circumvented the need for data entry in an office. (See Chapter 4 for more details on the Pocket PC application.) After the observation at each selected location was completed, the field data recorded in the Pocket PC were transferred to a desktop and were available for import into an analysis program. This chapter presents the statistical analysis results from these field data.

3.2. Area-Wide Study

Given that vehicle occupancy rates vary by time of day, different time periods were selected for analysis. The time periods of interest included the a.m. peak period (7:00 – 9:00 a.m.), midday period (11:00 a.m. – 1:00 p.m.), p.m. peak period (4:00 – 6:00 p.m.), off-peak period (9:00 – 11:00 a.m. and 1:00 – 4:00 p.m.), and the entirety of daylight hours for data collection taken as a whole (7:00 a.m. – 6:00 p.m.).

Because short-count data collection procedures were used, an expansion factor was required to expand raw person and vehicle counts to the total estimates of the respective time periods. For each observation location of a specific time period, the expansion factor was computed by driving direction as follows:

$$f_{di} = \frac{T}{t_{di}}$$

$$P_{di} = P_{rdi} \times f_{di}$$

$$V_{di} = V_{rdi} \times f_{di}$$

where

- f_{di} = the expansion factor for driving direction *d* at location *i*,
- T = the total time of the study time period,
- t_{dj} = the actual counting time for driving direction *d* at location *i*,
- P_{di} = the factored number of occupants for driving direction *d* at location *i*,
- P_{rdi} = the raw number of occupants counted for driving direction *d* at location *i*,
- V_{di} = the factored number of vehicles for driving direction *d* at location *i*, and
- V_{rdi} = the raw number of vehicles counted for driving direction *d* at location *i*.

This calculation assumed that the traffic volumes observed at each location were proportional to the actual traffic flow at the corresponding location. The following statistical analysis for vehicle occupancy data was made on the basis of different aggregate levels: location, facility type, and county. Each level was further divided into different time periods. The difference between AVO estimates derived from the use of different aggregate levels of occupancy data were also tested statistically.

3.2.1. Individual Location Level

The location AVO for each time period was computed by dividing the factored number of occupants by the factored number of vehicles for both driving directions, as follows:

$$AVO_i = \frac{P_i}{V_i}$$

where

AVO_i = average vehicle occupancy for location i,
P_i = the factored number of occupants for both driving directions at location i, and
V_i = the factored number of vehicles for both driving direction at location i.

Tables A-1 to A-15 of Appendix A show the location AVOs for different facility types for different time periods. Table 3-1 shows the facility-type measures from the perspective of individual location AVOs for different time periods. For all 48 observation locations, the location AVOs for different times of day ranged from a low of 1.0044 persons per vehicle (freeways during a.m. peak) to a high of 1.4205 persons per vehicle (freeways during midday). In terms of AVOs at the facility-type level for different times of day, they ranged from a low of 1.1030 persons per vehicle (freeways during a.m. peak) to a high of 1.2360 persons per vehicle (surface streets during p.m. peak).

The means of location AVOs for different facility type/time period combinations are plotted in Figure 3-1. When the observations were stratified by time of day, the p.m. peak experienced the highest AVOs for all three facility types, followed by either midday or off-peak AVOs. The lowest AVOs occurred during the a.m. peak. When the locations were classified by facility type, other than for the midday, the AVO descended in the order of surface streets, toll facilities, and freeways for other time-of-day periods. For the entire observation daylight hours (7:00 a.m. – 6:00 p.m.), the means of the location AVOs for the corresponding facility types were 1.2099, 1.1913, and 1.1670 persons per vehicle, respectively.

The location data were further analyzed among all selected observation locations to evaluate the overall AVOs that included all facility types. The results are provided in Table 3-2. As the means of the location AVOs for different time periods presented in Figure 3-2 show, the p.m. peak carried the highest AVO, at 1.2206 persons per vehicle. The second highest AVO was 1.2091 persons per vehicle for off-peak, followed by 1.1986 persons per vehicle for midday, and then 1.1422 persons per vehicle for the a.m. peak. For the entirety of daylight hours, the mean of the location AVOs was 1.1945 persons per vehicle.

Table 3-1. Facility-Type Level Statistics.

FT Stratum	Mean of AVO*i*	Standard Deviation	Minimum AVO*i*	Maximum AVO*i*	Sample Size
A.M. Peak Period (7:00 – 9:00 a.m.)					
Surface Streets	1.1641	0.0713	1.0189	1.3201	24
Freeways	1.1030	0.0675	1.0044	1.1758	12
Toll Facilities	1.1372	0.0816	1.0321	1.2732	11
Midday Period (11:00 a.m. – 1:00 p.m.)					
Surface Streets	1.2060	0.0676	1.0387	1.3374	24
Freeways	1.1956	0.1156	1.0393	1.4205	12
Toll Facilities	1.1857	0.0810	1.0635	1.2899	11
P.M. Peak Period (4:00 – 6:00 p.m.)					
Surface Streets	1.2360	0.0642	1.1025	1.3969	24
Freeways	1.1925	0.0755	1.0861	1.3255	12
Toll Facilities	1.2174	0.0906	1.0997	1.3766	11
Off-Peak Period (9:00 – 11:00 a.m. and 1:00 – 4:00 p.m.)					
Surface Streets	1.2252	0.0601	1.1428	1.3826	24
Freeways	1.1755	0.0742	1.0808	1.2967	12
Toll Facilities	1.2106	0.0454	1.1432	1.2730	12
Daylight Hours (7:00 a.m. – 6:00 p.m.)					
Surface Streets	1.2099	0.0545	1.1167	1.3475	24
Freeways	1.1670	0.0754	1.0609	1.3013	12
Toll Facilities	1.1913	0.0577	1.1128	1.2761	12

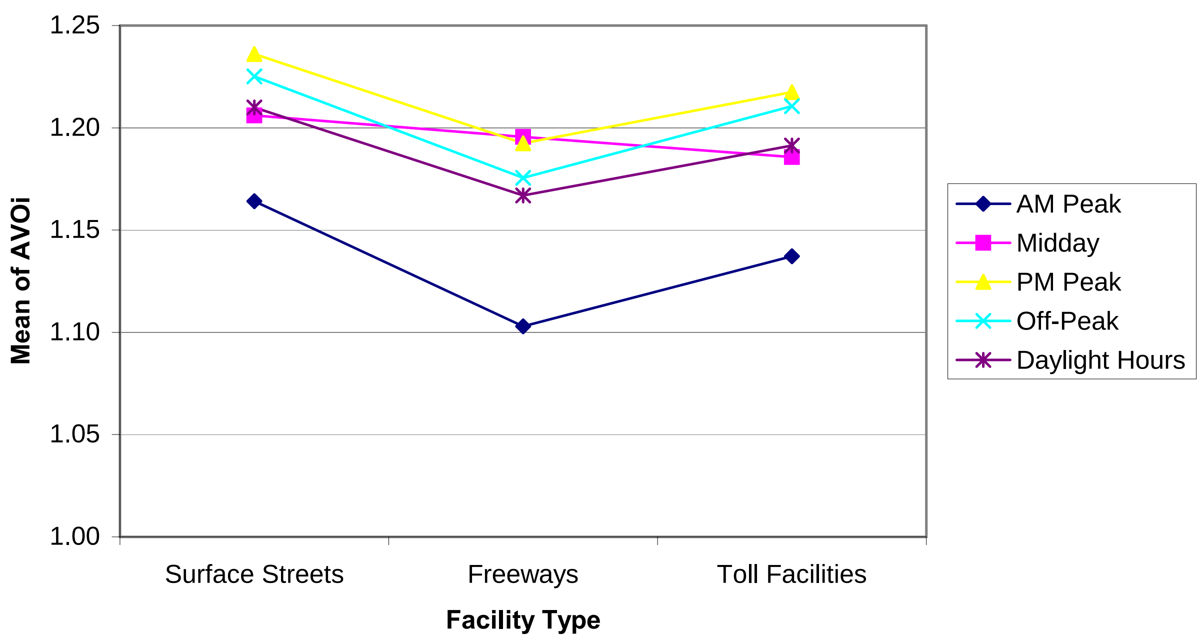


Figure 3-1. Comparisons of Facility-Type AVOs.

Table 3-2. Countywide AVO and Related Statistics.

Time-Period Stratum	Mean of AVO*i*	Standard Deviation	Minimum AVO*i*	Maximum AVO*i*	Sample Size
A.M. Peak	1.1422	0.0757	1.0044	1.3201	47
Midday	1.1986	0.0836	1.0387	1.4205	47
P.M. Peak	1.2206	0.0744	1.0861	1.3969	47
Off-Peak	1.2091	0.0629	1.0808	1.3826	48
Daylight Hours	1.1945	0.0623	1.0609	1.3475	48

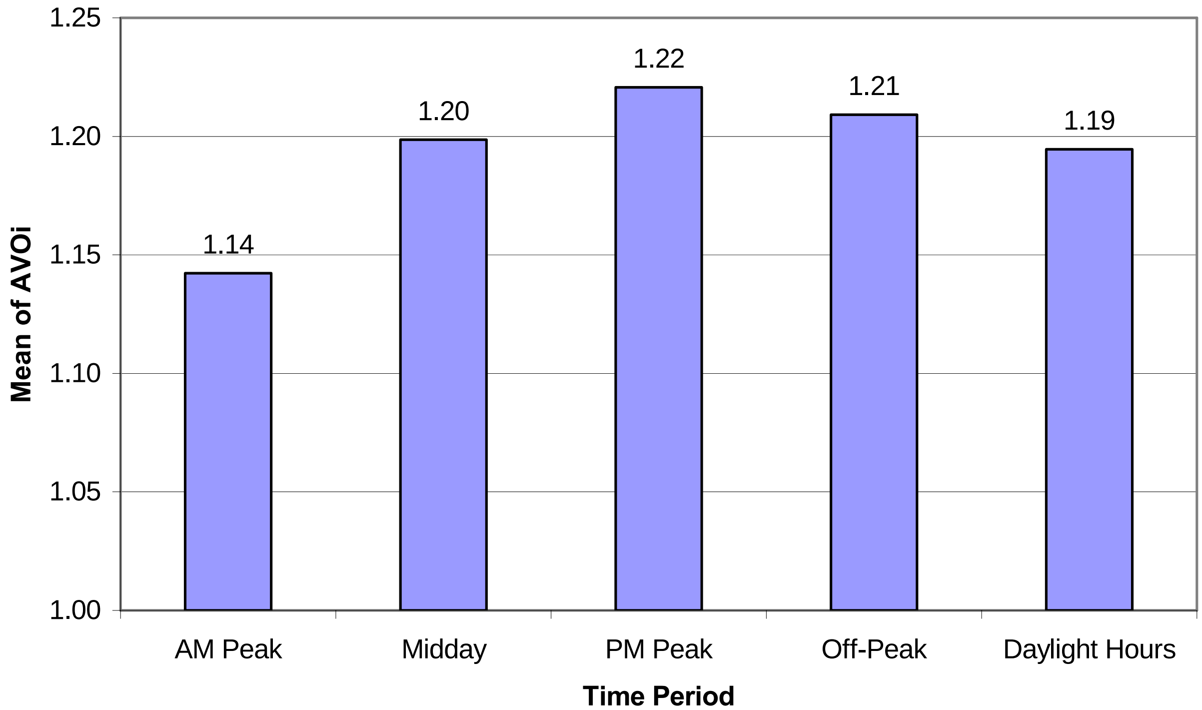


Figure 3-2. Comparisons of Countywide AVOs.

3.2.1.1. Normality Test

To provide a baseline for statistical analysis in the following sections, a normality test was performed to determine if the location AVOs are normally distributed. Because the sample sizes were all less than 50, the Shapiro-Wilk test was used for the normality test of sample distribution. A significance level of 0.05 was selected. The null and alternative hypotheses for testing the data set for a specific facility type and particular time period were:

H_0: location AVOs are normally distributed
Ha: location AVOs are not normally distributed

Table 3-3 shows the results of the normality tests. The majority of *P*-values for the sampling distribution of location AVOs were greater than the designed significance level of 0.05, except for freeways during the a.m. peak period (0.033) and surface streets during the off-peak period

(0.034). The data sets were statistically insignificant at 0.05, along with two that were slightly significant. The results indicated that the data do not provide sufficient evidence to reject normal distribution (H_0).

Table 3-3. Shapiro–Wilk Normality Test for the Distribution of Location AVOs.

FT Stratum	Statistic	Degrees of Freedom	*P*-Value
A.M. Peak Period (7:00 – 9:00 a.m.)			
Surface Streets	0.983	24	0.948
Freeways	0.846	12	0.033
Toll Facilities	0.927	11	0.383
All Facility	0.973	47	0.356
Midday Period (11:00 a.m. – 1:00 p.m.)			
Surface Streets	0.959	24	0.425
Freeways	0.961	12	0.801
Toll Facilities	0.918	11	0.304
All Facility	0.981	47	0.619
P.M. Peak Period (4:00 – 6:00 p.m.)			
Surface Streets	0.957	24	0.380
Freeways	0.940	12	0.497
Toll Facilities	0.941	11	0.532
All Facility	0.968	47	0.219
Off-Peak Period (9:00 – 11:00 a.m. and 1:00 – 4:00 p.m.)			
Surface Streets	0.909	24	0.034
Freeways	0.931	12	0.387
Toll Facilities	0.924	12	0.317
All Facility	0.979	48	0.533
Daylight Hours (7:00 a.m. – 6:00 p.m.)			
Surface Streets	0.933	24	0.114
Freeways	0.950	12	0.635
Toll Facilities	0.907	12	0.194
All Facility	0.985	48	0.790

3.2.1.2. One-Way ANOVA Test

To investigate the differences among the means of the location AVOs for different facility types, the one-way analysis of variance (ANOVA) was applied. The one-way ANOVA test requires that observations for each study group be independent random samples from normal distributions with the same population variance. Other than the prerequisite of the same population variance, which remains unknown, all other conditions were satisfied using the adopted sampling data collection procedure and the normality test performed. The Levene test was then used to examine the homogeneity of variances. The results in Table 3-4 show that all *P*-values were greater than a significance level of 0.05 and that there was no strong evidence in the data to dispute the hypothesis of equal variances.

The null and alternative hypotheses for one-way ANOVA are given below:

H_0: the means of the location AVOs for the three facility types are equal
Ha: the means of the location AVOs for the three facility types are not equal

Table 3-4 provides the summary statistics of the test. Because the *P*-values for the five study time periods were greater than a significance level of 0.05, it was concluded that the data failed to reject the null hypothesis that the means of the location AVOs for the three facility types were equal.

Table 3-4. Levene Test and One-Way ANOVA Test for Location AVOs.

Time-Period Stratum	**Levene Test**			**ANOVA Test**		
	Statistic	**Degrees of Freedom**	***P*-Value**	**Degrees of Freedom**	***F* Statistic**	***P*-Value**
A.M. Peak	0.603	2, 44	0.552	2, 44	2.838	0.069
Midday	2.610	2, 44	0.085	2, 44	0.224	0.800
P.M. Peak	1.126	2, 44	0.333	2, 44	1.406	0.256
Off-Peak	0.971	2, 45	0.386	2, 45	2.668	0.080
Daylight Hours	1.272	2, 45	0.290	2, 45	1.994	0.148

3.2.2. Facility-Type Level

At the facility-type level, the occupancy data from the individual survey locations were aggregated for the same types of facilities. The facility-type AVO, composite standard deviation, and actual precision with a 95% confidence level for different time periods were calculated as follows:

$$AVO_h = \frac{\sum_i P_i}{\sum_i V_i}$$

$$\sigma_h = \left[\frac{N_h \times \sum_i (P_i - AVO_h * V_i)^2}{\left(\sum_i V_i \right)^2} \right]^{1/2}$$

$$T_h = \left(\frac{Z^2 \times \sigma_h^{\ 2}}{N_h} \right)^{1/2} = \left(\frac{1.96^2 \times \sigma_h^{\ 2}}{N_h} \right)^{1/2}$$

where

AVO_h = the average vehicle occupancy for facility type *h*,
σ_h = the composite standard deviation for facility type *h*,
N_h = the number of observation sessions required for facility type *h*, and
T_h = the desired tolerance for facility type *h*.

Table 3-5 shows the AVO statistics at the facility-type level for different time periods. The AVOs estimated for different times of day ranged from a low of 1.0969 persons per vehicle for freeways during the a.m. peak to a high of 1.2281 persons per vehicle for surface streets during the p.m. peak. Compared to the facility-type AVOs estimated with the means of location AVOs, the minimum and maximum AVOs decreased by 0.0061 persons per vehicle (0.55%) and 0.0079 persons per vehicle (0.64%), respectively.

The facility-type AVOs are plotted in Figure 3-3 to verify the general pattern. When the observations were grouped by time of day, the p.m. peak and a.m. peak data for the three facility types consistently showed the highest and lowest AVOs, respectively, among the different time periods. When locations were grouped by facility type, the AVOs for freeways consistently showed the lowest values for each time-of-day period. On the other hand, the AVOs for surface streets consistently showed the highest values for all but the p.m. peak period. For estimates of the entirety of observation daylight hours (7:00 a.m. to 6:00 p.m.), the means of individual facility-type AVOs for surface streets, toll facilities, and freeways were 1.2059, 1.1912, and 1.1578 persons per vehicle, respectively. Compared to the values derived from the means of the location AVO, the facility-type data for surface streets decreased by 0.0040 persons per vehicle (0.33%), for toll facilities decreased by 0.0001 persons per vehicle (0.008%), and for freeways decreased by 0.0092 persons per vehicle (0.79%) for observation daylight hours.
.

Table 3-5. Facility-Type Level AVOs and Related Statistics

FY Stratum	AVO_h	σ_h	T_h
A.M. Peak Period (7:00 – 9:00 a.m.)			
Surface Streets	1.1454	0.0691	0.0276
Freeways	1.0969	0.0659	0.0373
Toll Facilities	1.1273	0.1023	0.0605
Midday Period (11:00 a.m. – 1:00 p.m.)			
Surface Streets	1.2172	0.0767	0.0307
Freeways	1.1814	0.1037	0.0587
Toll Facilities	1.1833	0.1184	0.0700
P.M. Peak Period (4:00 – 6:00 p.m.)			
Surface Streets	1.2281	0.0662	0.0265
Freeways	1.1887	0.0761	0.0431
Toll Facilities	1.2318	0.0792	0.0468
Off-Peak Period (9:00 – 11:00 a.m. and 1:00 – 4:00 p.m.)			
Surface Streets	1.2204	0.0567	0.0227
Freeways	1.1649	0.0681	0.0385
Toll Facilities	1.2119	0.0431	0.0244
Daylight Hours (7:00 a.m. – 6:00 p.m.)			
Surface Streets	1.2059	0.0485	0.0194
Freeways	1.1578	0.0693	0.0392
Toll Facilities	1.1912	0.0590	0.0334

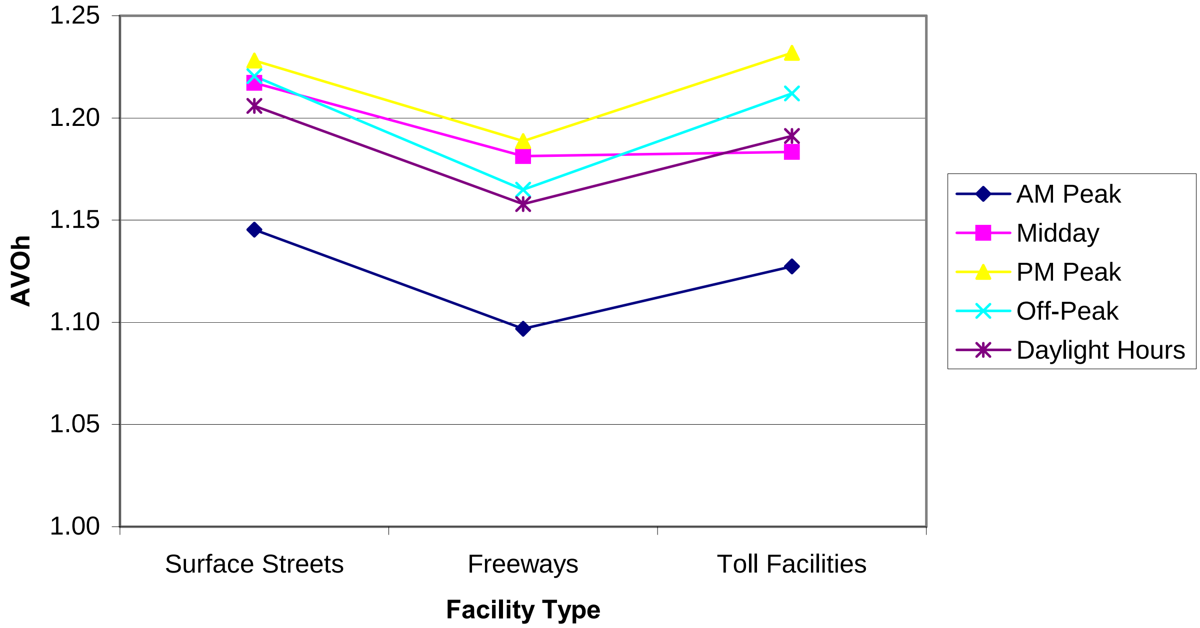


Figure 3-3. Comparisons of Facility-Type AVOs.

The facility-type AVOs for different time periods have been estimated by either the mean of the location AVOs or by the ratio of the total occupants to the total vehicles for an individual facility type. The results above showed no significant difference among the facility-type AVOs estimated from different aggregate levels of occupancy data. To further test whether these two facility-type AVOs were compatible, the one-sample *T* test was performed. Specifically, the hypotheses tested were:

H_0: the mean of the location AVOs for a specific facility type = AVO_h
Ha: the mean of the location AVOs for a specific facility type $\neq AVO_h$

Table 3-6 shows that the two-tailed *P*-values for all cases were greater than 0.05. Thus, the test failed to reject the null hypothesis at a significance level of 0.05. It was concluded that there was no significant difference between facility-type AVOs estimated with the means of location AVOs or by the ratio of total persons to total vehicles for individual facility types.

Table 3-6. One-Sample T-Test for Facility-Type AVOs.

FT Stratum	Sample Size	Mean AVOi	Standard Deviation	*t* Statistic	Degrees of Freedom	*P*-Value (two-tailed)
A.M. Peak Period (7:00 – 9:00 a.m.)						
Surface Streets	24	1.1641	0.0713	1.283	23	0.212
Freeways	12	1.1030	0.0675	0.315	11	0.758
Toll Facilities	11	1.1372	0.0816	0.404	10	0.694
Midday Period (11:00 a.m. – 1:00 p.m.)						
Surface Streets	24	1.2060	0.0677	-0.812	23	0.425
Freeways	12	1.1956	0.1156	0.426	11	0.679
Toll Facilities	11	1.1857	0.0810	0.100	10	0.922
P.M. Peak Period (4:00 – 6:00 p.m.)						
Surface Streets	24	1.2360	0.0642	0.606	23	0.551
Freeways	12	1.1925	0.0756	0.174	11	0.865
Toll Facilities	11	1.2174	0.0906	-0.528	10	0.609
Off-Peak Period (9:00 – 11:00 a.m. and 1:00 – 4:00 p.m.)						
Surface Streets	24	1.2252	0.0601	0.387	23	0.702
Freeways	12	1.1755	0.0742	0.496	11	0.629
Toll Facilities	12	1.2106	0.0454	-0.098	11	0.923
Daylight Hours (7:00 a.m. – 6:00 p.m.)						
Surface Streets	24	1.2099	0.0545	0.356	23	0.725
Freeways	12	1.1670	0..0754	0.423	11	0.681
Toll Facilities	12	1.1913	0.0577	0.005	11	0.996

3.2.3. Countywide Level

The overall AVOs at the county level were determined by combining the estimates of different facility types through appropriate weighting techniques. In other words, the AVO estimate, composite standard deviation, and actual level of precision for the countywide AVO were determined by weighting the respective counterparts for different facility types, as follows:

$$AVO = \sum_h \left(W_h \times AVO_h\right)$$

$$\sigma = \left[\sum_h \left(W_h^{\,2} \times \sigma_h^{\,2}\right)\right]^{1/2}$$

$$T = Z \times \left[\sum_h \left(\frac{W_h^{\,2} \times \sigma_h^{\,2}}{N_h}\right)\right]^{1/2} = 1.96 \times \left[\sum_h \left(\frac{W_h^{\,2} \times \sigma_h^{\,2}}{N_h}\right)\right]^{1/2}$$

where

AVO = overall average vehicle occupancy for multiple facility types,

σ = the overall composite standard deviation for multiple facility types,

W_h = the relative proportion of the total factored traffic volumes for facility type h,
N_h = the number of facility types, and
T = the overall desired tolerance for multiple facility types.

Table 3-7 shows the countywide statistics that were estimated with the aggregated occupancy data. As shown by the county AVO data for different time periods presented in Figure 3-4, the p.m. peak carried the highest AVO of 1.2199 persons per vehicle. The AVO of 1.2036 persons per vehicle for the off-peak period was the second highest, 1.2011 persons per vehicle for the midday period was third highest, and 1.1287 persons per vehicle for the a.m. peak was the lowest. Compared to the values measured by the means of the location AVOs, the p.m. peak decreased by 0.0007 persons per vehicle (0.06%), the off-peak decreased by 0.0055 persons per vehicle (0.45%), the midday period increased by 0.0025 persons per vehicle (0.21%), and the a.m. peak decreased by 0.0135 persons per vehicle (1.18%). For the estimate of the span of entire daylight hours, the county AVO was 1.1902 persons per vehicle. This corresponded to a decrease of 0.0043 persons per vehicle (0.36%) compared to the mean of the location AVOs. The composite standard deviation and the actual precision for the entire county were 0.0338 and 0.0382, respectively. Although this was slightly higher than the specified desired level of 0.03, the survey results were considered valid.

Table 3-7. Countywide Statistics Estimated with Weighted/Aggregated Occupancy Data.

Time-Period Stratum	AVO	σ	T
A.M. Peak	1.1287	0.0458	0.0519
Midday	1.2011	0.0550	0.0623
P.M. Peak	1.2199	0.0438	0.0495
Off-Peak	1.2036	0.0364	0.0411
Daylight Hours	1.1902	0.0338	0.0382

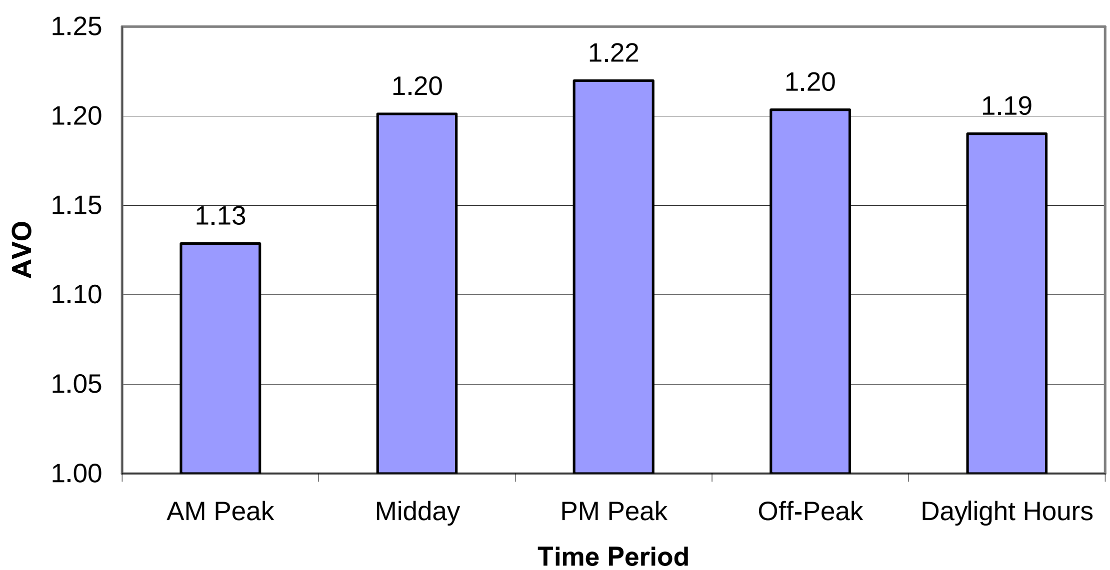


Figure 3-4. Comparisons of Countywide AVOs Estimated with Weighted/Aggregated Data.

It is not an unusual practice to use the countywide AVO of one time period to approximate its daylight-hour equivalent, especially by using either the a.m. or p.m. peak data. From the results provided in this study, note that the countywide AVO of the midday or off-peak period showed the closest values to the countywide AVO for all daylight hours. Therefore, if a vehicle occupancy study could only be conducted for one time period, the observation for either the midday or off-peak period would offer a better approximation of the full daytime estimate.

The difference in countywide AVOs for different time periods, as estimated by the means of the location AVO and the composite values of weighted facility-type AVOs, was also examined. The one-sample *T* test was again performed to determine whether these two county AVOs were compatible. Specifically, the hypotheses tested were:

H_0: the mean of the location AVOs for the entire county = AVO
Ha: the mean of the location AVOs for the entire county ≠ AVO

Table 3-8 shows that the two-tailed *P*-values for all cases were greater than 0.05. Thus, the data cannot provide enough evidence against the null hypothesis to favor the alternative hypothesis at a significance level of 0.05. It was concluded that there was no significant difference between the county AVOs estimated with the means of the location AVOs or with the composite values of weighted facility-type AVOs. Note that the standard deviation of the mean of the location AVOs was consistently higher than the associated composite standard deviation for each individual time period.

Table 3-8. One-Sample *T* Test for Countywide AVOs.

Time-Period Stratum	Sample Size	Mean AVOi	Standard Deviation	*t* Statistic	Degrees of Freedom	*P*-Value (two-tailed)
A.M. Peak	47	1.1422	0.0757	1.223	46	0.228
Midday	47	1.1986	0.0836	-0.205	46	0.838
P.M. Peak	47	1.2205	0.0744	0.060	46	0.953
Off-Peak	48	1.2091	0.0629	0.607	47	0.547
Daylight Hours	48	1.1945	0.0623	0.479	47	0.634

3.2.4. Comparisons between Moving and Stopped Vehicles

The primary goal of observing moving and stopped vehicles at the same locations was to identify the degree of difference in AVOs between the two. After data collection was conducted for about two months, feedback from some crew members indicated some difficulty with counting occupants in vehicles traveling at high speed or in vehicles that had tinted windows. It was decided that two sets of data would be collected at some selected sites at mid-block locations for moving vehicles, as well as at an upstream or downstream intersection stopline for stopped vehicles. The regular data collection effort performed in June and July 2006 was extended for this task, using the list of selected segments for surface street surveys.

Tables A-16 and A-20 in Appendix A show the raw counts, factored counts, and AVO for the selected three observation locations for different time periods. Because the observations for stopped vehicles targeted only the vehicles stopped at intersections, the observed population was much smaller than the population observed in moving vehicles. The ratio between stopped and moving vehicles observed ranged from 12% to 90% for different time periods over three observation locations.

Table 3-9 shows the difference in location AVO for the selected three locations. Some differences in occupancy were found between moving and stopped vehicles. For different time periods and locations, the differences in vehicle occupancy vary by up to 0.1354 persons per vehicle (11.8%) for the a.m. peak, 0.1205 persons per vehicle (9.91%) for midday, 0.0371 persons per vehicle (3.01%) for the p.m. peak, 0.0358 persons per vehicle (3.00%) for off-peak hours, and 0.0212 persons per vehicle (1.72%) for the entirety of daylight hours. Table 3-10 shows that the AVOs from stopped vehicles are consistently higher at all three locations for most time periods. Overall, the increase in AVO from stopped vehicles during the daylight hours was 0.0129 persons per vehicle, or 1.03%.

3.3. Site-Specific Study

One surface street site on Flagler Street was selected for the site-specific study. Data were collected from 2:00 to 6:00 p.m. for seven days within a single week. The time periods for analysis included the p.m. peak period (4:00 – 6:00 p.m.), off-peak period (2:00 – 4:00 p.m.), and p.m. period (2:00 – 6:00 p.m.). The field data collected using short-count techniques were expanded to a full-hour base. Tables A-21 and A-23 in Appendix A show the raw counts, factored counts, and AVO for each observation date for selected time periods.

With the same formula used for the area-wide study, the stratum statistics for different time periods are summarized in Table 3-11. No significant difference was found between the AVO of the p.m. peak and off-peak periods. Note that the precision levels obtained were relatively higher than the design value of 0.03. This was because the actual precision level accounted for the AVO daily variation from Monday through Sunday, while the design value was for weekdays' variation from Tuesday through Thursday.

3.3.1. Day-of-Week Variation

The AVO variation among the days within a week is shown in Figure 3-5. A general pattern confirmed that Sunday has the highest AVO for the study time periods, followed by Saturday and weekdays. In terms of the difference in AVO between the p.m. peak and off-peak, there was a relatively larger difference on Thursday and Friday. The AVOs of these two time periods for other days showed no significant difference. Likewise, there was no consistency to the pattern showing that the p.m. peak AVO was higher than the off-peak AVO among the different days of the week.

Table 3-9. Location AVO Difference Between Moving and Stopped Vehicles.

Survey Roadway	Intersecting Roadways	Date	Observed Vehicles	AVO_i	Diff.	%Diff.
A.M. Peak Period (7:00 – 9:00 a.m.)						
Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	1.1665	+0.0078	+0.67%
			Stopped	1.1743		
SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	1.1481	+0.1354	+11.80%
			Stopped	1.2835		
SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	1.1821	+0.0244	+2.07%
			Stopped	1.2066		
Midday Period (11:00 a.m. – 1:00 p.m.)						
Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	1.2525	+0.0861	+6.88%
			Stopped	1.3386		
SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	1.2155	+0.1205	+9.91%
			Stopped	1.3359		
SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	1.2428	-0.0099	-0.80%
			Stopped	1.2329		
P.M. Peak Period (4:00 – 6:00 p.m.)						
Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	1.2632	-0.0004	-0.03%
			Stopped	1.2628		
SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	-	-	-
			Stopped	1.1312		
SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	1.2325	+0.0371	+3.01%
			Stopped	1.2697		
Off-Peak Period (9:00 – 11:00 a.m. and 1:00 – 4:00 p.m.)						
Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	1.2956	-0.0046	-0.35%
			Stopped	1.2910		
SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	1.1963	+0.0358	+3.00%
			Stopped	1.2322		
SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	1.2638	+0.0022	+0.17%
			Stopped	1.2660		
Daylight Hours (7:00 a.m. – 6:00 p.m.)						
Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	1.2667	+0.0188	+1.48%
			Stopped	1.2854		
SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	-	-	-
			Stopped	1.2318		
SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	1.2312	+0.0212	+1.72%
			Stopped	1.2524		

Table 3-10. Aggregated AVO Difference between Moving and Stopped Vehicles.

Time-Period Stratum	Sample Size	Observed Vehicles	AVO	Diff.	%Diff.
A.M. Peak	3	Moving	1.1630	+0.0596	+5.13%
		Stopped	1.2227		
Midday	3	Moving	1.2328	+0.0749	+6.08%
		Stopped	1.3077		
P.M. Peak	2	Moving	1.2563	+0.0093	+0.74%
		Stopped	1.2656		
Off-Peak	2	Moving	1.2551	+0.0150	+1.20%
		Stopped	1.2702		
Daylight Hours	2	Moving	1.2585	+0.0129	+1.03%

Table 3-11. Site-Specific AVOs Statistics by Time Period.

Stratum	AVO_h	σ_h	T_h
P.M. Peak (4:00 – 6:00 p.m.)	1.3875	0.1758	0.1303
Off-Peak (2:00 – 4:00 p.m.)	1.3786	0.1990	0.1474
P.M. Period (2:00 – 6:00 p.m.)	1.3834	0.1853	0.1372

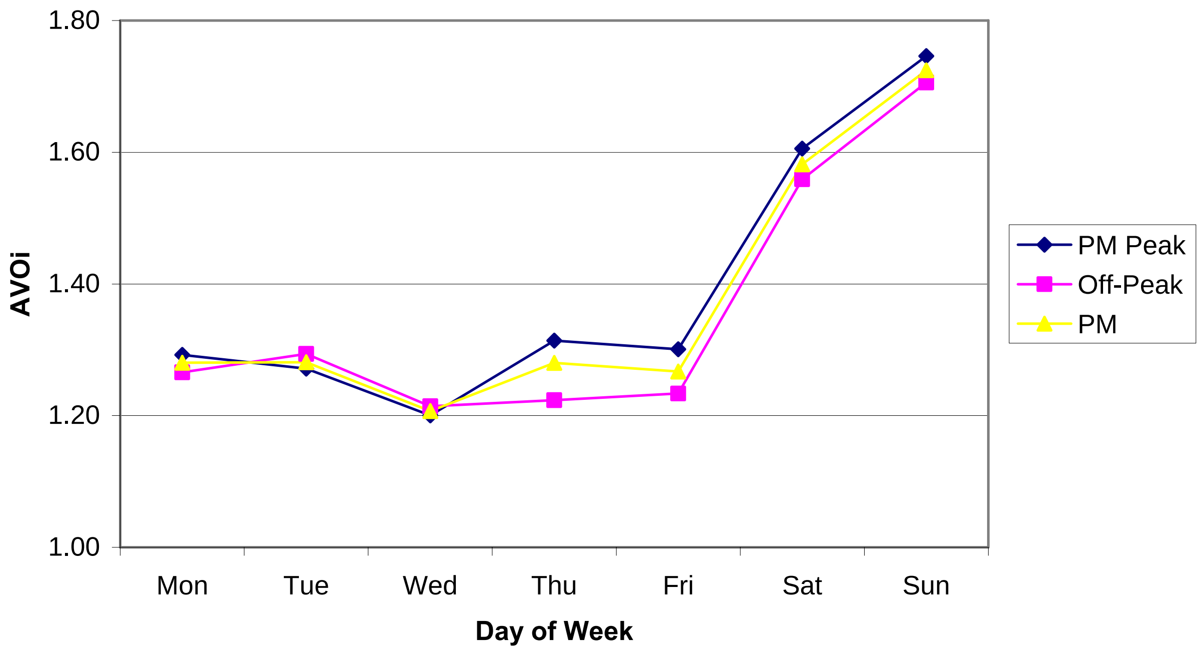


Figure 3-5. Day of Week Variations for Site-Specific Study.

3.3.2. Comparisons Among Multiple Locations in a Corridor

A primary purpose of the multiple-location counts was to determine the potential variation in vehicle occupancy along a corridor. Two additional locations, at SW/NW 82nd Ave. and SW/NW 108th Ave., were added to the SW/NW 90th Ave. location at which occupancy data were being collected throughout a week. The additional data collection at these new locations was performed only on Thursday of that week over the same time period (i.e., from 2:00 to 6:00 p.m.).

The raw counts, factored counts, and AVO for each observation location for selected time periods are provided in Table A-24 in Appendix A. As shown in Figure 3-6, the off-peak AVOs were consistently higher than the p.m. peak AVOs for the three locations. Compared to the results from the observation location near 90th Ave., the AVO varied by up to about +12% and +9% for off-peak and p.m. peak, respectively. This shows that the AVOs can vary significantly along one roadway. In this case, the AVO at SW/NW 82nd Ave. is significantly higher likely because of the higher proportion of shopping trips (which typically have a higher vehicle occupancy) to and from a major shopping center in the area (i.e., in the vicinity of the Mall of the Americas).

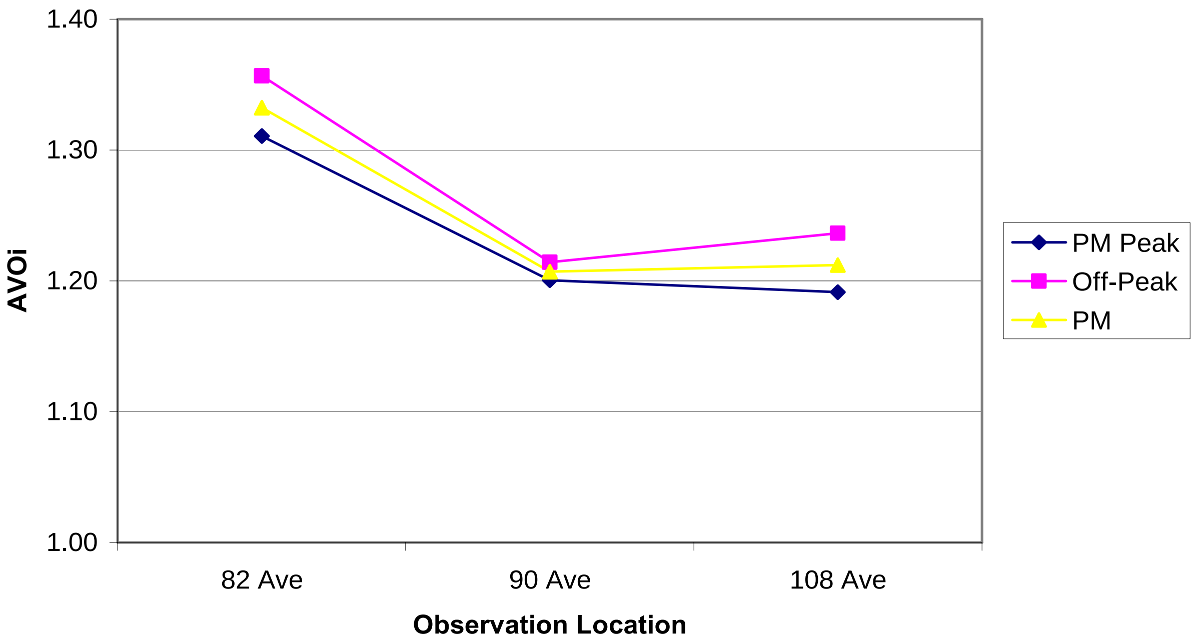


Figure 3-6. AVO Variations Among Multiple Locations Along a Selected Roadway.

CHAPTER 4
UPDATED POCKET PC FIELD DATA COLLECTION SYSTEM

4.1. Background

To facilitate field data collection, a Pocket PC application tool was developed as part of the Phase I study (Gan *et al.*, 2005). The tool attempts to eliminate the need for manual data post-processing by allowing the user to make use of the touch-screen interface on a Pocket PC to record the number of occupants for different types of vehicles and different lane numbers. Based on lessons learned from the data collection effort described in Chapter 2, the system was modified accordingly. The next section of this chapter documents all of the updates to the system, and the following sections present an updated version of the "User's Guide" that reflects these updates.

4.2. System Updates

Based on field experience, the original design of the tool was simplified in this Phase II study primarily to speed up the data recording process on location. Specially, the following modifications were made:

- The **Save** button was removed and replaced with instant recording as soon as a button is tapped.

- The buttons for recording the number of occupants were made larger, with the frequently-used buttons for "1" and "2" occupants made the largest. This makes the Pocket PC easier to tap and also reduces the potential for pressing the wrong button.

- A **Delete** button was added to allow quick deletion of a record that was just mistakenly entered.

- The option to specify a lane number was removed, as it later became obvious that applications that require lane numbers are rare. This option required an additional tap, which can become burdensome to users in the field.

- Similarly, the option to specify vehicle type was also removed, as potential applications for the system are likely to apply to passenger cars only. This option required an additional tap that could slow down operations in the field.

4.3. System Requirements and Installation

The Pocket PC application is a typical Windows installation designed to run on the Microsoft Windows CE operating system. The system can work with any Pocket PC that has a minimum viewing screen of at least 3.5". To install the system onto the Pocket PC, follow these steps:

1. Set up the connection between the Pocket PC and the desktop computer.
2. Insert the install CD into the CD-ROM drive.

3. Use Windows Explorer to find **Setup.exe** in the **CD1** folder on the CD-ROM drive and then double click the **Setup.exe** icon.
4. Choose a destination folder when prompted.
5. Continue to follow on-screen instructions until the screen shown in Figure 4-1 pops up.
6. Click **Yes** to select the default option.

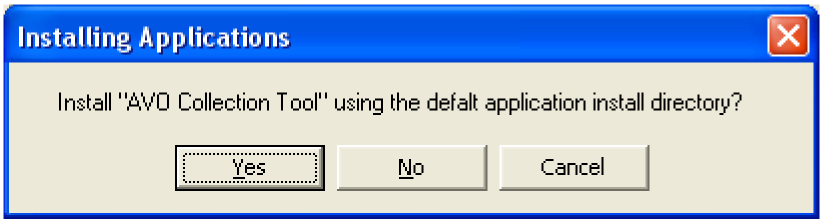


Figure 4-1. Determine Application Storage.

4.4. Main Screen

To start the application on the Pocket PC, tap the **Start|Programs** menu. This will bring up the screen shown in Figure 4-2. This screen allows the user to select whether to create a new file or open an existing file, as well as to input the general roadway location information.

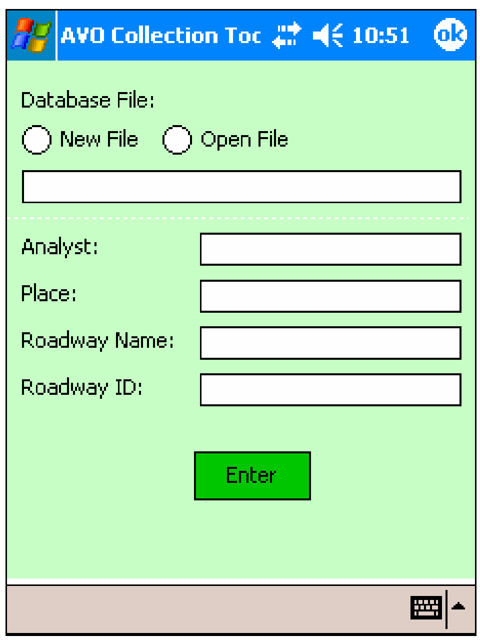


Figure 4-2. Input Screen for General Information.

4.4.1 Creating a New File

To create a new file, follow the steps below:

1. Tap the **New File** radio button to bring up the screen shown in Figure 4-3.
2. Enter a new file name in the textbox.

3. Choose the folder for saving the new file from the **Folder** list box.
4. Choose a storage location from the **Location** list box.
5. Tap **OK** to finish creating a new file. The file path and name will be shown in the text box under the radio buttons as shown in Figure 4-2.
6. Enter the rest of the information shown in Figure 4-2.

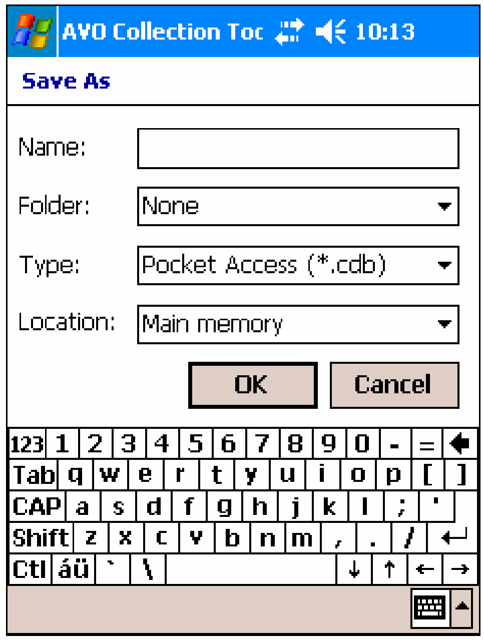


Figure 4-3. Create a New File.

4.4.2. Opening an Existing File

To open an existing file, follow the steps below:

1. Tap the **Open File** radio button to bring up the screen shown in Figure 4-4.
2. Select a folder name from the **Folder** list box. All of the files with the selected file type (*.cdb) in the folder will be displayed.
3. Double tap a file name to open. The file path and name will be shown in the textbox under the radio buttons in Figure 4-2.
4. Enter the rest of the information shown in Figure 4-2.

4.4.3. Entering Name and Location Information

The general location information shown in Figure 4-2 can be added or edited after a new file is created or an existing file is opened, as follows:

1. Tap the **Name** textbox.
2. Tap the  icon in the bottom right corner to bring up a keyboard to key in the name.
3. Repeat Steps 1 and 2 for Place, Roadway Name, and Roadway ID.
4. Tap **Enter** on the screen shown in Figure 4-2 to start entering occupancy data.

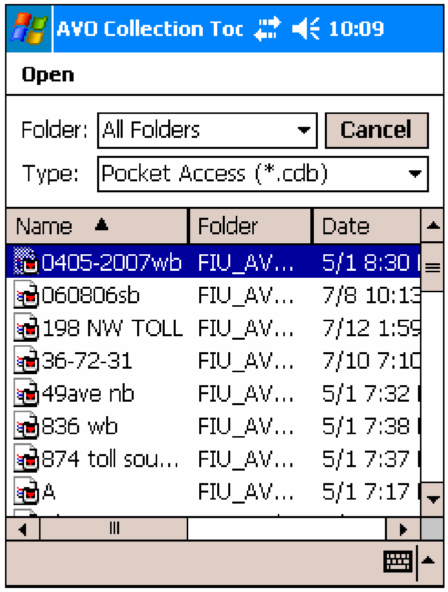


Figure 4-4. Open an Existing File.

4.5. Data Entry Screen

Figure 4-5 shows the data entry screen. The screen provides buttons to enter up to seven occupants in a vehicle. In the case when a vehicle has more than seven occupants, which is extremely rare, the user may record seven occupants for the current vehicle and add the difference to the total occupants of the next vehicle. For example, if a vehicle has eight occupants, it will be recorded as having had seven occupants, and the next vehicle will be recorded as having had the number of occupants in the vehicle plus one. This assures that all occupants are counted and that the average vehicle occupancy rate is not affected.

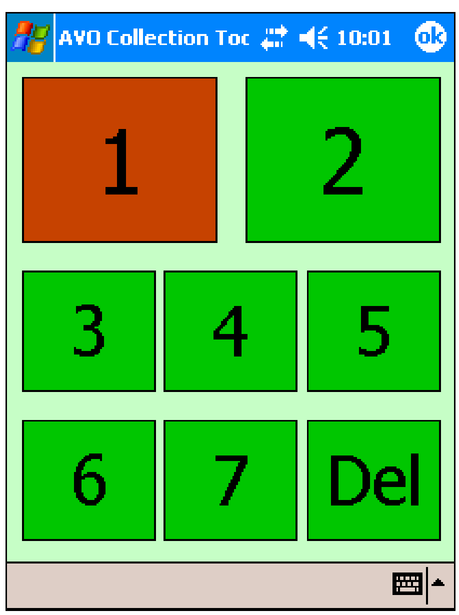


Figure 4-5. Data Entry Screen.

Note that a larger button is used for one- and two-occupant vehicles because, obviously, most vehicles have either one or two occupants. A number is recorded in the data file instantly as soon as one of these buttons is tapped on. The button will turn to red to signal that a number has been recorded. At the bottom right corner is a delete button that allows the user to quickly delete the preceding record that has just been entered incorrectly. After finishing a data collection session, simply tap the **ok** button to exit from the screen.

4.6. Transferring Field Data from Pocket PC to Desktop Computer

After each data collection session, data should be transferred to a desktop computer hosting the data collection process. The conversion of file format is automatically handled by ActiveSync, which is a synchronization program that is needed to transfer and synchronize data between the desktop computer and Windows Mobile devices. The program, which must be installed to the desktop computer separately, uses file filters to automatically handle conversions between desktop computer file formats and Windows CE–based device file formats. For more information about ActiveSync, please visit the following website: http://www.microsoft.com/windowsmobile/activesync/default.mspx.

During the file transfer process, the database file in the Pocket PC must be converted from its **.cbd** format to the **.mdb** format used in the desktop version. The Microsoft ActiveX Data Objects (ADO) for Windows CE SDK, or ADOCE, provides the file filter, Adofiltr.dll, to handle this conversion automatically. For more information about ADOCE, please visit the following website: http://support.microsoft.com/kb/265796.

The steps for transferring a database file from a Pocket PC to a desktop computer are as follows:

1. Select **Export Database Tables** from the **Tools** menu in the **Mobile Devices** window.
2. Type the path and filename of the database to be placed on the desktop computer in the **Location** box.
3. Select all of the tables to be copied in the **Select the tables to copy** box.
4. Select the box labeled **Overwrite existing tables and/or data**; click **OK**. Selecting this option will cause the converted table from the device to replace the table in the desktop database file.
5. Open the database file in Microsoft Access to see the transferred database.

CHAPTER 5
FACTORS AFFECTING AVO: EVIDENCE FROM ACCIDENT DATA

5.1. Introduction

While field collection methods have the benefit of being more up to date and can be tailored to specific application needs in terms of location, sample size, and accuracy, they are also much more costly to conduct, especially for purposes of continuous monitoring for which a time series of data must be collected. This has led several states (Ahuja and Hanscom, 1996; Asante *et al*., 1996; Gaulin, 1991) to consider using existing data sources, among which are traffic accident records. The number of occupants in a vehicle involved in an accident is routinely recorded in many states by police officers at the site of the accident. The use of this data source for vehicle occupancy data offers the following benefits over the traditional field data collection methods:

- It is both cost effective and safe as it involves no field observation.
- It does not require any data post-processing, which is tedious and time consuming.
- It covers all time periods, including night hours when field data collection cannot be performed.
- It counts all occupants, including small children, who are difficult for observers to see in the field.
- It is not subject to visibility problems due to tinted vehicle windows.
- It is not subject to data quality problems as a result of field crews experiencing fatigue, providing poor job performance, over- or under-counting, etc.

This chapter describes an effort to apply the vehicle occupancy data in Florida's accident records to examine the impacts the following factors may have on vehicle occupancy: accident year, accident month, accident day of week, accident time-of-day, county location, roadway type, accident severity, driver's age group, driver's gender, driver's race, and weather conditions.

5.2. Data Preparation

A total of 16 years (1990–2005) of accident records for Florida's state roadway system were used in the analysis in this chapter. The data were obtained from the Florida Department of Transportation (FDOT) and integrated into a single database. Only passenger cars were included. For each accident, the vehicle occupancy information for up to two vehicles involved in the accident was extracted, and the AVO for a specific category was calculated as follows:

$$AVO_j = \frac{\sum_i P_{ij}}{V_j}$$

where P_{ij} is the number of persons in vehicle i in category j and V is the total number of vehicles in category j.

One issue in the data preparation process was to determine the data intervals for some of the factors considered. The use of too few intervals can mask the differences in AVO. On the other hand, the use of too many intervals will result in sample sizes being too small to achieve the desired confidence in the AVO estimates. Based on these considerations, the original data intervals for some of the variables considered were re-classified for this analysis as follows:

- The original data include the specific hour in which the accident occurred. The hours were re-classified into the following intervals: 1) 6:00 a.m. – 6:59 a.m., morning period; 2) 7:00 a.m. – 8:59 a.m., morning peak period; 3) 9:00 a.m. – 3:59 p.m., off-peak period; 4) 4:00 p.m. – 5:59 p.m., afternoon peak period; 5) 6:00 p.m. – 10:59 p.m., evening period; and 6) 11:00 p.m. – 5:59 a.m., late night and early morning. The purpose of the 6:00 a.m. – 6:59 a.m. morning period was to evaluate the transition from the late-night period to the morning peak.

- Florida's counties were classified into three urban-size groups: 1) large urban counties with county populations over 500,000; 2) medium-size counties with county populations under 500,000 and over 100,000; and 3) rural counties with populations under 100,000.

- The original data included the specific age of each driver, which was re-classified into one of the following nine groups: 16-19, 20-24, 25-29, 30-39, 40-49, 50-59, 60-69, 70-79, and ≥80.

- Roadway functional classifications were re-classified from their original classes in FDOT's Roadway Characteristics Inventory (RCI) to the following four major groups: collectors, minor arterial, major arterial, and freeways.

5.3. Statistical Analysis Methods

Both parametric and non-parametric analyses of variance (ANOVA) were used to determine if there are significant differences in AVO among the different categories of independent variables (i.e., the factors being examined for their impact on the AVO). The general parametric ANOVA model used for the AVO variance analysis is defined as follows:

$$Y_{ij} = \mu_i + \varepsilon_{ij}$$

where

Y_{ij} = the jth observed vehicle occupant for group i,
μ_i = the group mean, and
ε_{ij} = the random error associated with individual observations.

Unlike parametric tests, nonparametric tests do not require the assumptions of stabilized variance and normally distributed data, which usually affect the F-test and t-test. Thus, the nonparametric tests were used essentially to check the conclusions of the parametric ANOVA tests.

The Kruskal–Wallis H-test (McClave and Benson, 1988) is often viewed as the nonparametric equivalent of the parametric one-way analysis of variance (one-way ANOVA). The advantage of the Kruskal–Wallis H-test is that no assumptions about the nature of the sampled populations are needed. The H-test statistic is given by:

$$H = \frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1)$$

where

n_i = the number of measurements in the ith sample,
n = the total sample size ($n=n_1+n_2+\ldots+n_k$), and
R_i = the rank sum of the ith sample.

Another nonparametric test called the Friedman F_r test (McClave and Benson, 1988) was also used to test for significant AVO differences across different factor groups, such as time-of-day interval and accident severity. Because the F_r test supported the alternative hypothesis, the Wilcoxon signed-rank test for paired-difference designs was used. With the Wilcoxon test, selected pairs of treatments are compared to identify which level of the group is significantly different with respect to AVOs. The Friedman F_r test is defined as follows:

$$F_r = \frac{12}{bp(p+1)} \sum_{i=1}^{p} R_i^2 - 3b(p+1)$$

where

b = the number of blocks (i.e., counties),
p = the number of treatments (i.e., time-of-day intervals, accident severity), and
R_i = the rank sum of the ith treatment, where the rank of each measurement is computed relative to its position within its own block.

The ANOVA test results based on the 2005 accident data (the latest available) are summarized in Table 5-1, which includes the overall, main effect, and contrast results. The overall F-test shown at the top of Table 5-1 is for all ten main effects in the model, and it indicates that at least one of these factors significantly affects AVO data at the 95% significance level.

The middle section of Table 5-1 lists the seven factors with ANOVA results for each. The F value associated with each factor is used to test the null hypothesis that the treatment (or level or group) means are equal. $Pr > F$ gives the level of significance associated with the F value.

The contrast section listed in the bottom of Table 5-1 shows ANOVA results for selected treatment levels. Contrasts compare treatment means to determine significant differences among the levels. For example, given that there were significant differences in AVO data among the time-of-day intervals, contrasts were used to test if the a.m. peak AVO data are significantly different from the p.m. peak AVO data.

Table 5-1. Results of ANOVA Test.

Source	DF	Sum of Squares	Mean Square	*F* Value	*Pr* > *F*
Model	45	7087.3421	157.4965	242.97	<.0001
Error	260444	168820.7461	0.6482		
Corrected Total	260489	175908.088			
Factors	**DF**	**Type I SS**	**Mean Square**	***F* Value**	***Pr* > *F***
Severity	2	1513.879176	756.939588	1167.75	<.0001
Weekday_Group	3	2446.706441	815.568814	1258.20	<.0001
Month_Group	3	26.786878	8.928959	13.77	<.0001
Hour_Group	6	821.791828	136.965305	211.30	<.0001
County_Group	2	333.004620	166.502310	256.87	<.0001
Functional Class	10	328.088703	32.808870	50.62	<.0001
Driver Age_Group	8	959.839016	119.979877	185.10	<.0001
Driver Race	3	510.087734	170.029245	262.31	<.0001
Driver Gender	1	100.919664	100.919664	155.69	<.0001
Weekday	3	32.582228	10.860743	16.76	<.0001
Weather	4	13.655780	3.413945	5.27	0.0003
Contrast	**DF**	**Contrast SS**	**Mean Square**	***F* Value**	***Pr* > *F***
Fall vs Summer	1	32.11088607	32.11088607	47.66	<.0001
Fall vs Winter	1	16.64394871	16.64394871	24.70	<.0001
Spring vs Winter	1	0.08336151	0.08336151	0.12	0.7250
Summer vs Winter	1	5.79238464	5.79238464	8.60	0.0034
Morning Period vs AM Peak	1	5.6275180	5.6275180	8.68	0.0032
AM Peak vs PM Peak	1	270.7720362	270.7720362	417.73	<.0001
PM Peak vs Early Evening	1	12.8135720	12.8135720	19.77	<.0001
PM Peak vs Late Evening	1	87.6609210	87.6609210	135.24	<.0001
Mon. vs Tue.&Thr.	1	3.5400978	3.5400978	5.33	0.0210
Tue.&Th.r vs Fri.	1	106.9256005	106.9256005	160.98	<.0001
Fri. vs Weekends	1	938.3923881	938.3923881	1412.76	<.0001
Thr. vs Fri.	1	46.1432708	46.1432708	69.48	<.0001
Fri. vs Sat.	1	565.2579437	565.2579437	851.19	<.0001
Sat. vs Sun.	1	34.1376941	34.1376941	51.41	<.0001
Mon. vs Tue.	1	3.5921517	3.5921517	5.41	0.0200
Tue. vs Wed.	1	0.6033771	0.6033771	0.91	0.3405
Wed. vs Thu.	1	6.7420803	6.7420803	10.15	0.0014
Mon. vs Fri.	1	43.1139781	43.1139781	64.91	<.0001
...					

5.4. Identification of Factors Affecting AVO

5.4.1. Accident Year

Figures 5-1(a), 5-1(b), and 5-1(c) show the AVO trends by year (from 1990 to 2005) based on all accidents, weekday accidents, and weekend accidents, respectively. It can be seen from all three figures that the AVOs have continued to drop over the period. The AVOs remained relatively stable during the second half of the 1990s, but started to drop again from the year 2001 onward. The ANOVA test results (*F* value=122.74, *Pr*>*F* < 0.0001) indicated that there were significant differences in AVOs from the different years, which means that the decrease in AVO over the years has been significant overall. The chi-square statistics (chi-square = 1802.528, *Pr*>chi-square < 0.0001) for the Kruskal–Wallis *H*-test confirms this conclusion. Figures 1(b) and 1(c) also show that the weekend AVOs are consistently higher than the weekday AVOs.

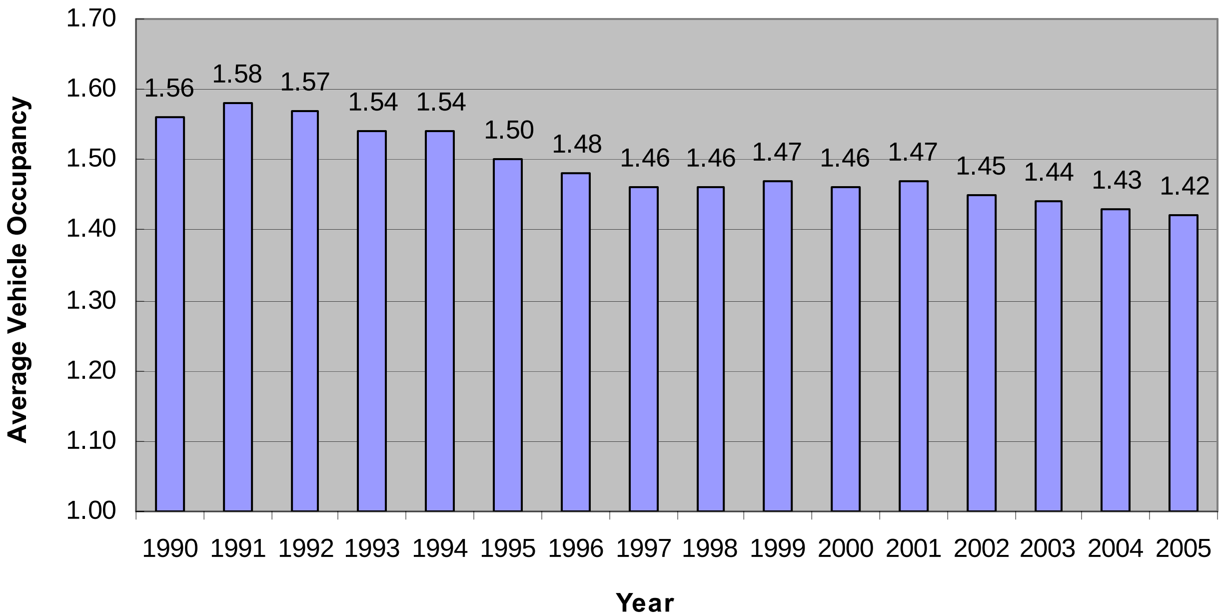


Figure 5-1(a). Daily AVO Variations by Year.

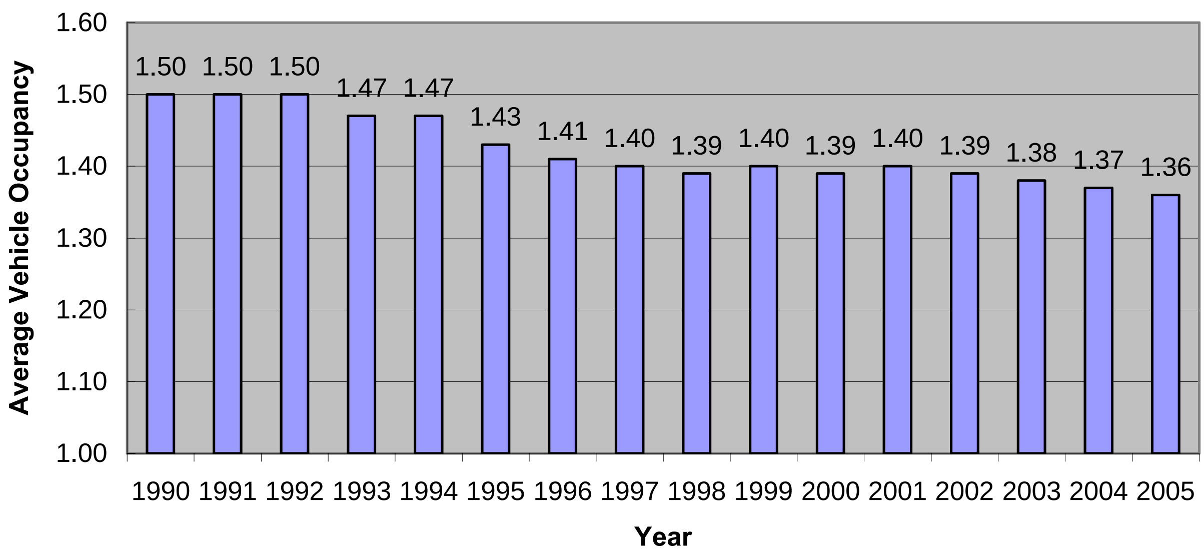


Figure 5-1(b). Weekday AVO Variations by Year.

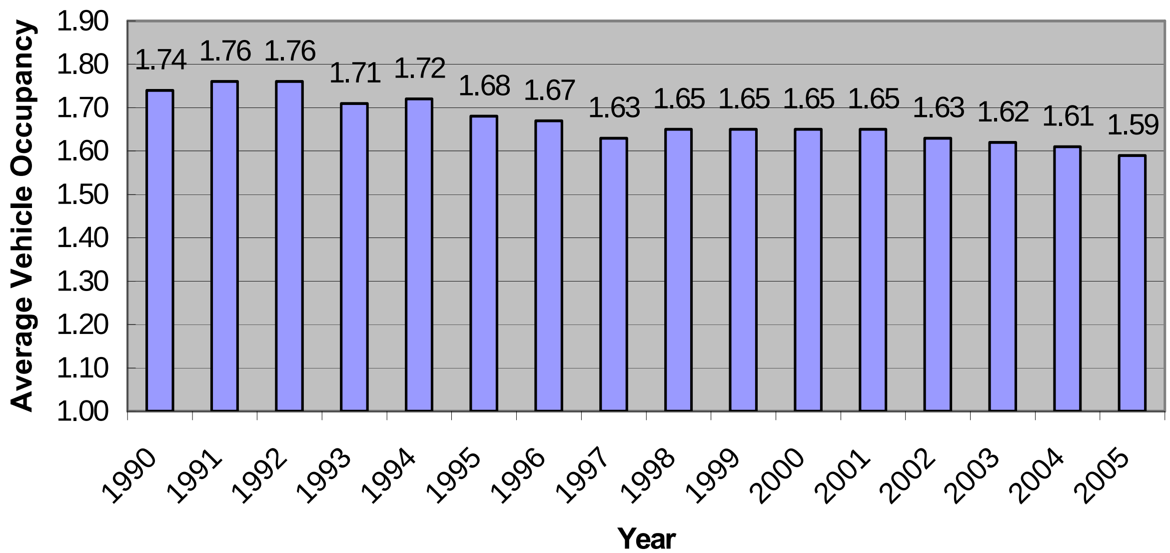


Figure 5-1(c). Weekend AVO Variations by Year.

5.4.2. Accident Month

Figure 5-2 shows the AVO trend by accident month based on the 2005 statewide accident data. The figure shows that the month of July experienced the highest AVO, while the months of August, September, and November experienced the lowest AVOs. In general, the summer months experienced higher AVOs and peaked in the month of July. Two other months that also experienced a higher AVO are March, which experienced traffic from spring breakers, and December, which experienced traffic from holiday shoppers and vacationers. Both the nonparametric and ANOVA tests indicate significant differences in AVO among the months of the year. The pair test result (*F* value=0.121, *Pr*>*F* = 0.7250) in Table 1 shows that there is no significant difference between the winter months (December through March) and the spring months (April through June).

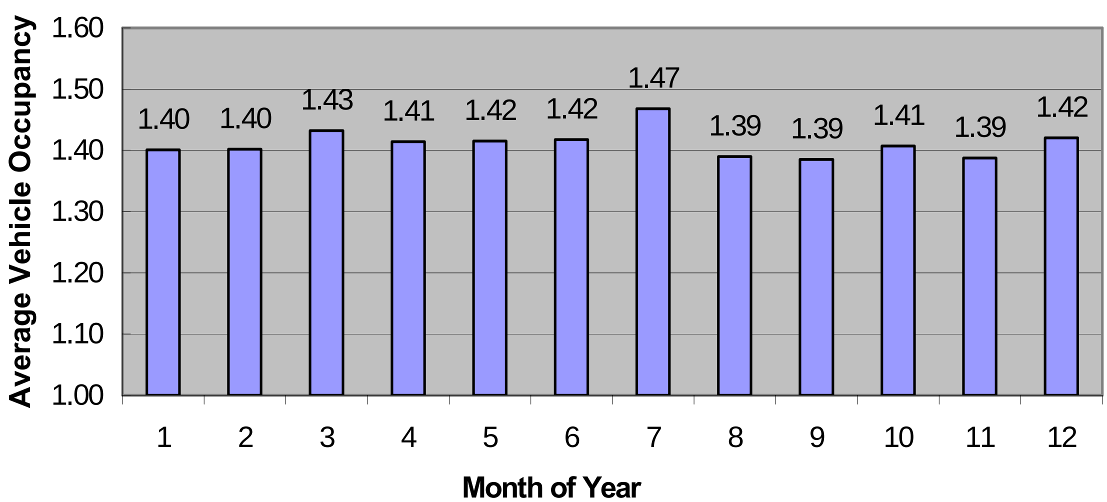


Figure 5-2. AVO Variations by Month.

5.4.3. Accident Day-of-Week

Figure 5-3 shows the AVO trend by the accident day-of-week, also based on the year 2005 statewide accident data. It is clear from the distribution that the weekday AVOs tend to be significantly lower than the weekend AVOs. The figure also shows that Sundays experienced the highest AVO, followed by Saturdays and Fridays. While Mondays and Fridays are generally excluded from data collection that aims to obtain data that are representative of a typical weekday, the distribution from Figure 3 shows that Mondays may not be that different from Tuesdays, Wednesdays, and Thursdays, which are typically days used for data collection. The AVO on Fridays is normally higher than that on other weekdays, but remains significantly lower than the AVO for weekends. The ANOVA pair test result (F value=0.91, $Pr>F$ = 0.3405) indicated that AVOs on Tuesday and Wednesday are similar, and are generally lower than other days of the week.

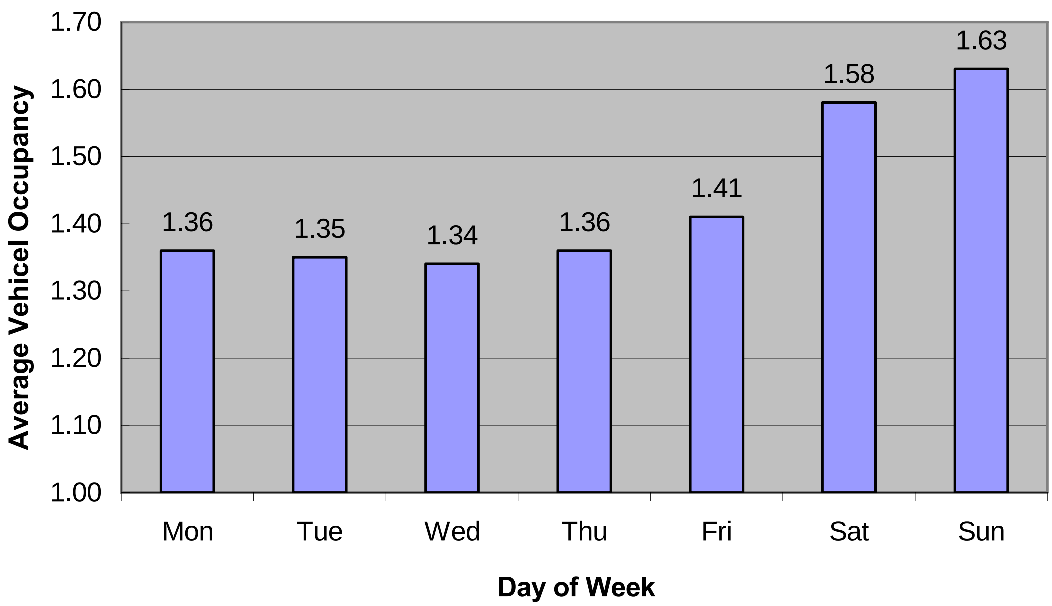


Figure 5-3. AVO Variations by Day-of-Week.

5.4.4. Accident Hour

Figure 5-4 shows that the AVOs are generally low in the early morning, increase after the morning peak period, remain level during the middle of the day, and reach a high point in the evening. The figure also shows that more vehicles involved carpools during the a.m. peak than during the p.m. peak, and that vehicles have the highest occupancy on average during the evening hours. The ANOVA test result confirmed significant differences in AVOs among the time-of-day intervals at a 95% significance level. The nonparametric Friedman F_r test was also used to test for significant AVO differences across time-of-day intervals. Each county was treated as a block, AVOs for time-of-day intervals were ranked within each block, and rank sums of each of the seven levels (time-of-day intervals) were computed. Figure 5-5 lists the test output in the SPSS statistical software. The Row Mean Scores Differ is the same as the Friedman's chi-square, and it can be seen that, with a value of 190.4363 and a p-value of

<0.0001, it is statistically significant. Hence, the distributions of the AVO for hour groups are significantly different.

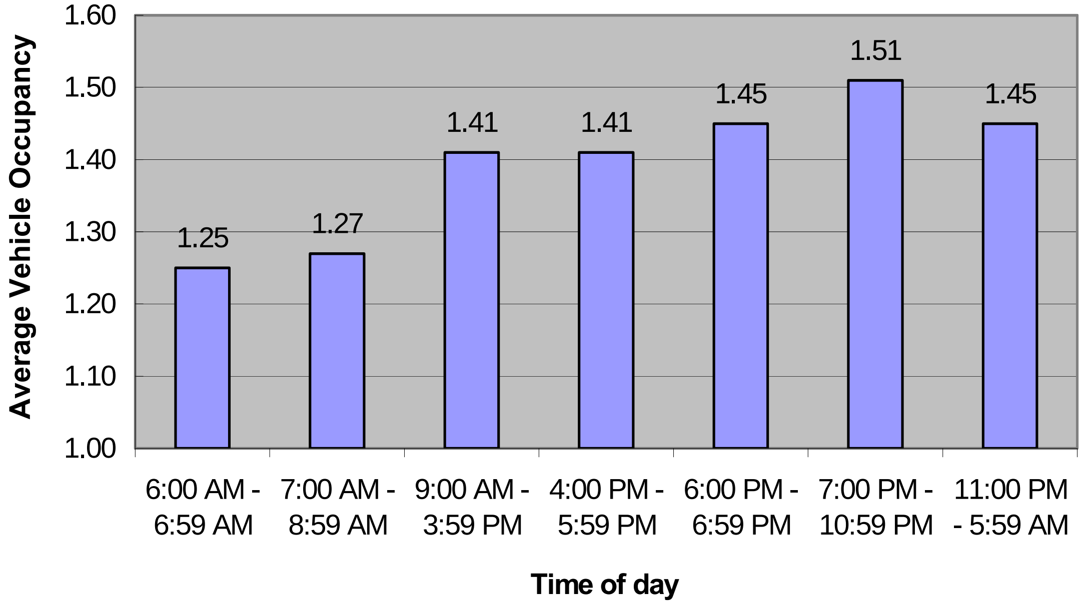


Figure 5-3. AVO Variations by Hours.

Summary Statistics for Hour_Group by AvgOfOccupants
Controlling for COUNTY

Cochran-Mantel-Haenszel Statistics (Based on Rank Scores)

Statistic	Alternative Hypothesis	DF	Value	Prob
1	Nonzero Correlation	1	11.4307	0.0007
2	Row Mean Scores Differ	6	190.4363	<.0001

Total Sample Size = 468

Figure 5-4. Friedman Test Output.

5.4.5. County

In this analysis, all 67 counties in Florida were classified into three urban-size groups: 1) large urban counties with county populations over one-half million; 2) medium-size counties with county populations under one-half million and over 100,000; and 3) rural counties with populations under 100,000. Figure 5-5 shows that the highest AVOs are present in small rural counties, and that the lowest AVOs are present in large urban counties, with medium-size urban counties ranked in the middle. The ANOVA test result (F value for this factor is 256.87, $Pr>F$ < 0.0001) in Table 5-1 and the Kruskal–Wallis H-test result (chi-square = 1636.5245, Pr>chi-square < 0.0001) both showed that the differences of AVOs for large urban counties, medium urban counties, and rural counties are significant.

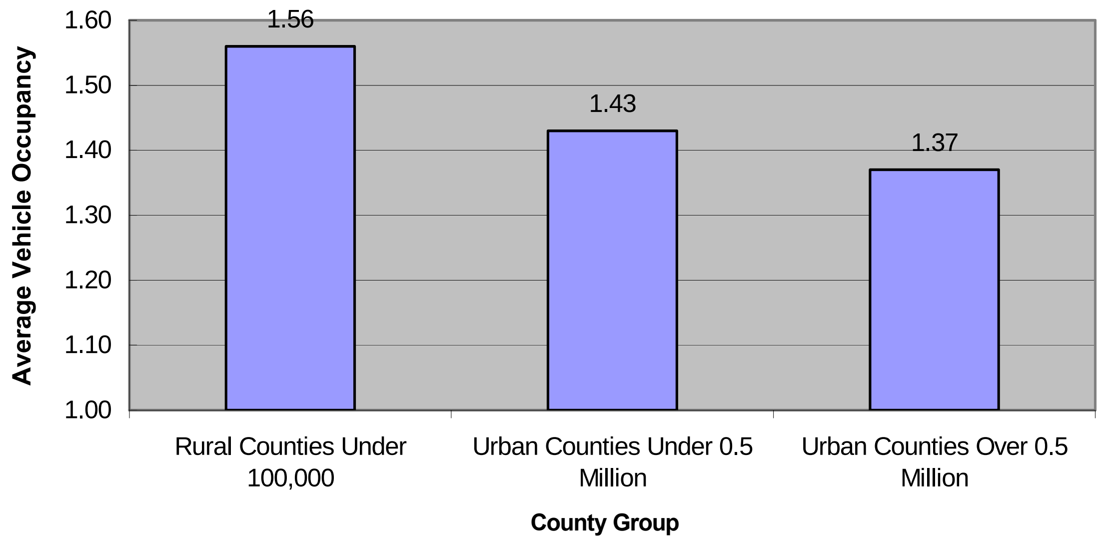


FIGURE 5-5. AVO Variations by County Group.

5.4.6. Roadway Type

Figure 5-6 shows the AVOs for four roadway functional classifications for rural and urban areas separately. In general, urban roadways with higher functional classifications experienced lower AVO as these roadways serve a higher proportion of single-occupant work trips. Interestingly, the trend is generally reversed in the case of rural roadways, as rural roadways with higher functional classifications in Florida serve a high proportion of tourists and visitors who tend to travel in groups. The ANOVA test result (*F* value for this factor is 50.62, *Pr*>*F* < 0.0001) in Table 5-1 and the Kruskal–Wallis *H*-test result (chi-square = 1074.2189, *Pr*>chi-square < 0.0001) confirmed that the differences among the AVOs are significant.

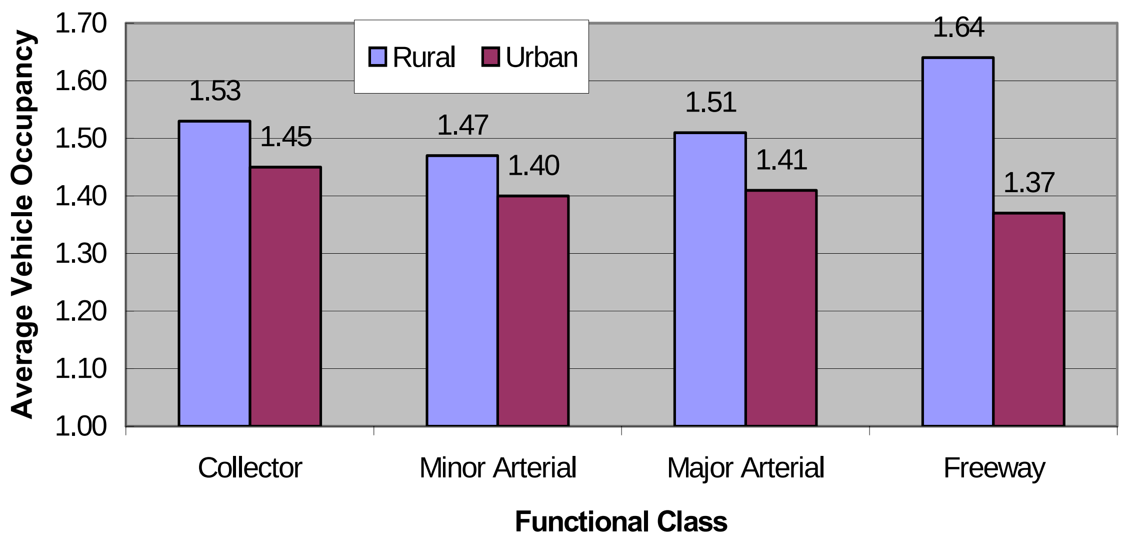


Figure 5-6. AVO Variations by Roadway Type.

5.4.7. Accident Severity

Each accident can be classified into one of three categories: property damage only (PDO), injury, and fatality. Figure 5-7 shows that fatality accident vehicles have the highest AVOs by a significant margin and that PDO accident vehicles have the lowest vehicle occupancy rates. The statistical tests also indicated that these differences are significant. These results were expected because multiple-occupant vehicles have a higher likelihood of injury and fatality than single-occupant vehicles in a given accident. The results from both the ANOVA test (F value for this factor is 1167.75, $Pr>F < 0.0001$) in Table 5-1 and the Kruskal–Wallis H-test (chi-square = 3122.1043, Pr>chi-square < 0.0001) confirmed that the differences among the AVOs are significant.

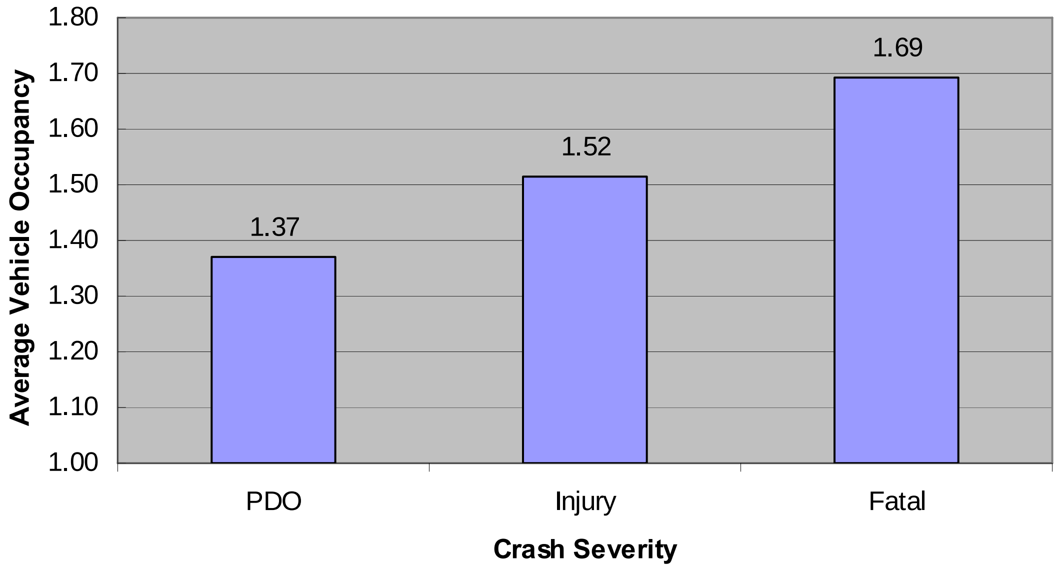


Figure 5-7. AVO Variations by Accident Severity.

5.4.8. Driver's Age

Figure 5-8 shows that the AVOs vary between different age groups. In general, the younger driver groups tend to have higher AVOs than the older driver groups, with the youngest driver group (16-19 years old) having the highest AVO. This is followed by the 30-39 and 25-29 driver age groups, respectively, which is likely due to a higher percentage of active parents with children in these age groups. The AVO dropped significantly for drivers in the 50-59 age group (i.e., the "empty nest" group) and then increased again in the 60-69 and 70-79 retired age groups. The ANOVA test result (F value for this factor is 185.10, $Pr>F < 0.0001$) in Table 5-1 and the Kruskal–Wallis H-test result (chi-square = 1559.6965, Pr>chi-square < 0.0001) confirmed that the AVOs for different driver age groups are significantly different.

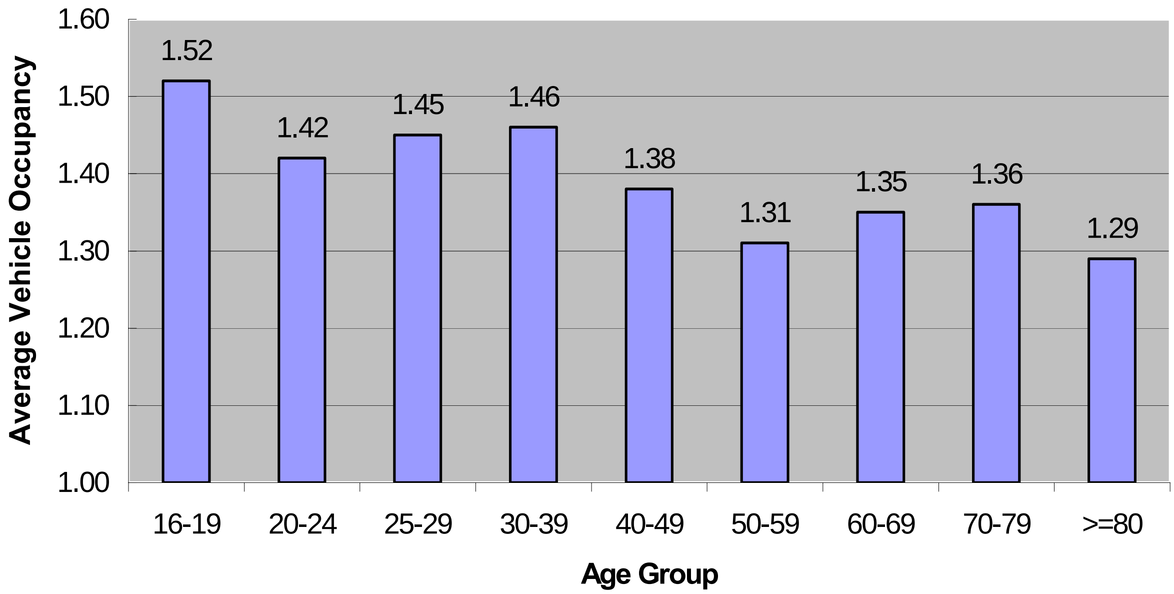


Figure 5-8. AVO Variations by Driver's Age.

5.4.9. Driver's Gender

Figure 5-9 shows that female drivers tend to have more occupants in their vehicles than male drivers. This observation was consistent throughout the different days of a week. One explanation for this travel behavior is that female drivers are more likely to be the ones to take their children to and from schools, daycare centers, doctor offices, etc. The ANOVA test result in Table 1 and the Kruskal–Wallis *H*-test result (chi-square = 110.2614, *Pr*>chi-square < 0.0001) confirmed that AVOs for vehicles driven by female drivers are significantly higher than AVOs for vehicles driven by male drivers.

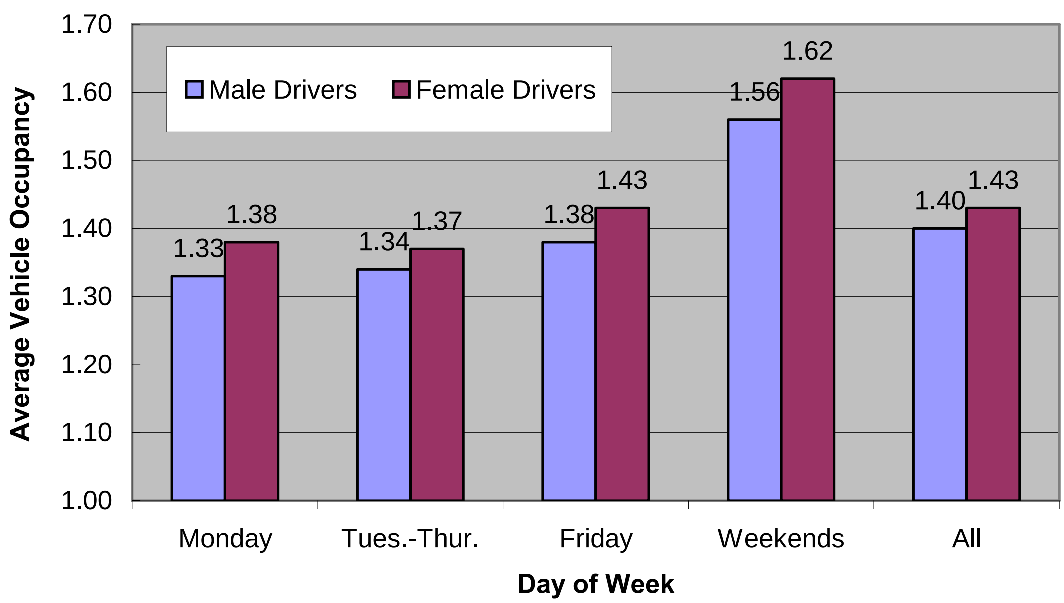


Figure 5-9. AVO Variations by Driver's Gender.

5.4.10. Driver's Race

Figure 5-10 shows the AVOs based on the driver's race. It shows that white drivers are more likely to be in a single-occupant vehicle than others, while blacks and Hispanics are more likely to carpool. This travel behavior is likely a direct result of the generally better economic well-being of the white population, which contributes to a higher vehicle ownership level and, thus, lowers their AVO. The ANOVA test showed that the difference is significant ($Pr>F < 0.0001$) at the 95% confidence level.

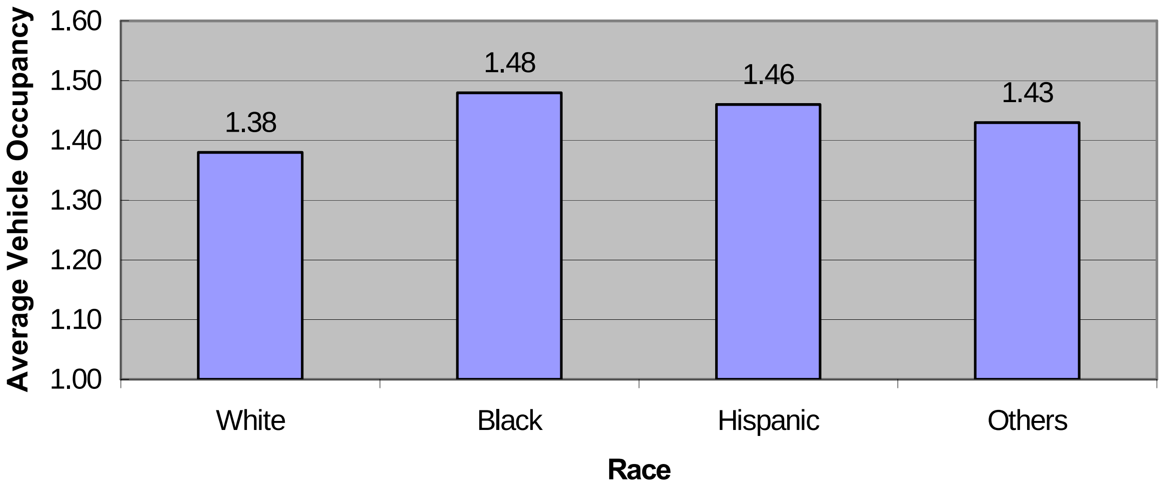


Figure 5-10. AVO Variations by Driver's Race.

5.4.11. Weather Conditions

Figure 5-11 shows the AVO trend by weather conditions. This figure shows that the vehicles involved in accidents that occurred during rain had a slightly higher AVO than vehicles involved in accidents during clear or cloudy conditions. The Kruskal–Wallis *H*-test result (chi-square = 437.6859, $Pr>$chi-square < 0.0001) indicated the AVO difference between different weather conditions is significant. Also, these vehicles occupy about 10% of the total vehicle population.

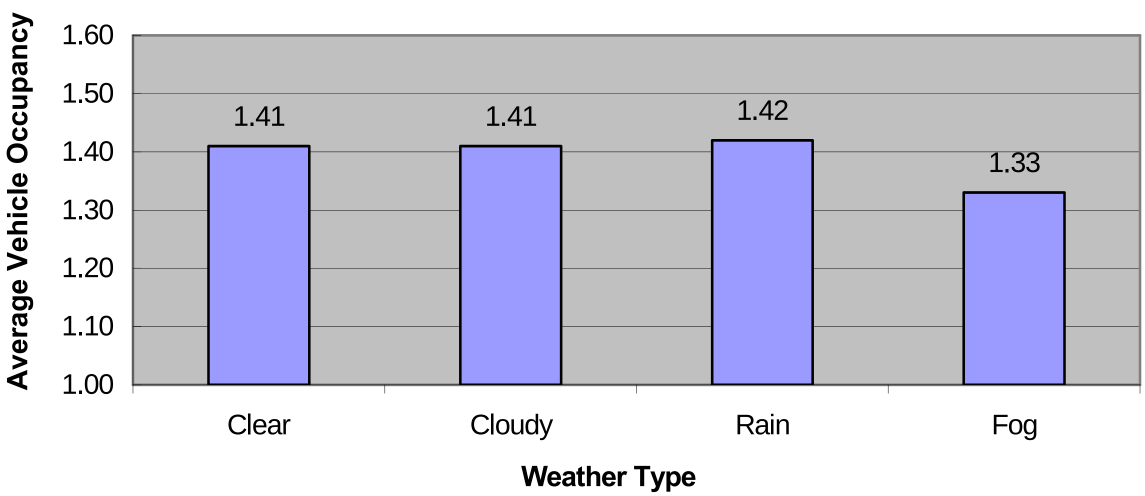


Figure 5-11. AVO Variations by Weather Type.

CHAPTER 6
ADJUSTMENTS FOR POTENTIAL BIASES IN ACCIDENT DATA

6.1. Introduction

A major problem associated with the use of accident data for vehicle occupancy has been the potential biases resulting from over-representation of younger drivers, alcohol- and drug-related accidents, and fatal accidents (Heidtman *et al.*, 1997; Ahuja and Hanscom, 1996; Chang and Mannering, 1997). The premise is that these types of accidents tend to involve vehicles with higher occupancies, thus causing the AVO to be overestimated. This chapter examines two of these potential factors, namely, accident severity and driver's age; develops the corresponding adjustment factors as needed; and discusses other potential factors that may affect the estimates of AVO from accident data. While other potential factors such as driver's gender and weather conditions are likely to also contribute to similar biases, adjustment for these factors cannot currently be performed due to the lack of exposure data needed to derive the adjustment factors.

6.2. Past Studies

A Connecticut DOT report (Gaulin, 1991) has served as the basic method to calculate vehicle occupancy from traffic accident data. In Gaulin's report, estimates from roadside windshield surveys, which were conducted in 1982 and 1984, were compared to estimates obtained from accident data. The results indicated a relative difference in estimates of less than 2.4% over comparable time periods. Several factors that can influence accident estimates were identified in the report as part of the verification process for using this new accident data procedure. For example, the impact of male versus female drivers, good versus bad weather, and alcohol/drug-related accidents were considered. In addition, sample size requirements for different tolerance levels were discussed. This report illustrates how this procedure can be used for assessing the viability and performance of facility-specific projects. It also shows that it is feasible to calculate vehicle occupancy rates from accident data.

To provide system-level average AVO data, the New York State Department of Transportation (NYSDOT) built upon Gaulin's procedure and tailored the algorithm (Asante *et al*., 1996). In the NYSDOT procedure, accident data were classified and cross-classified by year, time-of-day interval, day of week, month, and county. New York's 62 counties were classified into three urban-size groups for AVO analysis: 1) large urban counties with populations over 1 million; 2) large urban counties with county populations under 1 million but greater than 100,000; and 3) rural counties with populations under 100,000. The ANOVA test indicated that most of the variation in the means of accident-based automobile occupancy observations was explained by two main effects: the day-of-week groups and time-of-day intervals. Two other effects are the seasonal groups for months and population-size groups for counties.

Because the AVOs calculated from accident data were significantly higher than multiple-station roadside-observed AVOs, a simple linear regression model was developed to adjust the accident-based AAO estimate, $AVO_{(accident)}$, so that it would be comparable to roadside observer-based AVOs. The adjusted AVO, $AVO_{(adjusted)}$, from the fitted regression model was (Asante *et al.*,1996):

$$AVO_{(adjusted)} = 0.30 + 0.69 \times AVO_{(accident)}$$

Based on the statistical analyses reported, NYSDOT decided that accident-based AVO was adequate for purposes of network-level, area-wide CMS analysis processes. The NYSDOT analysis of accident-based AVO showed that these data accurately reflect the distribution of automobile occupancy during various periods of the day. Calculated occupancy rates were found to be the lowest during the morning peak and highest in the evening period. The weekday rates were lower than weekend rates. These findings were consistently observed across all counties and urban-area-size groups and were supported by other studies and data sources (Heidtman *et al*., 1997; Barton-Aschman Associates, 1989; Nationwide Personal Transportation Survey, 1990).

Several studies have investigated the potential biases from specific factors. Heidtman *et al.* (1997) studied this problem using the Chicago region accident data for years 1993 and 1994. It was found that occupancy rates vary by age of the driver for the Chicago area. As Figure 6-1 shows, AVO was clearly higher for the youngest drivers, dropped sharply by the age of 20, and increased slightly during childbearing years and retirement. To adjust for this bias, a weighted mean procedure using the census data was used in this evaluation. To obtain the overall AVO estimate, the weighted mean procedure would weight each age group's AVO in proportion to its age group's contribution to the overall driving population. Although there were substantial differences in the AVO estimates for various times of the week, the Chicago accident data set did not show significant differences between the unadjusted and census-weighted estimates. This lack of difference may be an anomaly peculiar to this one data set, that overrepresentation of vehicles driven by younger drivers may have been offset by the underrepresentation of vehicles driven by older drivers.

Heidtman *et al.* (1997) also investigated the impact of another potential biasing factor: unsafe drivers, such as those that are fatigued or under the influence of drugs or alcohol. The AVO for vehicles "more likely at-fault" was found to be significantly lower than that of the additional vehicles involved in the accident. However, the vehicle at-fault for the accident was judged personally by the reporting officer, and this information does not reflect the court's opinion of the vehicle at-fault or responsible for the accident.

A study by Asante *et al*. (1996) showed that accident records significantly overestimate vehicle occupancy. One primary explanation is that high-occupancy vehicles are more likely to be involved in severe accidents and are, thus, more likely to be reported in the accident database. This relationship arises from the fact that an increase in the number of people in the vehicle increases the likelihood of injury and fatality because the number of occupants exposed to the risk of being injured or killed increases with higher occupancies, while in vehicles with lower occupancies, unoccupied seat space provides protection from intrusion. A study by Chang and Mannering (1997) resulted in similar findings. In their study, a database containing all reported traffic accidents occurring on principal arterials, state highways, and interstate highways in King County (in Washington State) during 1994 compared the AVOs for accidents with different severity levels. It was found that multi-occupant vehicles were more likely to be involved in severe accidents.

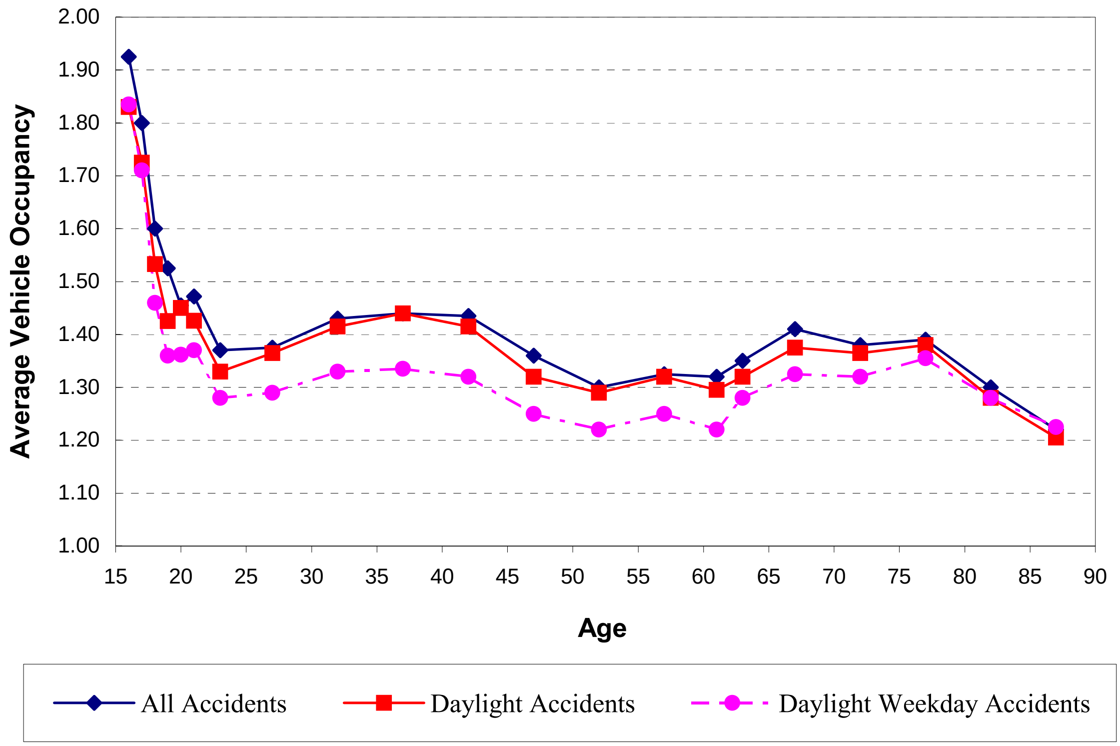


Figure 6-1. Average Vehicle Occupancy by Age for Chicago Area.

Based on past studies that examined variables that significantly influence accident severity probabilities (Lui *et al.*, 1988; Shankar *et al.*, 1996; O'Donnell and Connor, 1996), Chang and Mannering developed a nested logit model to estimate the probability of different occupancies and the probability of different accident severities. Estimated results from the model were then compared with actual observations for the same roadways to determine the appropriate adjustment factors to be applied in the model.

6.3. Examination of Potential Bias Factors

6.3.1. Accident Severity

The data from Miami-Dade County during the years 1999-2001 were used to test the potential bias in AVO estimation due to accident severity. Miami-Dade County was used due to the availability of field vehicle occupancy data, which were collected as part of this study. Data from these years were used to maintain consistency with the timeline of the 2000 Census data, which is necessary to derive the population exposure data. Table 6-1 lists the distribution of accident severity by vehicle occupancy. Of the 154,152 vehicles involved in accidents, the data show that multi-occupant vehicles have a tendency to produce more severe accidents than single-occupant vehicles. For example, injury and fatal accidents account for over 55% and 0.59%, respectively, of all multi-occupant vehicle accidents. In contrast, the total accident count (single- and multi-occupant accidents) shows that, overall, only about 48% of all accidents involved injury and only 0.42% of all accidents involved fatality. These statistics support the argument that vehicle occupancy affects accident severity. The data show that the AVOs of vehicles involved in accidents involving fatalities and injuries are significantly higher than those of vehicles involved in PDO accidents. There are two possible reasons for this relationship, the first of which is fairly obvious: an increase in the number of people in a vehicle increases the likelihood of injury and fatality because the number of occupants exposed to the risk of being injured or killed increases with higher occupancies. Also, in vehicles with lower occupancies, unoccupied seat space provides protection from intrusion.

Table 6-1. Distribution of Accident Severity by Vehicle Occupancy.

No. of Occupants	PDO	Injury	Fatality
1 occupant	61,555 (54.96%)	50,073 (44.70%)	380 (0.34%)
2 occupants	12,820 (43.57%)	16,429 (55.84%)	174 (0.59%)
3 occupants	2,893 (39.95%)	4,298 (59.35%)	51 (0.70%)
3+ occupants	2,055 (37.51%)	3,378 (61.65%)	46 (0.84%)
All	79,323 (51.46%)	74,178 (48.12%)	651 (0.42%)

Awareness of the relationship between occupancy and accident severity is the key to being able to use occupancy data from accident reports to estimate occupancy rates. As mentioned, some past studies have shown that accident records significantly overestimate vehicle occupancy (Asante *et al*., 1996). This occurs if the accident data over-represent multi-occupant vehicles. However, a problem also arises if the field vehicle data used for comparison with the accident vehicle data under-represent multi-occupant vehicles because observers in the field have unclear sight and/or limited time to count the number of occupants in moving vehicles. To examine this problem, Miami-Dade County 2006 vehicle occupancy field data were compared with vehicle occupancy data derived from Miami-Dade County 2005 accident vehicles. Table 6-2 shows a comparison of vehicle occupancy distribution between accident data and field data.

Table 6-2. Vehicle Occupancy Distributions of Accident and Field Data.

Roadway Type	Number of Occupants	Accident Data	Field Data
Urban Arterials	1	80.62%	80.52%
	2	13.32%	16.57%
	3	4.08%	1.25%
	3+	1.98%	1.65%
Freeways and Expressways	1	84.56%	83.70%
	2	11.0%	14.55%
	3	3.21%	1.21%
	3+	1.23%	0.54%
All	1	81.75%	81.74%
	2	12.57%	15.80%
	3	3.83%	1.23%
	3+	1.85%	1.23%
AVO		**1.26**	**1.23**

It can be seen from the table that, for a single occupant/driver, the vehicle percentages for both data sets are very close. This suggests that single-occupant vehicles did not under-represent nor over-represent the vehicle population in accident data. In other words, although multi-occupant (two and more than two occupants) vehicles occupy higher percentages in severe accidents (injury and fatality) than do single-occupant vehicles (see Table 6-1), the number of multi-occupant vehicles involved in accidents in general occupied almost the same percentage as that in the field data set. This suggests that multi-occupant vehicles are not over-represented in the accident database. However, high-occupancy (three and more than three) vehicles do appear with higher frequency in accident data than in field data. Obviously, there are other potential explanations for this difference, one of which might be that observers using the roadside windshield method missed children and infants, who were difficult to see.

6.3.2. Driver's Age

To detect potential bias resulting from driver's age, the year 2000 Miami-Dade County accident data were used to determine if the age distribution of drivers in the accident database was different from the age distribution for the entire driving population in Miami-Dade County. This can be analyzed by comparison with the 2000 census data for the same area. In this analysis, the driving population is defined as persons 16 years of age or older. A comparison of the distribution of ages obtained from both accident and census data was conducted and is shown in Figure 6-1. This figure indicates a significant difference between the ages of drivers involved in accidents and the ages of the general driving population in Miami-Dade County. Specifically, younger drivers were more likely to be involved in accidents than older drivers. Figure 6-2 shows that the AVOs vary significantly with the ages of drivers in the Miami-Dade County area. The figure shows that the AVOs for the youngest drivers are the highest and continue to drop over the age 20-50 groups. The AVOs are lower for drivers over 50 years old than they are for other groups.

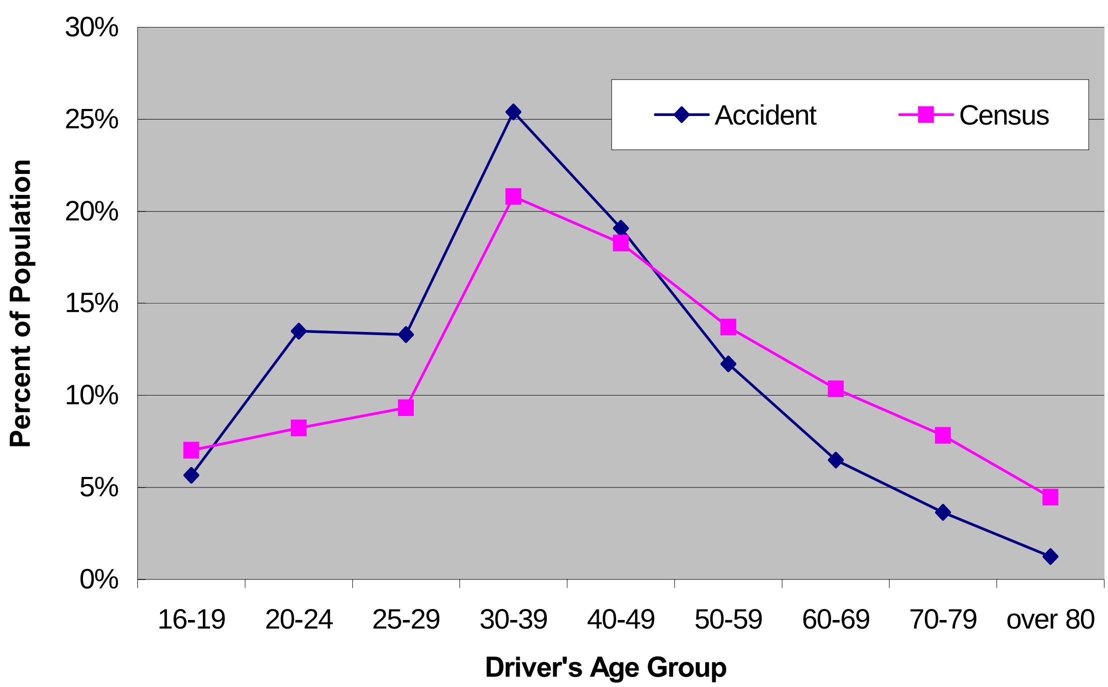


Figure 6-1. Distributions of Driver's Age from Accident and Census Data for Miami-Dade County.

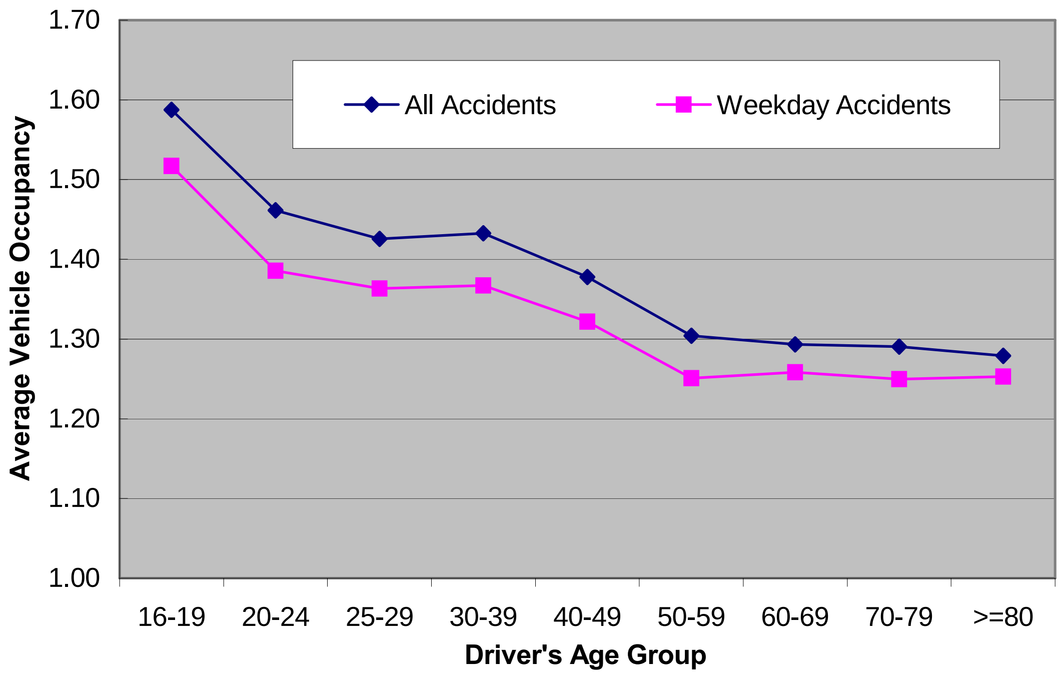


Figure 6-2. Average Vehicle Occupancy by Driver's Age for Miami-Dade County.

6.3.3. Other Potential Bias Factors

Figure 6-3, reproduced from Figure 5-9 of Subsection 5.4.9, shows that female drivers tend to have more occupants in their vehicles than male drivers and that this observation is consistent throughout the different days of the week.

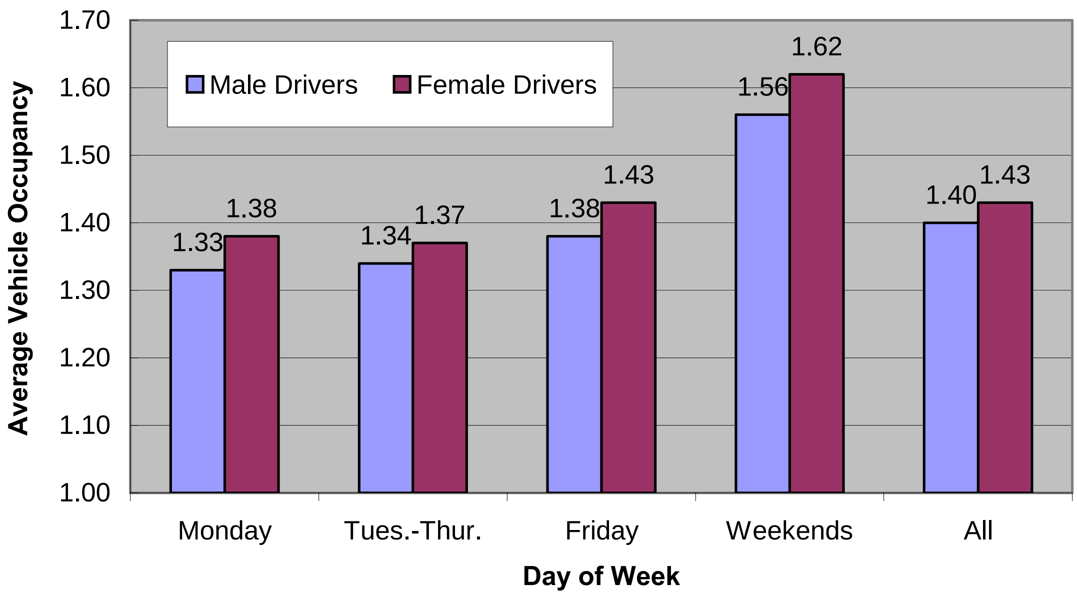


Figure 6-3. AVO Comparisons between Male and Female Drivers.

Table 6-3 lists accident vehicle frequency comparisons between male drivers and female drivers. On the whole, male drivers get in accidents more frequently than female drivers, especially during weekends. Based on 2000 Census demographic data, the male population percentage in the state of Florida is 48.79%, and the female population percentage is 51.21%. However, neither percentage number is helpful in investigating if there is a bias in the accident vehicle population. Male and female driving populations, male and female vehicle ownership information, as well as male and female vehicle exposure data, are needed for the further analysis.

Table 6-3. Accident Vehicle Frequency Comparisons Between Male and Female Drivers.

Weekday Type	**Male Driver**		**Female Driver**	
	Number	**Percentage**	**Number**	**Percentage**
Monday	58680	58.40%	41806	41.60%
Tuesday through Thursday	174526	57.81%	127378	42.19%
Friday	73615	59.34%	50431	40.64%
Weekends	107801	63.49%	62002	36.51%
All	414622	59.55%	281619	40.45%

Other potential factors, including the driver's race and weather conditions, have been shown to have an impact on AVO. Over-representation of one of these subgroups in traffic accidents may distort the AVO estimates from accident data. However, the lack of driving exposure data for different sub-groups prevents the adjustment factors from being developed.

<u>6.4. Development of Bias Adjustment Factors for Driver's Age</u>

Because of the drivers' age bias in the accident data, estimates of AVO derived from accident data should be adjusted to minimize the effect of this bias on AVO calculations. However, for monitoring AVO trends in a given area, it is not necessary that the adjustment factor be applied, as it is the relative values of AVOs, rather than absolute AVOs, that are important.

To adjust for driver's age bias, a weighted mean procedure using the census data was used (Heidtman *et al*., 1997). This procedure would weight each age group's AVO in proportion to its age group's contribution to the overall driving population. The assumptions for this procedure include: 1) each age group has a uniform percentage of vehicle driving activity; 2) each age group has a uniform accident rate in terms of vehicle miles driven and driving population. During this weighting procedure, the census population data for each county in Florida are grouped and calculated for each age group. The ratio of each age group's population to the whole driving population is then obtained as a weighting coefficient. To obtain the overall AVO estimate, the weighted mean procedure will weight the AVO of each age group's AVO by using that group's weighting coefficient. Hence, the sum of the adjusted AVO of each age group's adjusted AVO is the overall adjusted AVO. This procedure can be represented using the following formula:

$$AVO_{adj} = \sum_i \left(W_i \times AVO_i \right)$$

where

AVO_{adj} = the overall adjusted AVO,
W_i = the weighting coefficient for driver age group i,
AVO_i = the unadjusted AVO for driver age group i.

Table 6-4 lists each age group's weighting coefficient, the unadjusted AVO, and the weighted AVO for each age group for Miami-Dade County. This table also lists the final overall adjusted AVO, which is 1.39. (See Appendix B for weighting coefficients for all counties.)

Table 6-4. Weighting Coefficients for Miami-Dade County.

Age Group	Weighting Coefficient (W_i)	Unadjusted AVO(i)	Weighted AVO(i)
16-19	0.0702	1.59	0.1116
20-24	0.0824	1.46	0.1203
25-29	0.0932	1.43	0.1333
30-39	0.2079	1.43	0.2973
40-49	0.1827	1.38	0.2521
50-59	0.1372	1.30	0.1784
60-69	0.1035	1.29	0.1335
70-79	0.0783	1.29	0.1010
≥80	0.0446	1.28	0.0571
Overall	1.0	**1.41**	**1.39**

Table 6-5 lists the adjusted AVOs for all counties based on the obtained weighting coefficients. Although these differences appear small, because the over-representation of vehicles driven by younger drivers may have been offset by the under-representation of vehicles driven by older drivers, the paired-samples *T* test indicates that the differences between unadjusted AVOs and census weighted AVOs are significant ($T = 11.339$, P value < 0.0001) at the 95% confidence level.

Table 6-5 also lists the average adjustment factor (AAF) for each county, which was calculated as follows:

$$AAF = \frac{AVO_{adj}}{AVO_{unadj}}$$

Assuming that the age composition will not change from year to year, this average factor can be used in lieu of the weighting coefficients described above. Both should lead to the same adjustment if the composition of different subgroups does not change. To obtain the adjusted AVO, simply multiply the unadjusted AVO by the corresponding AAF for the respective county. In most cases, the AAF is a value below 1.0, which reduces the AVO to adjust for the overall over-representation of subgroups with higher AVOs in traffic accidents.

Table 6-5. AVOs and Average Adjustment Factors.

County No.	County Name	Unadjusted AVO (AVO_{unadj})	Census Adjusted AVO (AVO_{adj})	Average Adjustment Factor (AAF)
1	Charlotte	1.526	1.511	0.990
2	Citrus	1.481	1.443	0.974
3	Collier	1.567	1.527	0.974
4	DeSoto	1.653	1.652	0.999
5	Glades	1.660	1.652	0.995
6	Hardee	1.642	1.608	0.979
7	Hendry	1.535	1.527	0.995
8	Hernando	1.559	1.530	0.981
9	Highlands	1.577	1.529	0.970
10	Hillsborough	1.487	1.467	0.987
11	Lake	1.517	1.498	0.987
12	Lee	1.517	1.483	0.978
13	Manatee	1.475	1.450	0.983
14	Pasco	1.521	1.499	0.986
15	Pinellas	1.444	1.422	0.985
16	Polk	1.553	1.527	0.983
17	Sarasota	1.462	1.437	0.983
18	Sumter	1.702	1.651	0.970
26	Alachua	1.462	1.460	0.999
27	Baker	1.656	1.662	1.004
28	Bradford	1.533	1.517	0.990
29	Columbia	1.610	1.579	0.981
30	Dixie	1.572	1.556	0.990
31	Gilchrist	1.504	1.455	0.967
32	Hamilton	1.753	1.760	1.004
33	Lafayette	1.448	1.375	0.950
34	Levy	1.594	1.563	0.981
35	Madison	1.645	1.624	0.987
36	Marion	1.586	1.553	0.979
37	Suwannee	1.586	1.566	0.987
38	Taylor	1.515	1.496	0.987
39	Union	1.492	1.479	0.991
46	Bay	1.551	1.501	0.968
47	Calhoun	1.514	1.519	1.003
48	Escambia	1.414	1.397	0.988
49	Franklin	1.573	1.556	0.989
50	Gadsden	1.594	1.558	0.977
51	Gulf	1.497	1.417	0.947
52	Holmes	1.648	1.632	0.990
53	Jackson	1.605	1.583	0.986
54	Jefferson	1.664	1.683	1.011

Table 6-5. AVOs and Average Adjustment Factors (Continued).

55	Leon	1.450	1.440	0.993
56	Liberty	1.648	1.570	0.953
57	Okaloosa	1.496	1.476	0.987
58	Santa Rosa	1.479	1.465	0.991
59	Wakulla	1.611	1.588	0.986
60	Walton	1.618	1.591	0.983
61	Washington	1.638	1.606	0.980
70	Brevard	1.456	1.430	0.982
71	Clay	1.514	1.487	0.982
72	Duval	1.492	1.467	0.983
73	Flagler	1.580	1.523	0.964
74	Nassau	1.545	1.523	0.986
75	Orange	1.453	1.443	0.993
76	Putnam	1.538	1.501	0.976
77	Seminole	1.354	1.339	0.989
78	St. Johns	1.555	1.528	0.983
79	Volusia	1.502	1.464	0.975
86	Broward	1.446	1.431	0.990
87	Miami-Dade	1.408	1.385	0.984
88	Indian River	1.519	1.476	0.972
89	Martin	1.518	1.467	0.966
90	Monroe	1.634	1.599	0.979
91	Okeechobee	1.665	1.638	0.984
92	Osceola	1.658	1.650	0.995
93	Palm Beach	1.443	1.433	0.993
94	St. Lucie	1.555	1.507	0.969

CHAPTER 7
UPDATED AVO INFORMATION SYSTEM

7.1. Background

This chapter provides an updated description of an information system that was originally developed as part of the Phase I study to estimate AVOs using accident records for Florida's state roadway system. The system, called the Florida Accident Vehicle Occupancy Rate Information Estimator, or FAVORITE, can estimate AVOs for select roadway segments, corridors, or counties for specific time periods. The system also includes a number of variables that can be used for analysis, including district, county, hour of day, day of week, month of year, vehicle type, facility type, area type, and accident severity. Because the system makes use of a comprehensive statewide database, it can potentially be a highly cost-effective means for monitoring statewide, county, and possibly site-specific vehicle occupancy trends. The entire install package for FAVORITE is freely available for downloads at this website after user registration: http://lctr.eng.fiu.edu/FAVORITE.htm.

7.2. System Updates

7.2.1 Incorporation of Bias Adjustment Factors

Because of the drivers' age bias found in the accident data, any estimates of AVO derived from accident data should be adjusted to minimize the effect of this bias on AVO calculations. To adjust for this bias, a census weighting procedure as discussed in Chapter 6 was implemented in version 2.0 of the FAVORITE system. The system may choose whether or not to apply the adjustment factor. As noted earlier, it is not necessary that the adjustment factor be applied for AVO monitoring for trends in one area, as it is the relative values of AVOs, rather than the absolute AVOs, that are important in this case.

7.2.2 Incorporation of Minimum Sample Size

A second major design issue in the development of the AVO information system was to consider the minimum number of accident records needed to provide an AVO estimate that will meet the desired accuracy. Unlike other vehicle occupancy data collection methods, the sampling plan for the accident method is not used to determine the number of sample points to be collected. Instead, it is used to determine if the existing accident database contains a sufficient number of accident records to make the required estimation within a specified level of precision. The sampling unit is the vehicle(s) involved in an accident. Based on the defined population of interest in terms of geographic scope and temporal coverage, the number of vehicles required to estimate AVO within a specified precision level at a certain confidence level can be computed for each stratum by using the following formula (Ferlis, 1981):

$$N_h = \left(\frac{Z_{1-\alpha/2} \times \sigma_h}{T_h} \right)^2$$

where

N_h = the number of vehicles required for stratum *h,*
$Z_{1-\alpha/2}$ = the upper 1-α/2 percentile of the standard normal distribution,
σ_h = the composite standard deviation for stratum *h*, and
T_h = the desired tolerance for stratum *h*.

The standard deviation estimates of vehicle occupancy for different strata of accidents can be obtained from existing studies. To use the data, the population of interest in terms of geographic coverage and temporal conditions has to be clearly defined. Within each selected subpopulation, the variability in occupancy rates will dictate the number of vehicles needed, for which estimates can be obtained to achieve a specified precision level. For example, the required number of vehicles needed to derive an AVO estimate within 0.1, with 95% confidence, is:

$$N_h = \left(\frac{1.96 \times \sigma_h}{0.1}\right)^2 = 384.16 \times \sigma_h{}^2$$

Table 7-1 provides estimates of the standard deviation, σ_h, of passenger vehicle occupancy for several strata, as well as the number of reported vehicles that will be needed to estimate AVO. The results calculated are based on three years' (1999, 2000, and 2001) total number of accidents occurring in Florida, are restricted to drivers 16 years and older, and are restricted to passenger vehicles with fewer than seven occupants.

Table 7-1. Florida Accident Data Vehicle Occupancy Analysis.

	Actual # of Vehicles in Database	Standard Deviation (σ_h)	Minimum Required # of Vehicles
All accidents	154,152	0.810	253
Weekday	115,549	0.733	207
Weekend	38,603	0.982	371
Weekday a.m. rush	14,252	0.584	132
Weekday midday	45,980	0.689	182
Weekday p.m. rush	19,791	0.747	215
Weekend a.m. rush	1,757	0.722	201
Weekend midday	14,823	0.941	341
Weekend p.m. rush	4,667	1.047	422

Notes: Midday: 9:00 a.m.–4:00 p.m; a.m. rush: 7:00 a.m.–9:00 a.m; and p.m..rush: 4: 00 p.m.–6:00 p.m.
Required number of vehicles involved in accidents reflects 0.1 precision.

7.3. System Overview

The information system was developed using a combination of Visual Basic, Microsoft Access, and the ESRI MapObjects Developer Library. The current database includes the 1990-2005 accident data for the entire Florida State Roadway System. The data include the number of occupants of the vehicles in each accident for up to two vehicles. In addition, the database also includes the following variables:

- District
- County

- Section, subsection, beginning and ending mileposts
- State road number
- Hour of day
- Day of week
- Month of year
- Vehicle type
- Facility type
- Area type
- Accident severity

These variables allow accident records to be filtered to include only certain types of records for specific analysis needs. They also allow AVOs to be analyzed for their sensitivity with respect to location, roadway, vehicle, time, etc.

The major functionalities of the system include:

- Applying filters for time of day, day of week, month of year, type of vehicle, type of road, type of area, and accident severity.
- Defining a new variable by grouping the available categories of a variable.
- Calculating and displaying AVOs in a cross table of two variables, for example, the AVO for different days of a week for different FDOT districts. The total AVOs are also provided for all rows and columns of the cross table.
- Calculating and displaying AVOs on line, bar, or pie charts.
- Calculating and displaying AVOs on a GIS map at the district, county, and corridor levels.
- Exporting tables and charts to Excel.

7.4. Installation

The FAVORITE setup was packaged using the InstallShields install software. To install FAVORITE, insert the FAVORITE CD and wait several seconds for the install to automatically start the setup program, then follow the instructions on the screen to complete the installation. If an existing version of FAVORITE is detected on the computer, the user will be prompted to remove it before the new version can be installed.

7.5. Input Specifications

Figure 7-1 shows the main input interface of the program. The screen allows the user to make the following three major selections:

1. Accident data years: The user can select any number of years of accident data to include in his/her analysis.

2. Analysis locations: Location selection can be made at three different levels: district, county, and corridor.

3. Variable filters: The system includes filters for accident severity, hour of day, month of year, day of week, vehicle type, area type, and roadway type. This allows the user to include only a subset of accident records in the AVO estimates. For example, the user may be interested in only the occupancy from passenger cars. In this case, only "Automobile" should be selected. The user can further constrain the accident record set to, for example, weekday traffic, by not selecting the "Sat" and "Sun" categories.

The program also allows the user to group the different categories of a variable. A recategorized variable can be saved as a new variable that can then be used just like any other existing variable. This feature is particularly useful because the existing categories of a variable may not suit a particular analysis need.

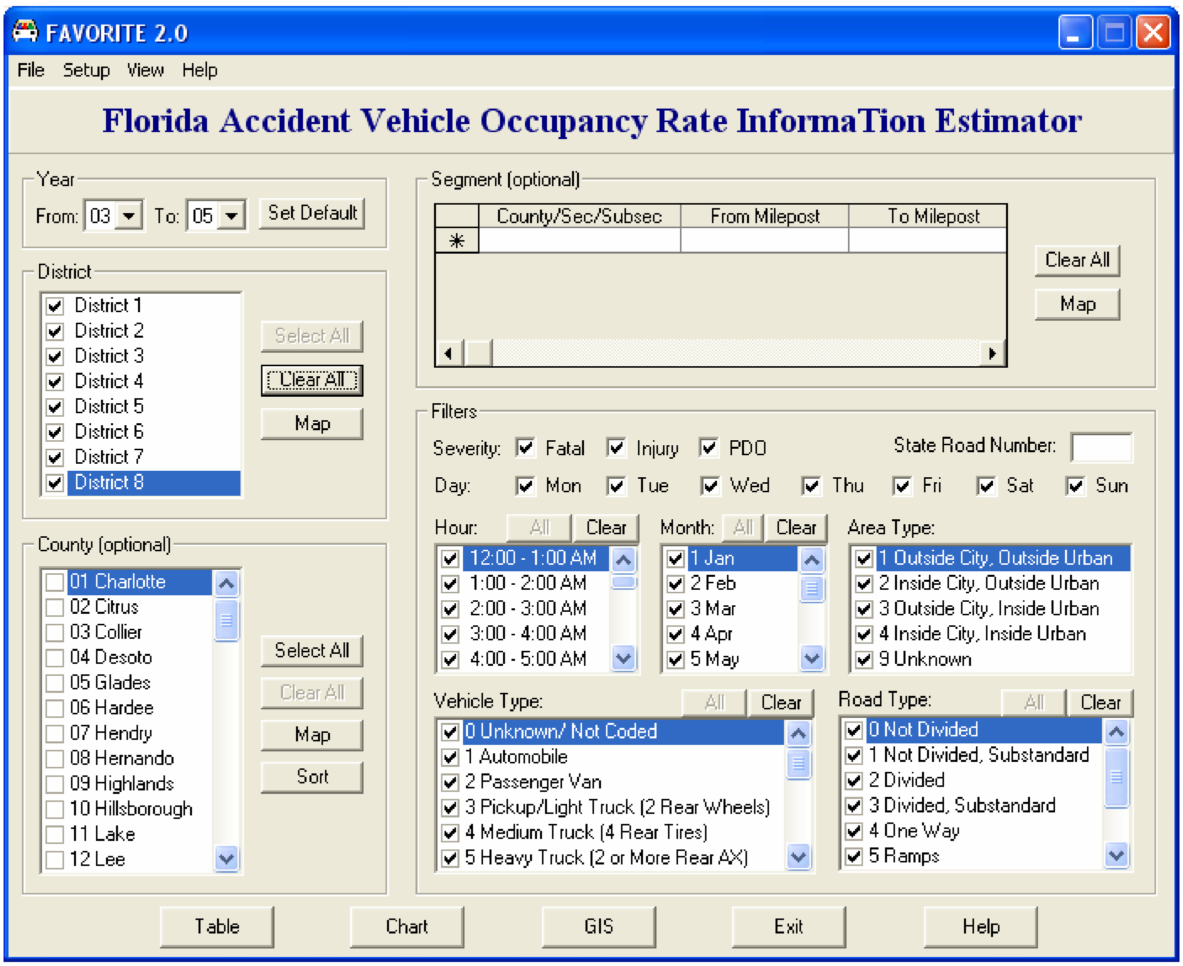


Figure 7-1. FAVORITE Main Screen.

7.5.1. Accident Data Years

Version 2.0 of FAVORITE includes the complete 1990–2005 accident records for Florida's state roadway system. The user can select any number of years of data within this timeframe to include in the analysis using the **From** and **To** dropdown lists on the main screen.

7.5.2. Location Selection

Location selection can be made at three different levels: district, county, and corridor. More than one item in each level can be selected. For example, one can select Districts 4 and 6 to cover the Southeast Florida counties. When a district is selected, all of the counties in it will be listed under the **County** list box. The selection of counties is optional. If no counties are selected, the selection is considered to have been made at the district level only, such that all counties in a selected district will be included. When a county is selected, only data for that county are included.

The selection of districts or counties is made by checking the appropriate checkboxes. Alternatively, one can click the **Map** button beside the **District** or **County** list box to select by map. Selection by map is convenient when the user wants to select a contiguous area such as selecting two adjacent counties. Figure 7-2 shows a map screen in which Miami-Dade and Broward counties are selected.

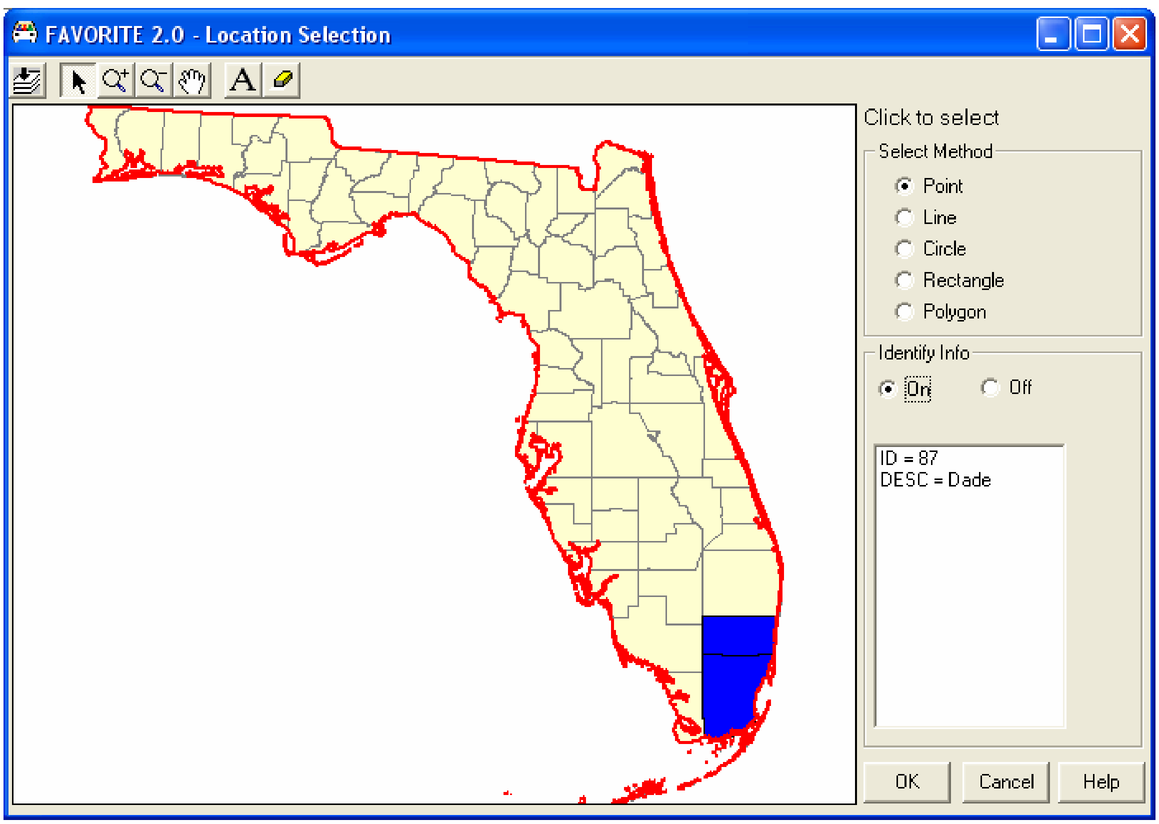
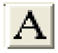


Figure 7-2. Select Locations by Map.

In this screen, the user may:

- Select a county by clicking the county polygon on the map. Selected counties are shown in blue. Note that only the counties in the selected districts can be selected. The selectable counties are enclosed by red borders.
- Click a selected county to unselect it.

- Click  to clear all selections.
- Click  to display county or district names.
- Click , , or  to zoom in, zoom out, or pan the map.
- Click  to display the complete map.
- Choose a different selection method such as “Rectangle” to select multiple features at once by drawing a rectangle with the mouse cursor.
- Click the “**On**” radio button to display information about a feature pointed to by mouse cursor.
- Click **OK** to exit the map view and return to the main screen with the chosen selections.

To select a specific corridor, the user can either enter the county/section/subsection standard roadway ID and the beginning and ending mileposts, or the user can click the adjacent **Map** button to select a particular roadway by pointing and clicking on the map.

7.5.3. Filters

In addition to accident data years and analysis locations, FAVORITE includes filters for the following variables:

- Accident severity
- Hour of day
- Month of year
- Day of week
- Vehicle Type
- Area type
- Road type

This allows the user to include only a subset of these variables by checking or unchecking the appropriate checkboxes for the variable options listed. By default, all options of a variable are included. At least one variable option must be selected.

7.6. System Output

Once the input specifications described in the preceding section are completed, the user can click on the **Table**, **Chart**, or **GIS** button at the bottom of the input screen to start computing AVOs. The **Table** and **Chart** output options are similar, and they share the same input interface. Figure 7-3 shows a table that is cross-classified by district and day of week. As Figure 7-4 shows, the **Chart** option simply displays the same AVOs, but on a chart. For both tables and charts, the user is given the following display options:

- Select any one or two variables from the two dropdown menus at the top of the screen to classify AVOs.

- Display occupancy rates, total number of vehicles, or total number of occupants by clicking one of the three corresponding radio buttons at the top of the screen.

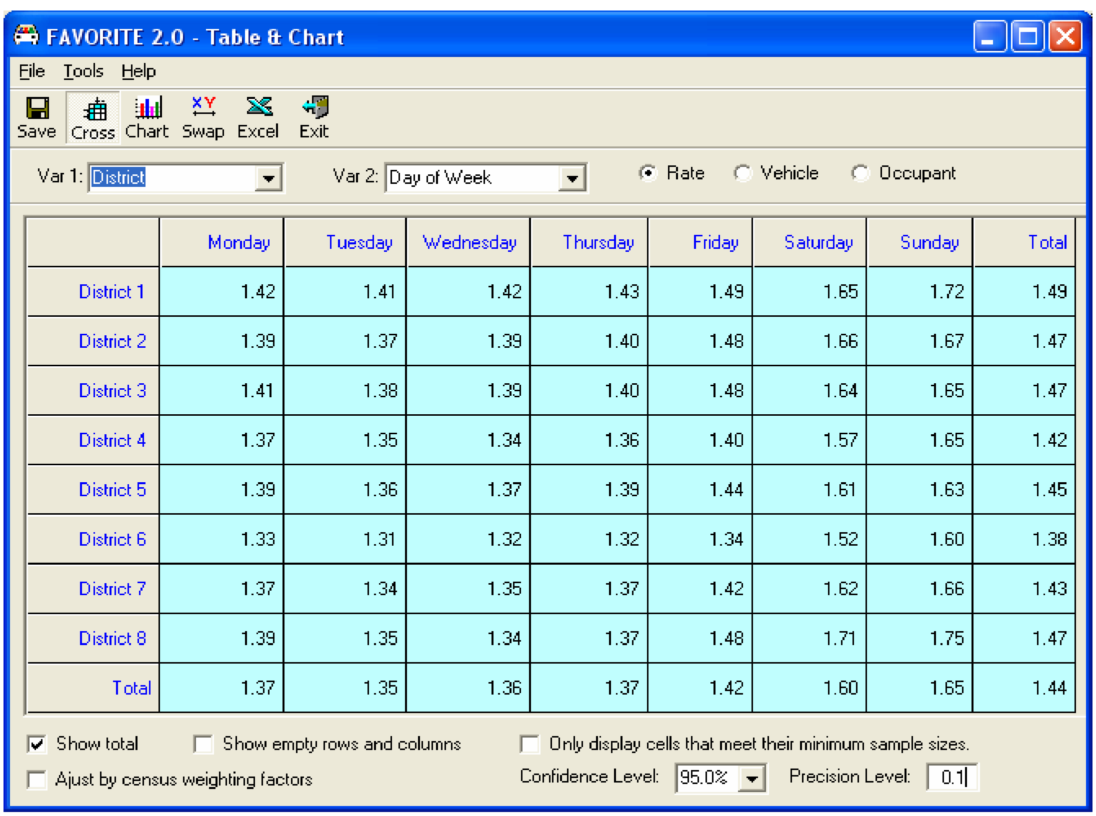
- Select whether or not to show the overall AVOs across each row and each column. For example, in Figure 7-3, the overall AVO for District 1 is 1.55 (shown under the “Total” column) and the overall AVO for Monday is 1.44. The table also gives an overall AVO of 1.50, which is shown in the bottom-right cell**.**

- The user can choose whether or not to display AVOs that do not meet the minimum sample sizes, which are computed by the system based on the sample size formula (see Section 7.2) for each user-selected cross-class. Thus, if a user chooses to require the minimum sample size, the corresponding cell will be displayed only if the number of vehicles (note: not the number of accidents) involved in the accidents used to calculate the AVO meets a minimal sample size.

- Select Census Weighting Correction Method to avoid the age bias found in the accident vehicle data.

7.6.1. Table Display

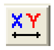
This option allows the user to display the AVOs on a cross table. Figure 7-3 shows a table that is cross-classified by district and day of week.



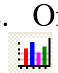
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Total
District 1	1.42	1.41	1.42	1.43	1.49	1.65	1.72	1.49
District 2	1.39	1.37	1.39	1.40	1.48	1.66	1.67	1.47
District 3	1.41	1.38	1.39	1.40	1.48	1.64	1.65	1.47
District 4	1.37	1.35	1.34	1.36	1.40	1.57	1.65	1.42
District 5	1.39	1.36	1.37	1.39	1.44	1.61	1.63	1.45
District 6	1.33	1.31	1.32	1.32	1.34	1.52	1.60	1.38
District 7	1.37	1.34	1.35	1.37	1.42	1.62	1.66	1.43
District 8	1.39	1.35	1.34	1.37	1.48	1.71	1.75	1.47
Total	1.37	1.35	1.36	1.37	1.42	1.60	1.65	1.44

Figure 7-3. AVOs Cross-Classified by FDOT District and Day of Week.

The following functions are available from the screen:

- The **Var 1** and **Var 2** dropdown lists allow the user to select up to two variables by which to cross classify the AVO estimates. By default, AVO estimates are displayed when the table is fist displayed.
- Click the **Vehicle** and **Occupant** buttons to display the corresponding cross tables for the number of vehicles and number of occupants, respectively, by clicking the appropriate radio buttons.
- Click  to export the current view to Excel.
- Click  to swap the rows and columns of the cross table.
- Click  to exit to the main screen.
- Uncheck the **Show total** option to exclude the summary column and row in the table.
- Check the **Minimum number of vehicles** option and then enter a threshold number to exclude cells that do not meet the minimum vehicle sample size.
- Check the **Show empty rows or columns** option to show rows and columns that are empty (i.e., with zero sample size for all cells across a row or a column).
- Select from the **View|X-Long or Short** or **View|Y-Long or Short** dropdown menu items to toggle between whether or not to show the variable option name after each option code.

7.6.2. Chart Display

The **Chart** option allows the user to display AVOs on a chart. The same interface is shared by both the **Cross Table** and **Chart** displays. Once the user has selected one of the two display options, the user can simply click  and  to switch between the two displays. Figure 7-4 shows a chart for automobile AVOs for different FDOT districts for different days of a week. The overall AVOs are also shown for each district and all districts combined.

7.6.3. GIS Display

While tables and charts are able to display AVOs that are cross-classified by variables, they cannot show the AVOs spatially. FAVORITE provides a GIS interface that can display AVOs by district, county, and segment. Figure 7-5 shows the main interface of the GIS display. The left side of the screen allows the user to make various selections, while the right side of the screen displays a map view of the state. The top-left corner lists the GIS layers and the corresponding colors used for display. Below this layer box is a **Variable** dropdown box that allows the user to specify the variable options to include in the calculation of AVOs. Once a variable is selected, all options will be displayed in the box below it. The user can select the options to include by checking the appropriate checkboxes.

Once a variable option is selected, the six specification boxes below the option list box will become active. The first of these boxes allows the user to select a theme to display by county, district, or segment. By default, the **Segment** option is selected.

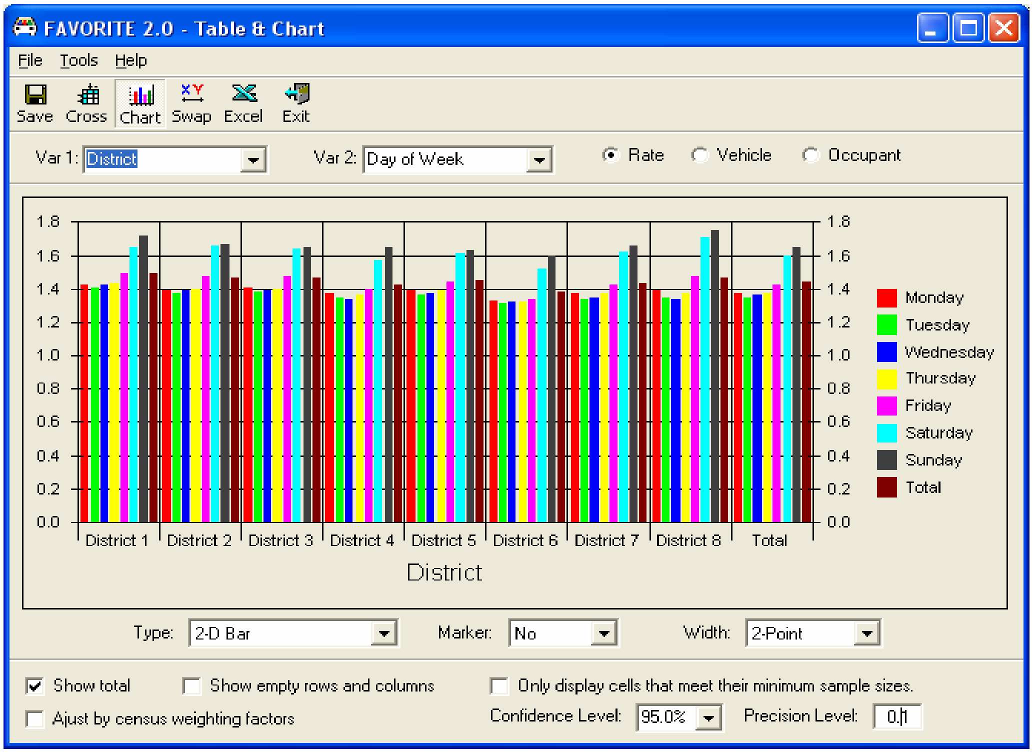


Figure 7-4. AVOs Cross-Classified by FDOT District and Day of Week.

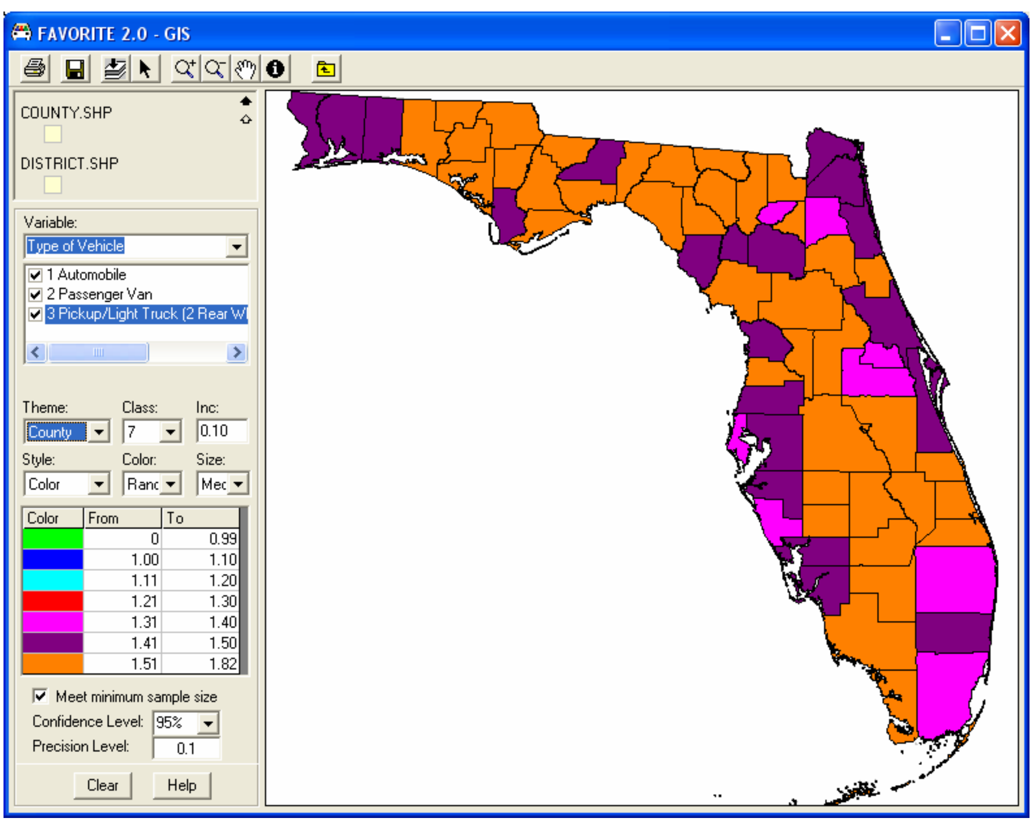


Figure 7-5. Automobile AVOs Displayed by County.

The **Class** dropdown list box allows the user to select the number of classes for the theme. The default number of classes is seven. The first class is always assigned to 0.00 to 0.99, which normally includes features that have no accidents. The last class includes any number above a certain threshold. All classes between these two boundary classes are divided based on the increment specified to the right. By default, the increment is 0.1.

The **Style** option allows the user to specify whether to show themes by color, line width, or a combination of both. The default option displays by different colors. Obviously, the line width option applies only to the **Segment** theme. The **Color** option allows the user to select a color scheme. By default, random colors are used. The user may choose to use the **Blue** and **Red** color schemes, which display features from gradual light to dark colors to indicate low to high AVOs. The GIS display is automatically refreshed as soon as any one of these specifications is changed. Figure 7-6 shows an example of AVOs displayed by segments.

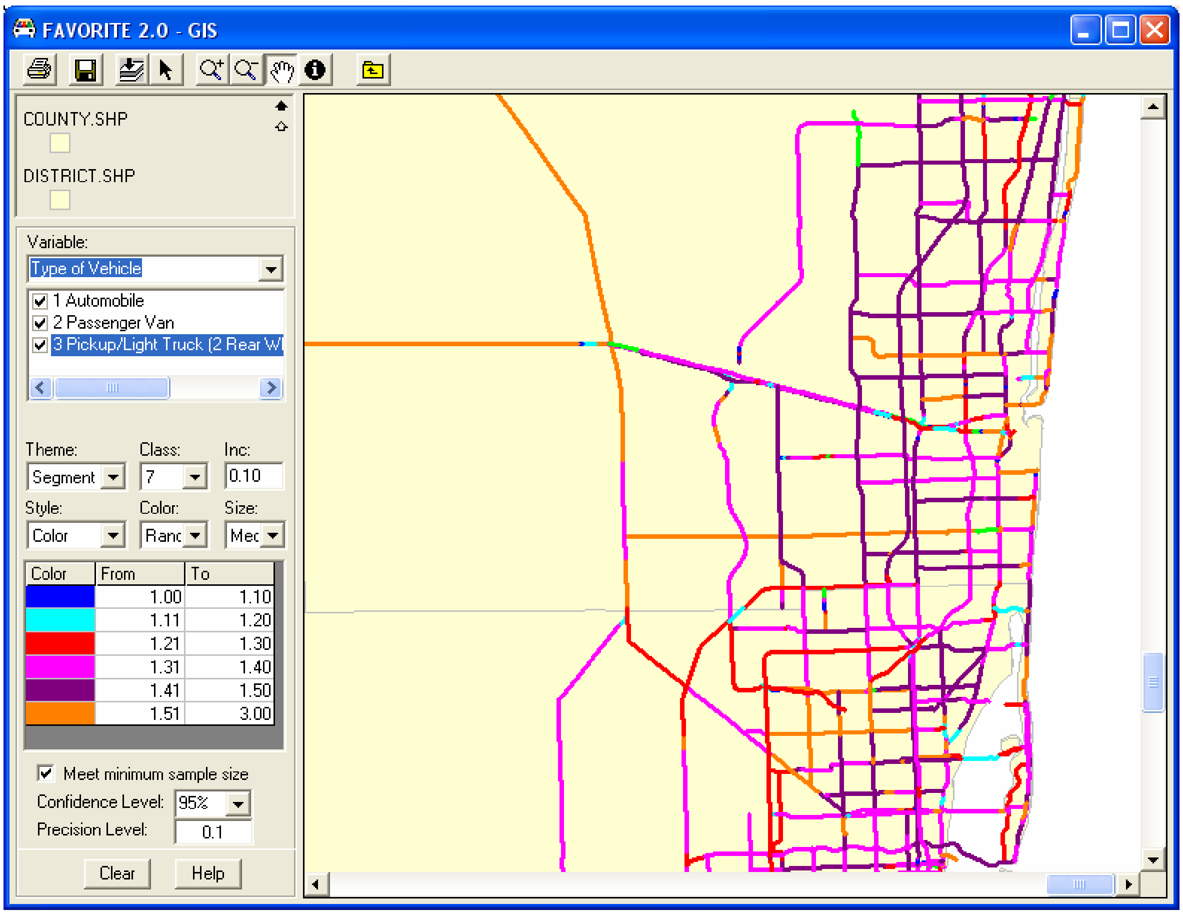


Figure 7-6. Automobile AVOs Displayed by Segment.

A number of tool buttons are available on the GIS screen. Clicking the  button will take the user to the **Print Layout** screen shown in Figure 7-7. In this screen, the user can:

- Single click any object on the screen and then drag it to re-position the object.

- Single click on an object to highlight the object and then drag the mouse cursor to enlarge or shrink the object.
- Double click “title” or “footnote” to enter a title or a footnote, respectively.
- Click to print the map to the default printer.
- Click to toggle between the “portrait” and “landscape” page orientation.
- Click to copy the print layout to the clipboard.
- Click to add a text box.
- Click to remove a text box.
- Click to add or remove the page border.

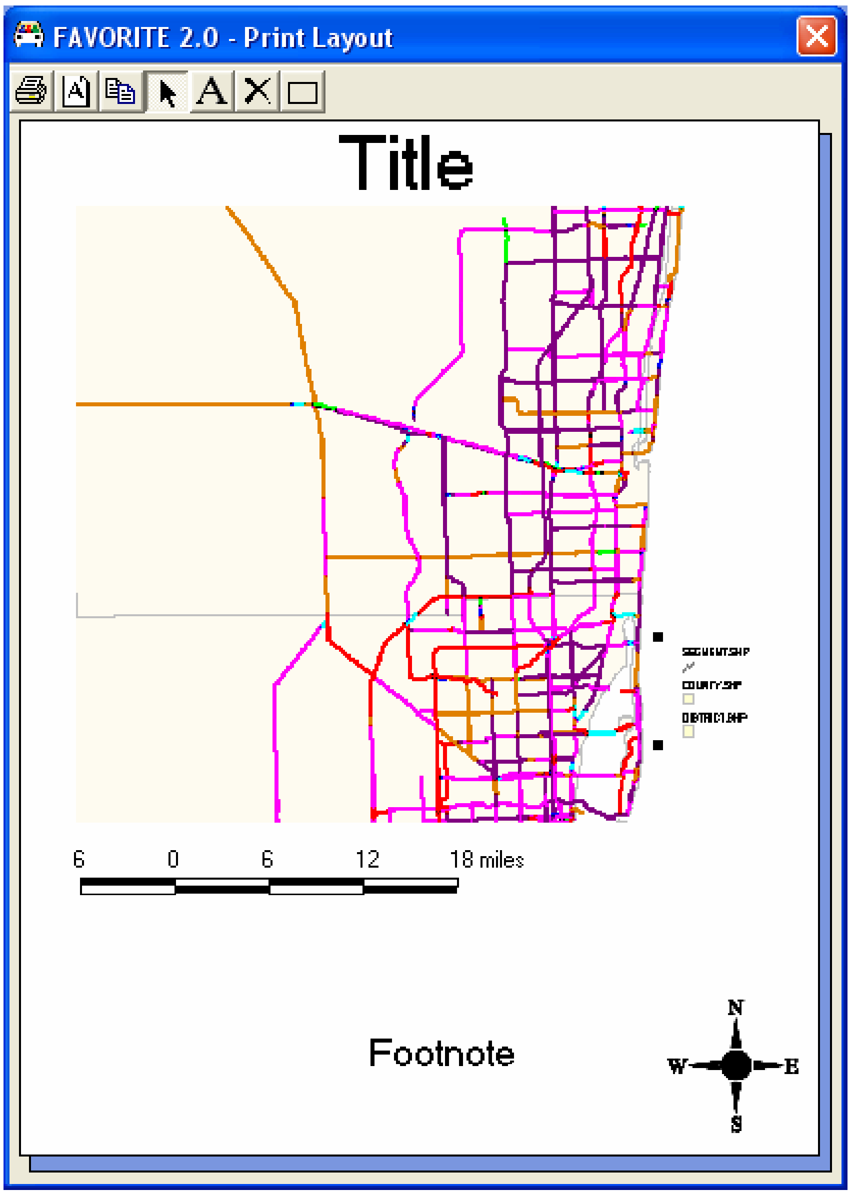


Figure 7-7. Print Layout.

In addition to the **Print** button, the user can:

- Click to save the map as a new shape file.
- Click to return to the mouse pointer.
- Click to display county or district names.
- Click , , or to zoom in, zoom out, or pan the map.
- Click to display the complete map.
- Click to identify features by mouse cursor.
- Click to exit to the FAVORITE main screen.

7.7. Variable Re-Categorization

FAVORITE allows the user to re-categorize the options of each variable. To add a new category, select the **Setup|Add Category** dropdown menu item from the main screen to invoke the screen shown in Figure 7-8.

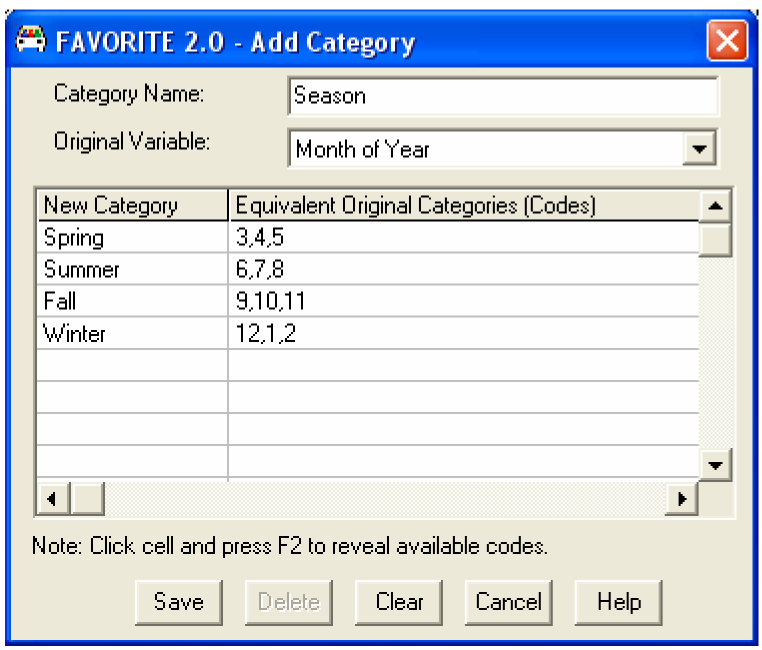


Figure 7-8. Screen for Adding a Category.

To create a new category, follow these steps:

- Enter a name for the new category.
- Select an original variable to be re-categorized.
- Enter the names of groups under the **Group Name** column.
- Enter the code numbers to be included in each group. Code numbers are separated by commas. For example, enter **3, 4, 5** to assign March, April, and May for the **Month of Year** variable. Alternatively, the user can enter **3-5**.

- If the user is not familiar with the code numbers, click the cell for which codes are to be entered, and then press the **F2** function key. This will invoke the screen shown in Figure 7-9, which lists all of the codes and option names for the selected variable. Check the boxes to be included and click **OK** to return the selected options to the **Add Category** screen.
- Click the **Save** button to save the new category and exit to the FAVORITE main screen.

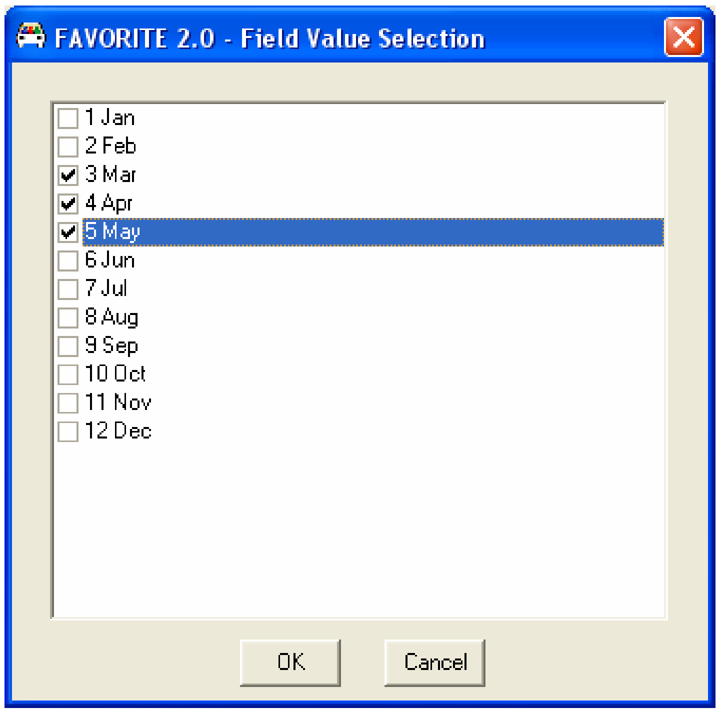


Figure 7-9. Screen for Specifying Options for Group.

To edit an existing category, select the **Setup|Edit Category** dropdown menu item. This will bring up a screen similar to the one in Figure 7-8. The screen allows the user to specify an existing category to edit.

CHAPTER 8
EVALUATION OF AVO ESTIMATES FROM ACCIDENT DATA

8.1. Introduction

In this chapter, the accuracy of AVO estimates from accident data are evaluated based on two approaches. The first is to determine if the AVO trends from the accident data are as expected. The second is to compare the AVOs from accident data with those collected from the field at the same locations. Details on the field data source are given in Chapters 2 and 3 of this report.

8.2. Reasonableness Checks

Reasonableness checks involve examining the AVO estimates to determine if they match expectations and known trends.

8.2.1. AVO Trends by Year and Month

Figure 8-1 shows that, as expected, weekend AVOs for passenger cars are higher than weekday AVOs, with Sunday having the highest AVOs, followed by Saturdays and Fridays. Furthermore, Fridays tend to have slightly higher AVOs than the other weekdays, which tend to have similar AVOs. These observations were consistent over each of the four years of data shown.

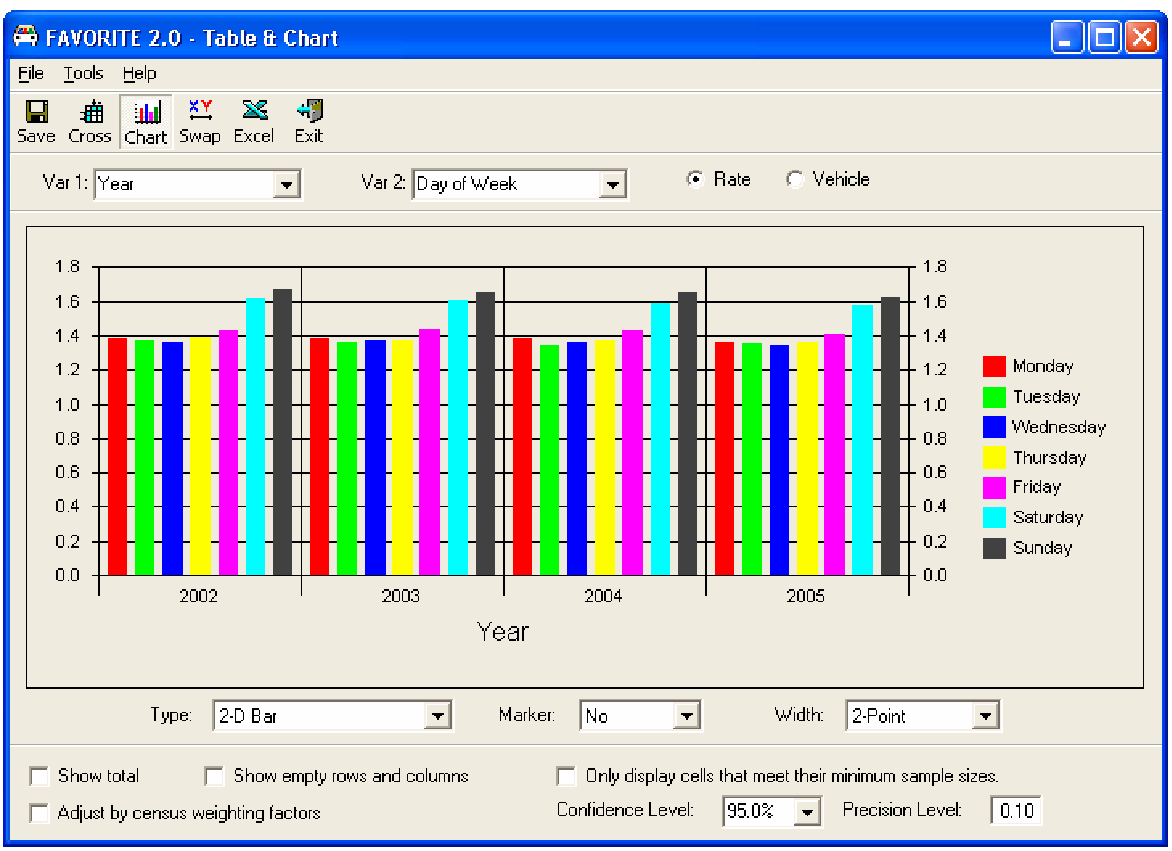


Figure 8-1. AVO Trend by Year and Day of Week.

8.2.2. AVO Trends by Month

Figure 8-2 shows that, as expected, the summer months of June and July tend to have higher AVOs, followed by the month of March, which coincides with Spring Break traffic in Florida, and the month of December, which coincides with Christmas holiday traffic. Overall, AVOs do not change significantly over the year.

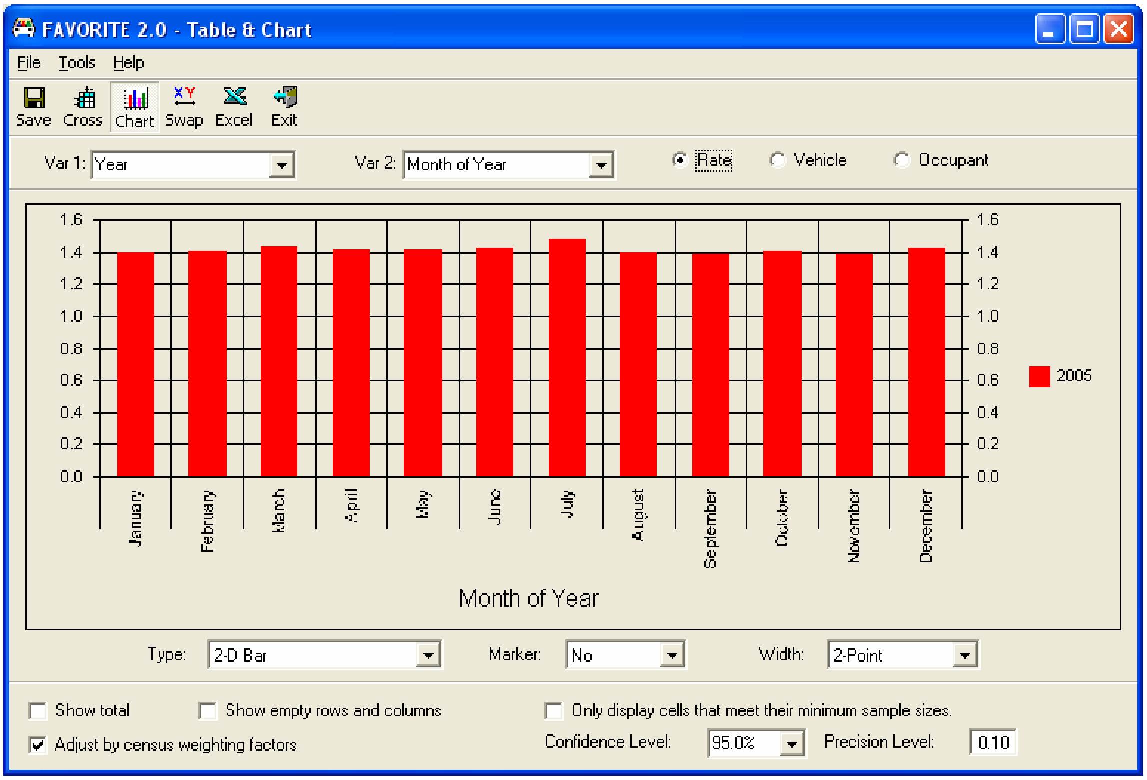


Figure 8-2. AVO Trend by Month.

8.2.3. AVO Trends by Hours

Figure 8-3 shows that, as expected, AVOs during the morning peak hours are lower than those of the afternoon peak hours and that daytime AVOs are lower than nighttime AVOs.

8.2.4. AVO Trends by Area Type

Figure 8-4 shows a GIS thematic map of AVO distribution by county. The darker the color, the higher the AVO. The map shows that, as expected, rural counties generally have higher AVOs than do urbanized counties.

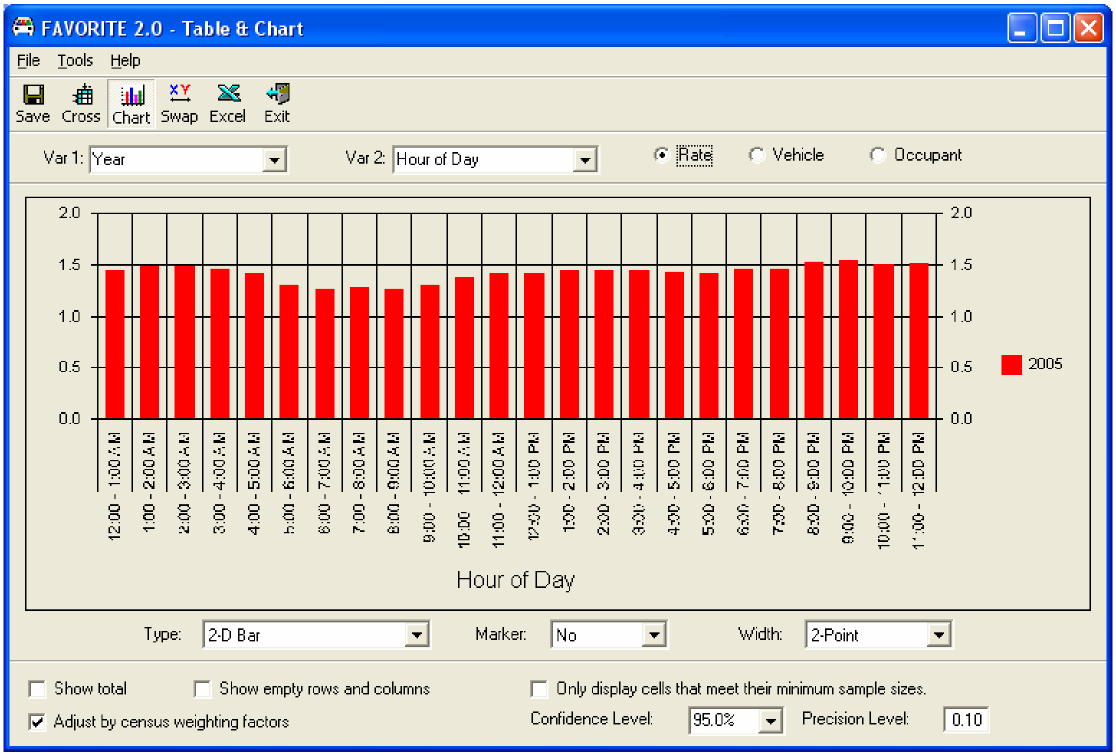


Figure 8-3. AVO Trend by Time of Day.

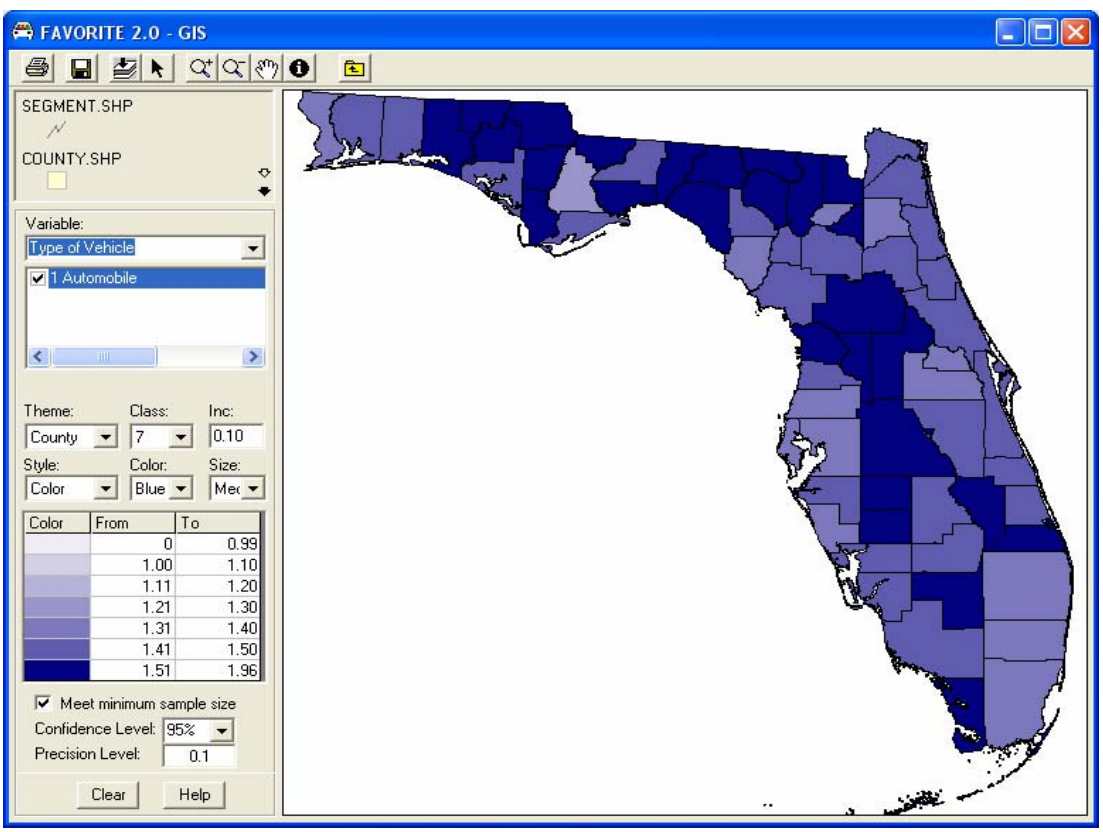


Figure 8-4. AVO Trend by County.

8.2.5. AVO Trends by Vehicle Type

Figure 8-5 shows the AVOs for different types of vehicles. The AVOs obtained appear reasonable compared to the expected AVOs for different vehicle types. Some observations include:

- AVOs of passenger vans are higher than those of passenger cars (automobiles).
- Buses have a significantly higher AVO than any other vehicle types.
- Bicycles have the lowest AVOs.

These observations were consistent throughout the four years of data used.

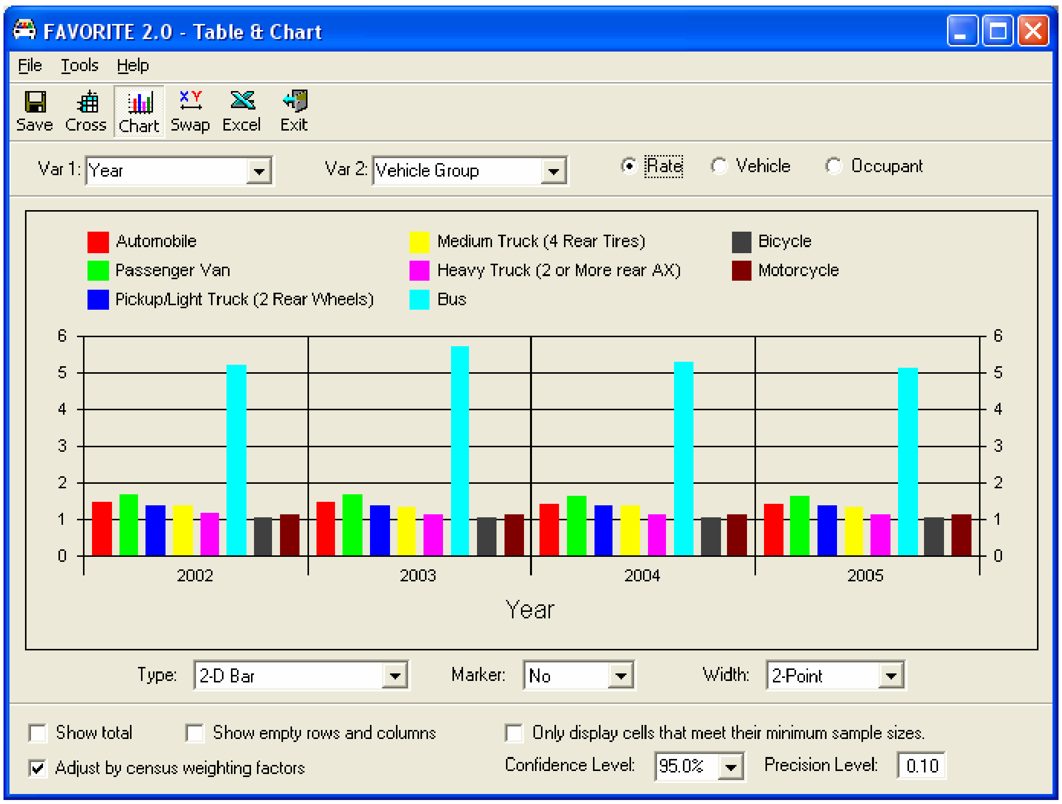


Figure 8-5. AVO Trend by Vehicle Type.

8.3. Comparisons with Field Data at the County Level

To compare the AVOs obtained by the two data sources, the Miami-Dade County year 2005 accident data were tailored to match the field data collection time (7:00 a.m. to 6:00 p.m.) and days of the week (Tuesday through Thursday) of a 2006 field collection study. Given that vehicle occupancy rates vary by time of day, critical time periods during the aforementioned 7:00 a.m. to 6:00 p.m. time span were selected for separate analysis. The time periods of interest included the a.m. peak period (7:00 to 9:00 a.m.), midday period (11:00 a.m. to 1:00 p.m.), p.m. peak period (4:00 to 6:00 p.m.), and off-peak period (9:00 to 11:00 a.m. and 1:00 to 4:00 p.m.).

Also, the locations of interest were classified into three facility types: surface streets, toll facilities, and freeways.

Figure 8-6 shows that the AVOs from accident records are consistently slightly higher for all time periods. Figure 8-7 shows that the estimates are very close for freeway facilities, but are slightly higher for those from accident records for the surface street and toll facility locations. These results are expected because small children are difficult to see using the windshield method. On the other hand, in the carousel method that was used to collect the freeway data, because the observer vehicle moves in parallel with the observed vehicles, the observers had more time to observe the occupants, including smaller children, hence the closer results for the freeway AVOs.

8.4. Comparisons with Field Data at the Site-Specific Level

To compare the field and accident AVOs gathered at the same survey points, accident data from one mile upstream and one mile downstream of the survey point were included. Figure 8-8 shows that a positive relationship exists between the two data sources. However, the AVO estimates from the accident data tend to be higher than the field estimates. Again, this is likely due to infants and small children missed by observers using the windshield method.

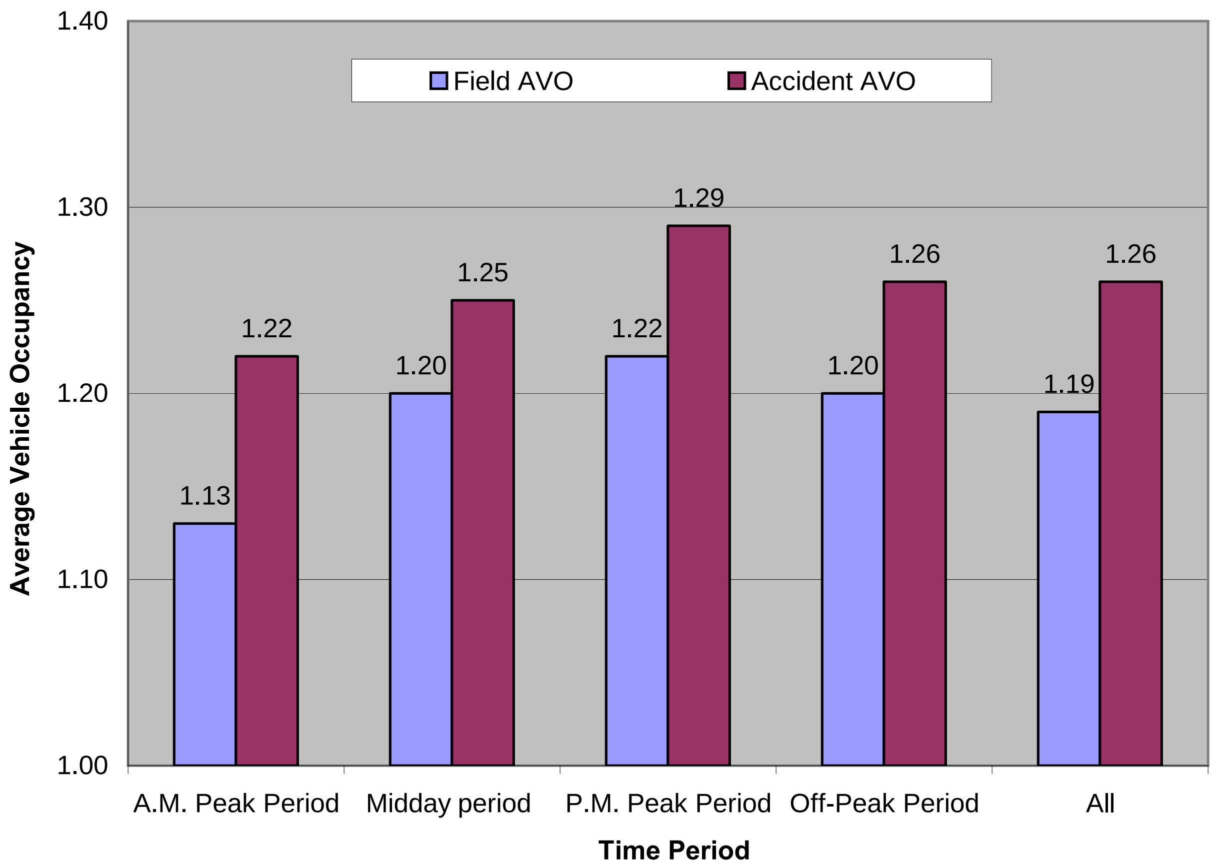


Figure 8-6. Comparisons of Countywide AVOs for Different Time Periods.

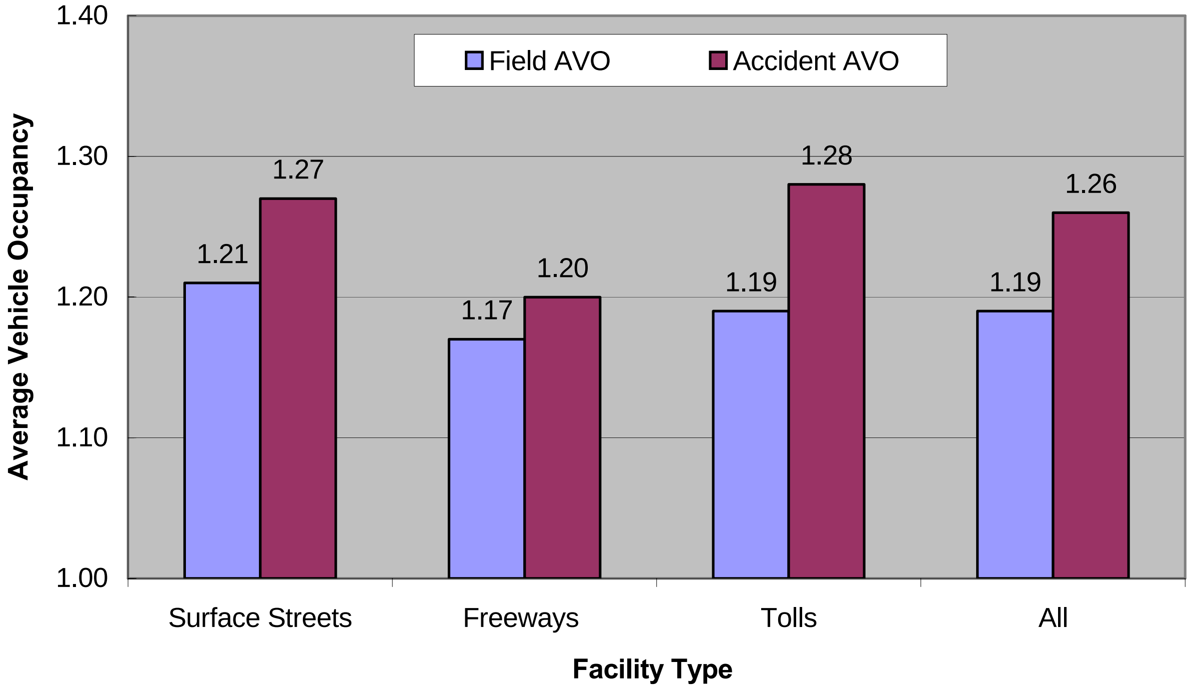


Figure 8-7. Comparisons of Countywide AVOs for Different Facility Types.

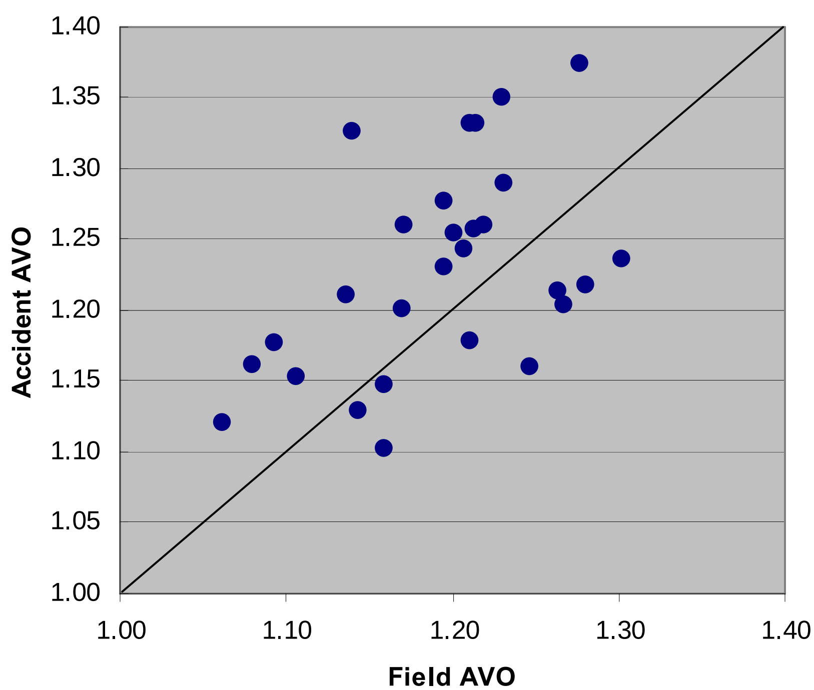


Figure 8-8. Comparisons of AVOs from the Field and from Accidents.

CHAPTER 9
VEHICLE OCCUPANCY PREDICTION MODELS

9.1. Introduction

While historical occupancy information can be obtained from accident records, and the current occupancy information can be collected using the field collection method, there have been no known methods developed to predict future occupancy rates. This chapter describes an effort to explore the feasibility of developing prediction models that can be used to estimate the expected vehicle occupancy rates given the future socioeconomic conditions of the study areas.

9.2. Data Sources

The Census 2000 demographic data from Summary Tape File #1 (STF #1) and Summary Tape File #3 (STF #3) were the main source of data for this study. The demographic data include age, gender, race and ethnic origin, household income level, vehicle ownership, families, housing units, and transit level of transit service, etc. The data by age are generally limited to persons of working age, defined as 16 years and older.

The 2002 Info USA employment data are also used in this study. The employment data are categorized by industry, service, and commercial employees. The 2002 employment data were the closest to the 2000 Census that were available for this study. Both census demographic and employment data were aggregated into the census blockgroup GIS layer for analysis. Table 9-1 lists the attributes from the two data sources.

In addition, the following five variables were calculated from two or more of the attributes from Table 9-1:

1. YOUNG_AGE: Total population with age in the range of 0–14 years.
2. OLD_AGE: Total population with age equal to or greater than 70.
3. TOTAL_VEH: Total number of vehicles.
4. HH_GT_1VEH: Household units with two or more vehicles.
5. PERPVEH: Average persons per vehicle.

The vehicle occupancy data were only derived from years 1999 and 2000 accident data to maintain compatibility with the census year. These accident data were filtered by vehicle type and weekday type, leaving only passenger vehicles involved in weekday accidents.

Table 9-1. Socioeconomic Attributes at Census Blockgroup Level.

Attribute Name*	Description
TOTAL_POP	Total population
WHITE	Total White population
BLACK	Total Black or African-American population
INDI_ALASK	Total American Indian and Alaska Native population
ASIAN	Total Asian population
PACIFIC	Total Native Hawaiian and Other Pacific Islander population
OTHER_RACE	Total population of some other race
MIXED_RACE	Population of two or more races
HISPANIC	Total population of Hispanic or Latino origin
MALE	Total male population
FEMALE	Total female population
AGE_0_4	Number of persons between 0 and 4 years old
AGE_5_9	Number of persons between 5 and 9 years old
AGE_10_14	Number of persons between 10 and 14 years old
AGE_15_17	Number of persons between 15 and 17 years old
AGE_18_19	Number of persons between 18 and 19 years old
AGE_20_24	Number of persons between 20 and 24 years old
AGE_25_29	Number of persons between 25 and 29 years old
AGE_30_39	Number of persons between 30 and 39 years old
AGE_40_49	Number of persons between 40 and 49 years old
AGE_50_59	Number of persons between 50 and 59 years old
AGE_60_69	Number of persons between 60 and 69 years old
AGE_70_79	Number of persons between 70 and 79 years old
AGE80_OVER	Number of persons 80 or above years old
MEDIAN_AGE	Median age
HOUSE_UNIT	Total number of housing units
OCPIED_HU	Number of occupied housing units
VACENT_HU	Number of vacant housing units
OWNER_HU	Number of housing units occupied by owners
RENTER_HU	Number of housing units occupied by renters
TOTAL_HH	Total number of households
HH_W1_PERS	Households with one person
HH_W2_PERS	Households with two persons
HH_W3_PERS	Households with three persons
HH_W4_PERS	Households with four persons
HH_W5_PERS	Households with five persons
HH_W6_PERS	Households with six persons
HH_W7_PERS	Households with seven or more persons
AV_HH_SIZE	Average household size
TOTAL_EMP	Total employees (source: InfoUSA employment data)
IND_EMP	Total industry employees (source: InfoUSA employment data)
COM_EMP	Total commercial employees (source: InfoUSA employment data)
SER_EMP	Total service employees (source: InfoUSA employment data)

Table 9-1. Socioeconomic Attributes at Census Blockgroup Level (continued).

Attribute Name*	Description
FORGN_BORN	Foreign-born population
DRIVEALONE	Drive alone to work for workers 16 years or over
CARPOOLED	Carpooled to work for workers 16 years or over
TRANSIT	Take transit to work for workers 16 years or over
OTHR_MODES	Use other modes to work for workers 16 years or over
WORKATHOME	Work at home for workers 16 years or over
TT_LT_15M	Travel time to work less than 14 min for workers 16 years or over
TT_15_29M	Travel time to work is 15-29 min for workers 16 years or over
TT_30_59M	Travel time to work is 30-59 min for workers 16 years or over
TT_GT_60M	Travel time to work is 1 hour or more for workers 16 years or over
TTT_LT_30M	Transit travel time to work is less than 30 min for workers 16 years or over
TTT_30_44M	Transit travel time to work is 30-44 min for workers 16 years or over
TTT_45_59M	Transit travel time to work is 45-59 min for workers 16 years or over
TTT_GT_59M	Transit travel time to work is 1 hour or more for workers 16 years or over
TOTAL_DISB	Total population 5 years and over with disabilities
SENSO_DISB	Total population 5 years and over with sensory disabilities
PHY_DISB	Total population 5 years and over with physical disabilities
MENTL_DISB	Total population 5 years and over with mental disabilities
EMPLY_DISB	Total population 5 years and over with employment disabilities
OTHER_DISB	Total population 5 years and over with other disabilities
EMPLOYED	Employed population 16 years or over
UNEMPLOYED	Unemployed population 16 years or over
INC_<10K	Household income less than $10,000
INC_10<20K	Household income from $10,000 to $19,999
INC_20<30K	Household income from $20,000 to $29,999
INC_30<40K	Household income from $30,000 to $39,999
INC_40<50K	Household income from $40,000 to $49,999
INC_50<60K	Household income from $50,000 to $59,999
INC_60<75K	Household income from $60,000 to $74,999
INC75<100K	Household income from $75,000 to $99,999
INC_>100K	Household income $100,000 or more
AVG_HH_INC	Average household income
HH_0_VEH	Housing units with no vehicle
HH_1_VEH	Housing units with one vehicle
HH_2_VEH	Housing units with two vehicles
HH_3_VEH	Housing units with three vehicles
HH_>3_VEH	Housing units with three or more vehicles

Note: Except for MEDIAN_AGE, AV_HH_SIZE, and AVG_HH_INC, all other variables were converted to density (i.e., divided by the total area) in the analysis.

9.3. Weekday AVO Models at Area Level

AVO can differ from one location to another. The statistical analysis in Chapter 3 indicated that the AVOs for different counties were significantly different from each other. To model the relationship between an area's AVO and the associated socioeconomic characteristics, the AVO for the area was calculated from vehicles involved in accidents that occurred inside the area. The census blockgroup data were aggregated at the area level. In this study, only two area levels are analyzed: county level and census blockgroup level.

1. *County level*: The AVOs for all 67 counties in the state of Florida were calculated from vehicles involved in accidents, and the census blockgroup data were aggregated into the county level.

2. *Census blockgroup level*: All vehicles involved in accidents that were located inside each census blockgroup were counted. A 0.25-mile buffer size was applied to each census blockgroup to extend the influence of the areas to include vehicles involved in accidents that occurred on the roadway between two or more census blockgroups. Also, the AVO for each blockgroup was calculated to model the relationship between the AVO and socioeconomic variables at the census blockgroup level.

9.3.1. AVO Model at County Level

Tables 9-2a and 9-2b list the Statistical Package for the Social Sciences (SPSS) output for this model. The stepwise method in the SPSS statistical analysis package selected two predictors: HH_GT_1VEH (i.e., household density with more than one vehicle) and TT_30_59M (i.e., worker density with travel time to work in the range of 30–59 minutes). However, the variance inflation factor (VIF) value for each of these two predictors is 19.125. This is obviously much larger than four, indicating that there is a high correlation between the two predictors. Hence, TT_30_59M was deselected in the final model refinement procedure because it contributes a very small part to R^2 (0.059). The final weekday AVO model at the county level (R^2/adjusted R^2 = 0.439/0.430) has the following form:

$$AVO = 1.667 - 0.040 \times \ln(HH\_GT\_1VEH)$$

In this model, the negative sign of the coefficient of predictor HH_GT_1VEH is also meaningful. It indicates that a higher household density with more than one vehicle will decrease the AVO. Figure 9-1 shows the fit of this model for the given data.

Table 9-2a. AVO Weekday County Model Summary[b]

Model	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate	Change Statistics				Durbin-Watson
					F Change	df1	df2	Sig. *F* Change	
1	0.663[a]	0.439	0.430	0.05970	53.660	1	65	0.000	2.429

a Predictors: (Constant), LOG_VEH_GT_1VEH
b Dependent Variable: AVO

Table 9-2b. AVO Weekday County Model Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.556	0.007		210.341	0.000		
	LOG_VEH_GT_1VEH	-0.043	0.006	-0.672	-7.325	0.000	1.000	1.000

a Dependent Variable: AVO

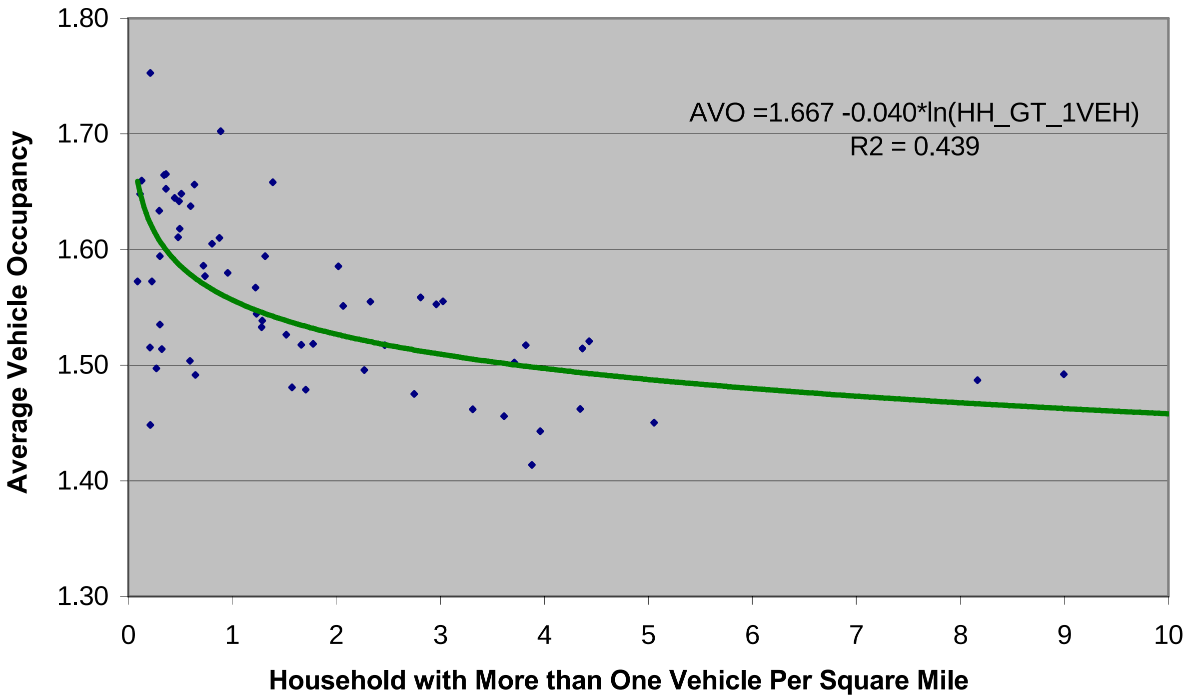


Figure 9-1. Weekday County AVO Model.

9.3.2. AVO Model at Census Blockgroup Level

For this modeling, Miami-Dade County census blockgroup data and vehicle occupancy data were used. The stepwise method selected many more variables: HH_0_VEH, HH_2_VEH, VACANT_HU, MEDIAN_AGE, AV_HH_SIZE, BLACK, AVG_HH_INC, IND_EMP, and COM_EMP. Tables 9-3a and 9-3b list the SPSS output for this model. They indicate that the AVO in each census blockgroup is related to average household size, average household income, industry and commercial employee density, vacant household unit density, and household density without a vehicle and with two vehicles. In this model, the signs of the coefficients are as expected. For instance, the negative sign for AVG_HH_INC indicates a higher average household income with lower average vehicle occupancy because of a higher possibility of multiple vehicle ownership. The positive sign for HH_0_VEH indicates that the higher density of a household with no vehicles will increase the possibility of carpooling, which will result in a higher occupancy rate. However, the R^2 in this model is relatively low, at 0.088.

Table 9-3a. Miami-Dade County AVO Weekday Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				Durbin-Watson
					F Change	df1	df2	Sig. F Change	
1	0.297[a]	0.088	0.080	0.07745	11.050	8	913	0.000	1.370

a Predictors: (Constant), VACANT_HU, IND_EMP, AVG_HH_INC, MEDIAN_AGE, COM_EMP, AV_HH_SIZE, HH_0_VEH, HH_2_VEH
b Dependent Variable: AVO

Table 9-3b. Miami-Dade County AVO Weekday Model Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.342	0.020		66.284	0.000		
	IND_EMP	-0.004	0.001	-0.105	-3.206	0.001	0.923	1.084
	COM_EMP	0.003	0.001	0.096	2.766	0.006	0.834	1.200
	AVG_HH_INC	-2.88E-007	0.000	-0.079	-2.227	0.026	0.793	1.261
	AV_HH_SIZE	0.018	0.004	0.147	4.035	0.000	0.751	1.331
	MEDIAN_AGE	-0.001	0.000	-0.074	-2.146	0.032	0.837	1.194
	VACANT_HU	0.006	0.001	0.155	4.052	0.000	0.686	1.458
	HH_0_VEH	0.004	0.001	0.116	2.902	0.004	0.628	1.592
	HH_2_VEH	-0.012	0.003	-0.169	-4.728	0.000	0.782	1.278

a Dependent Variable: AVO

9.4. AVO Model at Corridor Level

Different roadway types serve different people for different trip purposes. The federal roadway functional classification system defines the five urban roadway types, as given in Table 9-4. In this study, these roadway types were regrouped into two major groups for analysis: urban freeways, consisting of those with class codes 11 and 12, and urban arterials, consisting of those with class codes 14 and 16. Codes 17 and 19 are not modeled in this study.

Table 9-4. Urban Roadway Types.

Functional Classification Code	Definition
11	Urban - Principal Arterial - Interstate
12	Urban - Principal Arterial - Other Freeways and Expressways
14	Urban - Principal Arterial - Other
16	Urban - Minor Arterial
17	Urban - Collector
19	Urban - Local

For urban arterials, all urban counties are also classified into two categories: large urban counties with populations over 500,000 and medium-size urban counties with populations over 100,000 but less than or equal to 500,000. Table 9-5 lists all large urban counties in the state of Florida.

Table 9-5. Large Urban Counties.

County Number	County Name	Total Population
87	Miami-Dade	2,253,362
86	Broward	1,623,018
93	Palm Beach	1,131,184
10	Hillsborough	998,948
15	Pinellas	921,482
75	Orange	896,344
72	Duval	778,879

9.4.1. Data Preparation

9.4.1.1. Segmentation

In Florida, traffic and geometric information for the state roadway system is stored in the Roadway Characteristics Inventory (RCI) system, which includes more than 200 roadway features (e.g., functional classification, AADT, number of lanes, median width, etc.). Three basic fields (i.e., RoadwayID, BeginMilepost, and EndMilepost), were used to identify segments with special geometric characteristics. To model the relationship between the AVO in each corridor and the socioeconomic characteristics along the corridors, each state roadway is divided into segments based on the roadway functional class type, defined in the field FUNCLASS. Each of these segments has a unique functional class, and all have different lengths.

In the preliminary experiments, to achieve the best possible modeling results, each urban arterial was divided into 1-, 2- and 4-mile segments. Also, each of these segments had a unique roadway functional class. However, this fixed-length segmentation method did not provide good results. It was found that models based on this fixed-length segmentation method generally had much smaller R^2 values than those models that were based only on roadway function class types. Hence, only the roadway function class type is used to split up the urban arterials.

9.4.1.2. Aggregation

The key fields in the accident database are Roadway ID and Milepost. Each field is referred to as an accident location spatially. Vehicles involved in accidents located inside each segment are aggregated, and the corresponding vehicle occupants and vehicle numbers are counted. Table 9-6 shows a sample of how the AVO for each segment was calculated.

Table 9-6. Segmentation and Aggregation Results.

Roadway	BeginPost	EndPost	FUNCLASS	Occupants	Vehicles	AVO
88010000	0	10.13	14	879	633	1.39
88010000	17.131	17.681	14	22	14	1.57
88010000	18.581	20.981	14	111	84	1.32
88060000	21.82	32.142	14	825	583	1.42
88060000	32.142	33.592	16	70	50	1.40
88060001	0	1.364	14	104	79	1.32

9.4.1.3. Buffer Sizes

During the compilation of the socioeconomic data around each roadway segment, the GIS buffer function was used to create buffers around roadway segments to compile data for regression analysis. Buffer sizes of 0.5, 0.75, 1, 1.25, 1.50, and 2 mile(s) were used.

9.4.1.4. Predictor Selection

In the preliminary procedures, all independent variables and the dependent variable AVO for each buffer data set were loaded into the SPSS system. By using a linear regression stepwise method, all significant predictors for each buffer size data set were selected based on the following rules:

1. Each predictor must be significant at the 0.05 confidence level.
2. Variance inflation factors (VIF) must be less than four to avoid a high correlation between independent variables.

9.4.2. AVO Model for Arterials in Large Urban Counties

Large urban counties, in which there were a total of 266 urban arterial segments, possess different socioeconomic characteristics than medium-size urban counties. Along these arterial segments, different buffers with different buffer sizes were created for model selection. Table 9-7 lists the initial results of the preliminary procedures. In this table, a buffer size of 1.50 miles gives the highest R^2 value. For all of these initial models, three predictors were chosen: INC75_100K (i.e., household density with household income from $75,000 to $99,999), IND_EMP (i.e., industry employee density), and AVG_HH_INC (i.e., average household income). In other words, these predictors are more representative than others.

Table 9-7. Model Predictors Selected by Stepwise Procedure.

Buffer Size (miles)	Model Predictors	R^2 /Adjusted R^2
0.50	INC75_100K, IND_EMP, PERPVEH, AVG_HH_INC	0.299/0.289
0.75	INC75_100K, IND_EMP, AVG_HH_INC, OTHER_ENG, WORKATHOME	0.335/0.320
1.00	INC75_100K, IND_EMP, AVG_HH_INC, OTHER_RACE	0.340/0.327
1.25	INC75_100K, IND_EMP, AVG_HH_INC, TT_GT_60M, OTHER_ENG	0.343/0.331
1.50	INC75_100K, IND_EMP, AVG_HH_INC, TT_GT_60M, OTHER_ENG, MENTL_DISB	0.360/0.346
2.00	INC75_100K, IND_EMP, AVG_HH_INC, MENTL_DISB, COM_EMP	0.335/0.326

Note: All independent variables are explained by density (per acre) except average variables, such as AVG_HH_INC.

The next steps involve making curve estimations for selected predictors, as well as filtering out some predictors that contribute a very small part of R^2. Also, abnormal predictors were deleted from the models. Table 9-8 lists the final refined models for different buffer sizes. At 1.5 miles, the model reaches the highest R^2 value (0.357) and adjusted R^2 value (0.351).

Table 9-8. Models for Different Buffer Sizes.

Buffer Size (miles)	Model	R^2/Adjusted R^2
0.50	AVO = 1.363-0.039×ln(INC75_100K)-0.032×ln(IND_EMP) -1.66*E*-006 ×AVG_HH_INC	0.293/0.285
0.75	AVO = 1.362-0.042×ln(INC75_100K)-0.032×ln(IND_EMP) -1.79*E*-006 ×AVG_HH_INC	0.316/0.309
1.00	AVO = 1.361-0.045×ln(INC75_100K)-0.032×ln(IND_EMP) -1.87*E*-006 ×AVG_HH_INC	0.336/0.328
1.25	AVO = 1.354-0.047×ln(INC75_100K)-0.031×ln(IND_EMP) -1.81*E*-006 ×AVG_HH_INC	0.351/0.344
1.50	AVO = 1.349-0.049×ln(INC75_100K)-0.030×ln(IND_EMP) -1.75*E*-006 ×AVG_HH_INC	0.357/0.351
2.00	AVO = 1.348-0.047×ln(INC75_100K)-0.031×ln(IND_EMP) -1.68*E*-006 ×AVG_HH_INC	0.350/0.344

During the buffer analysis process, different buffer sizes were applied for urban major arterial and minor arterial subgroups. When mixed arterial buffer sizes (1.5 miles for major arterials and 1.0 mile for minor arterials) were applied to all urban county arterials, the R^2 (0.360) for the final model did not improve significantly compared to a uniform buffer size for all urban arterials. Hence, the following model created using a buffer size of 1.50 miles was selected:

$$AVO = 1.349 - 0.049 \times \ln(INC75\_100K) - 0.03 \times \ln(IND\_EMP) - 1.75E\text{-}006 \times AVG\_HH\_INC$$

Tables 9-9a and 9-9b give the SPSS output for this model, and Figures 9-2, 9-3, and 9-4 plot the scatter charts for each of the three predictors, respectively.

Table 9-9a. Summary for AVO Model for Arterials in Large Urban Counties[b].

Model	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate	Durbin-Watson
1	0.597[a]	0.357	0.351	0.08027	1.906

a Predictors: (Constant), AVG_HH_INC, LOG_INC75_100K, LOG_IND_EMP
b Dependent Variable: AVO

Table 9-9b. Coefficients for AVO Model for Arterials in Large Urban Counties [a].

Model		Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.342	0.020		66.284	0.000		
	LOG_INC75_100K	-0.049	0.008	-0.368	-6.067	0.000	0.639	1.564
	LOG_IND_EMP	-0.030	0.007	-0.289	-4.584	0.000	0.591	1.692
	AVG_HH_INC	-1.75*E*-006	0.000	-0.212	-3.824	0.000	0.763	1.311

a Dependent Variable: AVO

Figure 9-2. AVO vs. Industry Employees

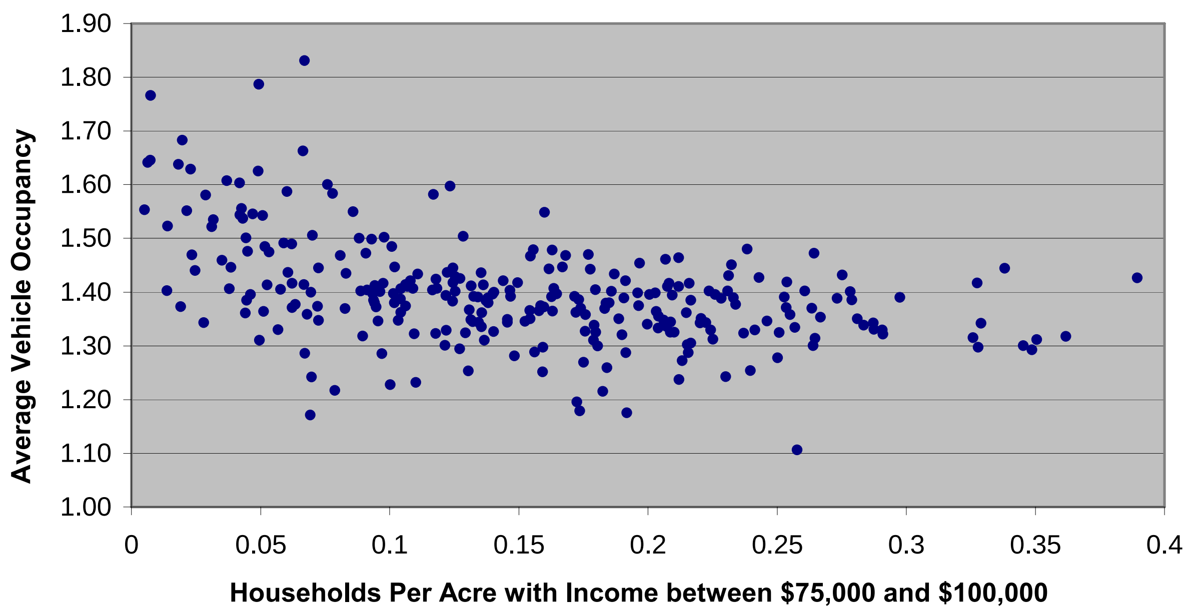


Figure 9-3. AVO vs. Average House Income Between $75,000 and $100,000.

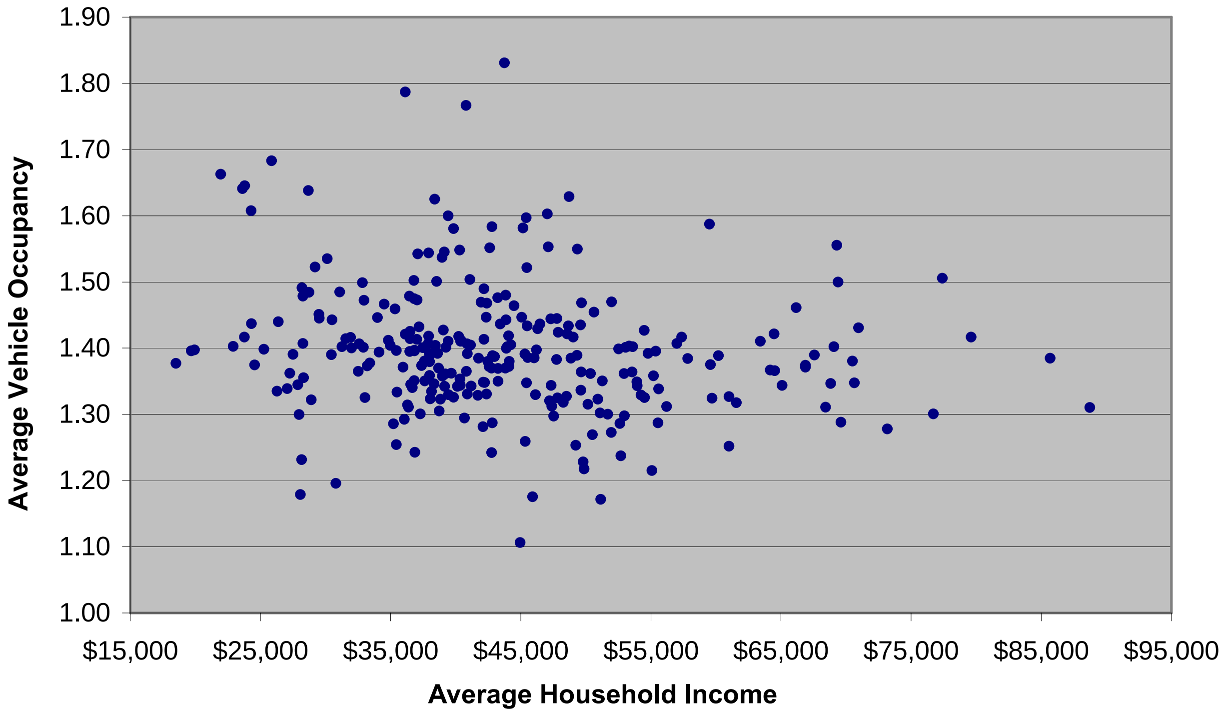


Figure 9-4. AVO vs. Average Household Income.

9.4.3. AVO Model for Arterials in Medium-Size Urban Counties

Counties with populations under 500,000 and above 100,000 were grouped into the medium-size urban county group. The urban arterials in these counties were aggregated to model the relationship between average vehicle occupancy and socioeconomic characteristics. The same buffering processes used earlier for large urban county arterial models were applied. For different buffer sizes, each model includes some common predictors: HH_2_VEH (i.e., household density with two vehicles), VACANT_HU (i.e., vacant household density), HH_W6_PERS (i.e., household density with six family members), and IND_EMP (i.e., industry employee density). Some other abnormal predictors, such as SPAN_ONLY (i.e., density of population speaking only Spanish), were also deselected from the final model. At a buffer size of 1.0 mile, the R^2 value and adjusted R^2 value reach 0.182 and 0.169, respectively. The final model is given as follows:

$$\begin{aligned} \text{AVO} = {} & 1.461 + 3.332 \times \text{HH\_W6\_PERS} - 0.376 \times \text{HH\_2\_VEH} - 0.131 \times \text{IND\_EMP} \\ & + 0.151 \times \text{VACANT\_HU} + 0.101 \times \text{COM\_EMP} \end{aligned}$$

The SPSS output for this model is listed in Tables 9-10a and 9-10b. In this model, the signs of the coefficients for all predictors are significant. For instance, the negative sign for IND_EMP indicates that a higher industry employee density will decrease the AVO due to more work-based trips.

Table 9-10a. Medium-Size County Arterial AVO Weekday Model Summary[b].

Model	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate	Durbin-Watson
1	0.427[a]	0.182	0.169	0.08941	1.671

a Predictors: (Constant), COM_EMP, HH_W6_PERS, VACANT_HU, IND_EMP, HH_2_VEH
b Dependent Variable: AVO

Table 9-10b. Medium-Size County Arterial AVO Weekday Model Coefficients[a].

Model		Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.461	0.011		134.249	0.000		
	HH_2_VEH	-0.376	0.051	-0.611	-7.427	0.000	0.381	2.621
	VACANT_HU	0.151	0.053	0.169	2.857	0.005	0.735	1.361
	HH_W6_PERS	3.332	0.739	0.354	4.508	0.000	0.418	2.391
	IND_EMP	-0.131	0.036	-0.287	-3.600	0.000	0.406	2.464
	COM_EMP	0.101	0.035	0.257	2.932	0.004	0.337	2.970

a Dependent Variable: AVO

9.4.4. AVO Model for Urban Freeways

Because freeways are fully access-controlled, the AVOs for freeways reflect vehicle occupancy over a much larger area. The common predictor selected for this facility by the stepwise method is HH_2_VEH (i.e., household density with two vehicles), and, at a buffer size of 2 miles, the initial model has the highest R^2 value. This initial model selected has two predictors: HH_2_VEH and CARPOOLED (i.e., carpooling population density). However, the VIF for each predictor is 5.505, which is greater than four, and because predictor CARPOOLED contributes a very small part to R^2, it was deleted. Tables 9-11a and 9-12b list the SPSS output for the final model, given as follows:

$$\text{AVO} = 1.29 - 0.119 \times \ln(\text{HH\_2\_VEH})$$

This model has an R^2 value of 0.386 and an adjusted R^2 value of 0.379. Figure 9-5 shows the scattered plot of this model.

Table 9-11a. Freeway Weekday AVO Model Summary[b].

Model	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate	Durbin-Watson
1	0.622[a]	0.386	0.379	0.12384	2.001

a Predictors: (Constant), LOG_HH_2_VEH
b Dependent Variable: AVO

Table 9-11b. Freeway Weekday AVO Model Coefficients[a].

Model		Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.290	0.022		57.692	0.000		
	LOG_HH_2_VEH	-0.119	0.016	-0.622	-7.315	0.000	1.000	1.000

a Dependent Variable: AVO

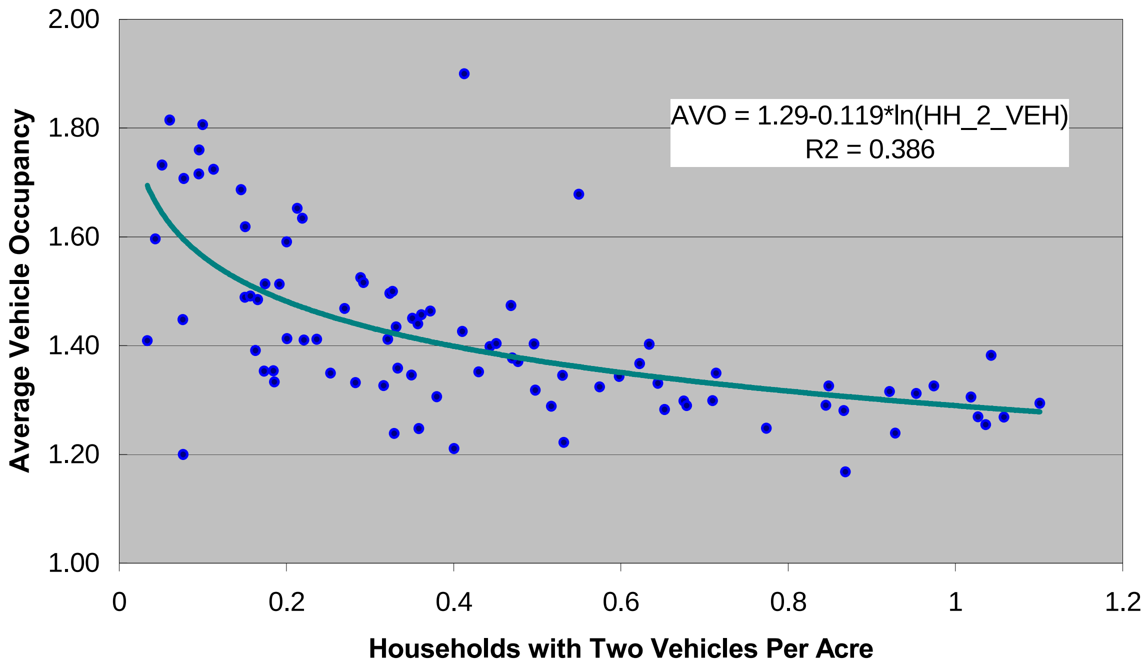


Figure 9-5. Freeway Weekday AVO Model.

9.5. Summary of Final Models

All final weekday AVO models are listed in Table 9-12. These models include those for countywide weekday AVO, large urban county arterial weekday AVO, medium-size urban county arterial weekday AVO, and urban freeway weekday AVO. The model for census blockgroup level weekday AVO is not included as one of the recommended models in the table because of its low R^2 value.

The R^2 values for these models are not high. Because accident vehicle occupancy data do not explicitly represent the context in which accident vehicle trips were made, these data do not deal explicitly with choices people make about how many automobiles to own, where to live, or where to work. Particularly for smaller areas, the vehicles involved in accidents inside these areas may not have much to do with the socioeconomic factors specific to these areas. This is also the reason that the AVO model based on census blockgroup level has a small R^2 value. For large areas, however, such as those at the county level, higher R^2 values were achieved because large-scale trends in travel patterns can often be accounted for by changing demographics.

Table 9-12. Final Models and Buffer Sizes.

Model Name	Model Form	R^2 / Adjusted R^2	Buffer Size (miles)
County Level	$AVO=1.667-0.040\times\ln(HH\_GT\_1VEH)$	0.439/0.430	N/A
Large Size Urban County Arterial	$AVO = 1.349-0.049\times\ln(INC75\_100K)-0.03\times\ln(IND\_EMP) -1.75E\text{-}006 \times AVG\_HH\_INC$	0.357/0.351	1.5
Medium Size Urban County Arterial	$AVO=1.461+3.332\times HH\_W6\_PERS - 0.376\times HH\_2\_VEH-0.131\times IND\_EMP +0.151\times VACANT\_HU+0.101\times COM\_EMP$	0.182/0.169	1.0
Freeway	$AVO = 1.29-0.119\times\ln(HH\_2\_VEH)$	0.386/0.379	2.0

CHAPTER 10
SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

10.1. Sampling Process

A statistical sampling procedure was applied to collect vehicle occupancy data in Miami-Dade County, Florida using both the roadside windshield and carousel methods. A systematically random sampling approach was applied to select the observation locations and dates. Sites were selected for roadways classified as surface streets, freeways, and toll facilities. An unbiased list of 48 sampling sites was, thus, generated to ensure that the observations represent true countywide AVO. The short-count procedure was conducted for 20- or 40-minute intervals per hour from 7:00 a.m. to 6:00 p.m. Data were collected for passenger vehicles, including pick-ups, on selected Tuesdays, Wednesdays, and Thursdays over a one-year span.

10.2. Statistical Analysis

A rigorous statistical analysis was performed on the vehicle occupancy data collected. The vehicle occupancy data were analyzed at the level of individual locations, facility types, and the whole county for a.m. peak, midday, p.m. peak, off-peak, and entire daylight hours.

- At the individual location level, the AVOs ranged from 1.0044 for freeway segments during the a.m. peak to 1.4205 for freeway segments during midday.

- At the facility-type level, AVOs ranged from 1.0969 for freeways during the a.m. peak to 1.2281 for surface streets during the p.m. peak.

- Countywide the AVOs ranged from 1.1287 for the a.m. peak to 1.2199 for the p.m. peak. Regardless of facility type, the p.m. peak and a.m. peak data consistently showed the highest and lowest AVO among different times of day, respectively.

- Countywide AVO and its composite standard deviation for the entirety of daylight hours were 1.1902 and 0.0338, respectively, and the corresponding 95% confidence interval was 1.1902 ± 0.0382. The data analysis showed that, in general, either the midday or off-peak AVO can best represent the AVO of the entire daylight hours.

- Freeways consistently experienced the lowest AVOs among the facility types regardless of the time of day. In contrast, the surface streets consistently experienced the highest AVOs for all but the p.m. peak.

10.3. Moving vs. Stopped Vehicles

To determine the potential difference in AVOs between observing moving and stopped vehicles, data were collected at three mid-block locations for moving vehicles and at upstream or downstream intersection stoplines on the same roadway segment for stopped vehicles. The data show that the AVOs collected based on stopped vehicles can be up to 11.8% higher than the AVO collected based on moving vehicles. While the AVO based on stopped vehicles are generally higher, the overall difference, at 1.03%, is both insignificant and inconclusive. It was also seen that the number of vehicles that could be observed while performing AVO counts only on stopped vehicles was much smaller than that of the stopped vehicles' moving counterparts. This suggests that the potentially better accuracy that could be achieved from observing only stopped vehicles might be offset by a lower degree of accuracy from a smaller sample size.

10.4. Site-Specific Study

As part of the data collection effort in this study, seven days of occupancy data were collected over a one-week (seven-day) period at a specific location on a major corridor. The results did not show significant differences in AVOs among the weekdays. However, the AVOs for Saturday and Sunday were significantly higher, with Sunday experiencing the highest AVO. To examine potential differences in AVOs along a corridor, data were collected at two additional locations on the same roadway. The results show that the AVOs could vary significantly along a corridor, which suggests a need for collecting data at multiple locations for a corridor study.

10.5. Updated Field Data Collection System

To facilitate field data collection, a Pocket PC application tool was developed as part of the Phase I study. The tool replaces the traditional manual data recording and post-processing by allowing the user to make use of the touch-screen interface on a Pocket PC to record the number of occupants. Based on the lessons learned from the data collection effort in this study, the system was improved to allow the user to enter the number of occupants more easily and quickly. This was achieved mainly by increasing the size of touch-screen buttons, recording data at the instant of button tapping, and removing unnecessary option selections.

10.6. Factors Affecting Vehicle Occupancies

Parametric and nonparametric statistical tests were applied to examine the contributing factors affecting AVOs in the state of Florida. The following factors were analyzed: year, month, day-of-week, time periods, county, driver's age, driver's gender, driver's race, accident severity, facility type, and weather conditions. Both parametric and non-parametric analyses of variance (ANOVA) were applied, and it was found that AVOs were affected by all of the factors examined to various degrees. Despite continued efforts over the past decades to encourage people to carpool, the data show that the overall AVO in Florida has continued to decline over the years, from a high 1.58 occupants per vehicle in the 1990 down to 1.42 occupants per vehicle in 2005, or a 10% decrease. This study also found that a.m. peaks tend to have the lowest AVO in a day and that weekend AVOs were significantly higher than weekday AVOs. In addition, younger drivers were found to have higher AVOs than older drivers, female drivers tend to have more occupants in their vehicles than male drivers, black and Hispanic Americans tend to have higher AVOs than white Americans, and rural AVOs are significantly higher than urban AVOs.

10.7. Potential Biases and Adjustment Factors

As a potential source of vehicle occupancy data, accident data has met with some doubt due to its possible biases. Based on findings from past studies, two possible biases were analyzed and discussed in detail: accident severity and driver's age. By comparing accident vehicle data with field data, however, analysis results showed that although multi-occupant (two and more than two) vehicles occupy higher percentages of severe accidents (injury and fatality) than do single-occupant vehicles, multi-occupant vehicles in the whole accident vehicle population were not overrepresented in the accident database. However, a driver's age bias was found in the accident data. By comparing the year 2000 Miami-Dade County accident data and the 2000 census demographic data, it was found that there is a significant difference between the distribution of the ages of drivers involved in accidents and the ages of the general driving population in the county. A census weighting method was used to adjust for this bias in the AVO estimates. Other potential bias factors may include driver's gender, driver's race, and weather conditions. However, adjustment factors for these potential biases cannot currently be developed because of the lack of driving exposure data associated with their population subgroups.

10.8. FAVORITE Information System Updates

FAVORITE is a user-friendly information system capable of estimating average vehicle occupancies from multiple years of accident records for Florida's state roadway system. As part of the continued development of the system, the potential biases resulting from accident severity and driver's age were examined and the corresponding adjustment factors for driver's age were developed and implemented in the system. Also incorporated in the system in this Phase II study was consideration given to the minimum required number of accident records necessary to meet the desired accuracy in the AVO estimates.

Version 2 of the system includes the 1990-2005 accident data that are cross-classified by year, month, day, and hours, making it possible to perform temporal monitoring. The database also includes district, county, roadway section, and area type that can be used for spatial comparisons and monitoring. Comparisons can also be made by vehicle type, facility type, and accident severity. Because the system makes use of a comprehensive, statewide database, it can potentially be a highly cost-effective means of monitoring statewide, regional, and site-specific vehicle occupancy trends.

10.9. Evaluation of AVO Estimates from Accident Data

A reasonableness check of the results from the FAVORITE system shows AVO estimates that are consistent with expectations. In addition, comparisons of AVOs from accident data with the field estimates show that the two data sources produce results that are generally consistent. The comparisons also show that the AVO estimates from accident data tend to be slightly higher, most likely because accident records are able to include infants and small children who are often difficult to see during field observation.

10.10. AVO Prediction Models

Regression models for the purpose of predicting weekday AVOs were developed in this study using census demographic data integrated with 2002 InfoUSA employment data. Four regression models were developed: a weekday county area level model, a weekday large urban county arterial level model, a medium urban county arterial level model, and a weekday urban freeway model. Essentially, these models expressed the average occupancy rate for arterials and areas as a function of several statistically significant socioeconomic variables.

For the weekday county area level AVO model, the R^2 value is 0.452, which is considered acceptable. During the model development, a weekday model for the census blockgroup level was also developed. However, the R^2 value for this model is relatively low. Hence, this model was not recommended. The R^2 values for the three recommended arterial models are 0.357 for the large urban county arterial level model, 0.386 for the urban freeway model, and 0.182 for the medium-size urban county arterial level model. These models show that such socioeconomic factors as income, vehicle ownership, and employment play a part in vehicle occupancy forecasting models.

Although the AVO prediction models developed were statistically significant, their R^2 values are not high. The accident vehicle occupancy data do not explicitly represent the context in which accident vehicle trips were made. As more accident vehicle trip information and driver and passenger information become available, an update of the model parameters and predictors may be conducted to produce more accurate predictions. Consequently, one of the main future studies could involve developing a survey data method to obtain the needed data and a procedure for automatically integrating these survey data into the current accident database.

10.11. Further Development

This study has shown that accident records provide a viable and reliable data source for estimating AVOs, especially at the statewide and regional levels. As identified in this study, the use of accident records for AVO estimation offers the following advantages over the traditional field data collection methods:

- It is both cost effective and safe as it involves no field observation.
- It does not require any data post-processing, which is tedious and time consuming.
- It covers all time periods, including night hours when field data collection cannot be performed.
- It counts all occupants, including small children, who are difficult for observers to see in the field.
- It is not subject to visibility problems due to tinted vehicle windows.
- It is not subject to data quality problems as a result of field crews experiencing fatigue, providing poor job performance, over- or under-counting, etc.

Accordingly, it is recommended that the Department continues to develop the FAVORITE prototype, which is already a very powerful system considering its rich set of integrated accident records (since the year 1990), its ease of use, and its many capabilities and functionalities, including variable re-classification, variable filtering, data cross-classification, GIS visualization, chart plotting, etc.

While it is not necessary that AVOs derived from accident records be adjusted for potential biases for continuous AVO monitoring, further development may address other potential biases and possibly develop the corresponding adjustment factors for the benefit of applications that require absolute AVO estimates. Although FAVORITE is already freely available through web download, it is recommended that a web version be developed using ArcGIS Server as the software platform to take advantage of the instant accessibility of web applications. Additional functionalities can also be developed, for example, the ability to automatically upload new accident records as they become available. The install file of the current version of FAVORITE is freely available for downloads at this website: http://lctr.eng.fiu.edu/FAVORITE.htm.

REFERENCES

1. Ahuja, V., and Hanscom, E., "Feasibility Study to Estimate the Average Vehicle Occupancy by Utilizing a Traffic Accident Database," Presented at the Annual Meeting of the Transportation Research Board, Washington, DC, January 1996.

2. Asante, S. A., L. H. Adams, J. J. Shufon, and J. P. McClean, "Estimating Average Automobile Occupancy from Accident Data in New York State," *Transportation Research Record 1553*, 1996, pp. 115-123.

3. Barton-Aschman Associates, Inc., *Vehicle Occupancy Determinators*, Final Report Prepared for Arizona Department of Transportation, August 1989.

4. Chang, L. Y. and F. L. Mannering, "Predicting Vehicle Occupancies from Accident Data: An Accident Severity Approach," *Transportation Research Record 1635*, Transportation Research Board, Washington, DC, pp. 93-104, 1998.

5. Ferlis, R. A., *Guide for Estimating Urban Vehicle Classification and Occupancy*, Final Report Prepared for FHWA Office of Highway Planning, March 1981.

6. Gan, A., R. Jung, K. Liu, X. Li, and D. Sandoval, *Vehicle Occupancy Data Collection Methods*, Final Report Prepared for the Transportation Statistics Office, Florida Department of Transportation, February 2005.

7. Gaulin, R., *A Procedure to Calculate Vehicle Occupancy Rates from Traffic Accident Data*, Final Report Prepared for the Connecticut Department of Transportation, Bureau of Planning, April 1991.

8. Heidtman, K., B. Skarpness, and C. Tornow, *Improved Vehicle Occupancy Data Collection Methods*, FHWA Office of Highway Information Management, April 1997.

9. Levine, N. and M. Wachs, "Factors Affecting Vehicle Occupancy Measurement," *Transportation Research, Part A, Policy and Practice*, Vol. 32A, No. 3, pp.215-229,1998.

10. Lui, K. J., D. McGee, P. Rhodes, and D. Pollock, "An Application of a Conditional Logistic Regression to Study the Effects of Safety Belts, Principal Impact Points, and Car Weights on Drivers' Fatalities," *Journal of Safety Research*, 19, pp. 197-203, 1988.

11. McClave, J. T., and P. G. Benson, *Statistics for Business and Economics*, 4th ed., Dellen and MacMiallan, 1988.

12. O'Donnell, C. and D. Connor, "Predicting the Severity of Motor Vehicle Accident Injuries Using Models of Ordered Multiple Choice," *Accident Analysis and Prevention*, 28(6), pp. 739-753, 1996.

13. Shankar, V. N., F. L. Mannering, and W. Barfield, "Statistical Analysis of Accident Severity on Rural Freeways," *Accident Analysis and Prevention*, 28(3), pp. 391-401, 1996.

14. Ulberg, C. G and E. McCormack, "Accuracy and Other Factors Affecting a Continuous Vehicle Occupancy Monitoring Program," *Transportation Research Record 1206*, Transportation Research Board, Washington, DC, pp. 35-47, 1988.

15. Ulberg, C. G. and E. McCormack, *Auto Occupancy Monitoring Study*, Final Report Submitted to Washington State Department of Transportation, June 1988.

16. URS Consultants, Inc., *Vehicle Occupancy Data Collection and Analysis*, Final Report Prepared for the Florida Department of Transportation, Systems Planning Office, December 1997.

APPENDIX A

SUMMARY OF FIELD VEHICLE OCCUPANCY DATA

Table A-1. Vehicle Occupancy Data for Surface Streets During A.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	NW 72nd Ave	NW 36th St and NW 31st St	2/28/2006	1,138	994	3,414	2,982	1.1449
2	NW 116th Wy	NW South River Dr and NW 100th Rd	3/7/2006	1,001	872	3,003	2,616	1.1479
3	SW 82nd Ave	SW 24th St and SW 28th St	3/24/2006	489	422	1,467	1,266	1.1588
4	NW 58th St	NW 87th Ave and NW 97th Ave	3/29/2006	1,354	1,199	3,725	3,281	1.1353
5	S Dixie Hwy	SW 24th Ave and SW 22nd Ave	4/12/2006	4,603	4,165	13,809	12,495	1.1052
6	SW 184th St	SW 132nd Ave and SW 127th Ave	4/18/2006	983	783	3,043	2,432	1.2509
7	W 29th St	W 8th Ave and W 11th Ave	5/3/2006	651	543	2,467	2,056	1.1999
8	SW 152nd St	SW 152nd Ave and SW 148th Ct	5/16/2006	1,121	848	3,838	2,907	1.3201
9	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	314	271	3,337	2,861	1.1665
10	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	713	620	4,124	3,592	1.1481
11	SW 88th St	SW 79th Ave and SW 77th Ave	7/11/2006	1,954	1,726	6,107	5,394	1.1322
12	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	733	620	2,699	2,283	1.1821
13	NW 37th Ave	NW 3rd St and W Flagler St	8/4/2006	855	763	2,565	2,289	1.1206
14	Old Cutler Rd	SW 157th Te and SW 168th St	8/15/2006	547	428	1,961	1,533	1.2788
15	Granada Bd	SW 8th St and Venetia Te	9/14/2006	836	703	1,822	1,525	1.1953
16	NW 20th St	NW 10th Ave and NW 11th Ave	10/4/2006	1,474	1,170	2,578	2,047	1.2598
17	NE 2nd Ave	NE 95th St and NE 90th St	10/26/2006	2,047	1,750	3,071	2,625	1.1697
18	S Dixie Hwy	SW 380th St and SW 384th St	11/2/2006	1,154	943	1,770	1,449	1.2216
19	SW 127th Ave	SW 76th St and SW 80th St	11/8/2006	1,813	1,690	3,626	3,380	1.0728
20	NE 190th St	NE 29th Ave and Country Club Dr	12/6/2006	1,173	1,122	1,805	1,727	1.0447
21	NE 2nd Ave	NE 117th St and NE 114th St	12/14/2006	2,907	2,853	4,651	4,565	1.0189
22	NW 215th St	Florida TP and NW 7th Ave	1/4/2007	1,626	1,448	3,252	2,896	1.1229
23	W 37th St	W 14th Ave and W 16th Ave	1/17/2007	916	757	1,865	1,541	1.2101
24	SW 117th Ave	SW 64th St and SW 72nd St	2/15/2007	1,751	1,549	2,802	2,478	1.1304

Table A-2. Vehicle Occupancy Data for Freeways During A.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Julia Tuttle CY	Biscayne Bd and N Bay Rd	3/16/2006	537	457	3,745	3,188	1.1745
2	SR 826 EX	W 63rd St and W 52nd St	4/6/2006	603	582	1,929	1,863	1.0352
3	SR 826 EX	NW 17th St and NW 15th St	5/23/2006	673	585	3,454	2,987	1.1564
4	SR 826 EX	NW 48th St and NW 43rd St	6/8/2006	861	734	4,326	3,679	1.1758
5	SR 836 EX	NW 36th Ave and NW 31st Ave	7/13/2006	483	423	3,744	3,270	1.1450
6	SR 826 EX	SW 75th St and SW 85th St	8/10/2006	326	300	2,332	2,149	1.0855
7	SR 836 EX	NW 57th Ave and Perimeter Rd.	9/28/2006	506	435	2,526	2,167	1.1659
8	SR 826 EX	NW 41st St and NW 36th St	10/18/2006	945	907	6,574	6,303	1.0430
9	SR 836 EX	NW 111th Pl. and NW 107th Ave	11/14/2006	332	330	2,722	2,710	1.0044
10	I-95	NW 5th Ct and SR 836 EX	12/28/2006	513	440	2,466	2,106	1.1709
11	SR 826 EX	NW 35th Te and NW 34th St	1/24/2007	836	794	5,165	4,896	1.0549
12	SR 826 EX	NW 12th St and NW 7th St	2/20/2007	638	623	3,487	3,401	1.0251

Table A-3. Vehicle Occupancy Data for Toll Facilities During A.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	SR 821 EX	SW 154th St and SW 180th St	3/22/2006	1,152	901	3,255	2,557	1.2732
2	SR 821 ET	SW 134th St and Louis St	4/25/2006	722	598	2,380	1,966	1.2105
3	SR 821 HY	SW 24th St and SW 35th Te	5/11/2006	1,858	1,565	5,574	4,695	1.1872
4	Florida TP	NW 183rd St and NW 170th St	6/22/2006	859	774	2,482	2,238	1.1090
5	Florida TP	NW 202nd St and W 194th St	7/27/2006	622	550	1,866	1,650	1.1309
6	SR 821 ET	SW 106th Ave and SW 112th Te	8/24/2006	1,118	932	3,287	2,740	1.1996
7	SR 874 EX	SW 117th St and SW 120th St	9/21/2006	3,604	3,016	5,879	4,914	1.1964
8	SR 874 EX	SW 56th St and SW 66th St	10/12/2006	-	-	-	-	-
9	Florida TP	NW 194th St and NW 186th St	11/22/2006	2,041	1,953	9,313	9,024	1.0321
10	Opa Locka EX	NW 135th St and NW128th St	12/9/2006	2,219	2,140	3,329	3,210	1.0369
11	Florida TP	NW 186th Te and NW 183rd St	1/10/2007	787	753	1,259	1,205	1.0452
12	Florida TP	Near NW 27th Ave	2/7/2007	1,081	995	2,048	1,881	1.0888

Table A-4. Vehicle Occupancy Data for Surface Streets During Midday Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	NW 72nd Ave	NW 36th St and NW 31st St	2/28/2006	1,462	1,257	4,386	3,771	1.1631
2	NW 116th Wy	NW South River Dr and NW 100th Rd	3/7/2006	762	629	2,286	1,887	1.2114
3	SW 82nd Ave	SW 24th St and SW 28th St	3/24/2006	300	262	900	786	1.1450
4	NW 58th St	NW 87th Ave and NW 97th Ave	3/29/2006	978	845	2,934	2,535	1.1574
5	S Dixie Hwy	SW 24th Ave and SW 22nd Ave	4/12/2006	3,642	2,780	10,392	7,904	1.3148
6	SW 184th St	SW 132nd Ave and SW 127th Ave	4/18/2006	929	764	2,787	2,292	1.2160
7	W 29th St	W 8th Ave and W 11th Ave	5/3/2006	727	601	2,273	1,882	1.2081
8	SW 152nd St	SW 152nd Ave and SW 148th Ct	5/16/2006	571	487	1,713	1,461	1.1725
9	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	1,746	1,394	6,286	5,019	1.2525
10	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	1,078	879	7,616	6,266	1.2155
11	SW 88th St	SW 79th Ave and SW 77th Ave	7/11/2006	2,032	1,625	6,096	4,875	1.2505
12	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	389	313	1,167	939	1.2428
13	NW 37th Ave	NW 3rd St and W Flagler St	8/4/2006	790	646	2,942	2,423	1.2143
14	Old Cutler Rd	SW 157th Te and SW 168th St	8/15/2006	563	451	1,689	1,353	1.2483
15	Granada Bd	SW 8th St and Venetia Te	9/14/2006	755	613	1,211	982	1.2334
16	NW 20th St	NW 10th Ave and NW 11th Ave	10/4/2006	2,197	1,642	2,974	2,224	1.3374
17	NE 2nd Ave	NE 95th St and NE 90th St	10/26/2006	1,210	991	1,815	1,487	1.2210
18	S Dixie Hwy	SW 380th St and SW 384th St	11/2/2006	1,175	909	1,816	1,415	1.2835
19	SW 127th Ave	SW 76th St and SW 80th St	11/8/2006	1,246	1,135	2,176	1,982	1.0981
20	NE 190th St	NE 29th Ave and Country Club Dr	12/6/2006	1,825	1,668	3,023	2,760	1.0954
21	NE 2nd Ave	NE 117th St and NE 114th St	12/14/2006	1,008	969	1,814	1,746	1.0387
22	NW 215th St	Florida TP and NW 7th Ave	1/4/2007	1,632	1,352	2,448	2,028	1.2071
23	W 37th St	W 14th Ave and W 16th Ave	1/17/2007	756	616	1,538	1,254	1.2267
24	SW 117th Ave	SW 64th St and SW 72nd St	2/15/2007	1,757	1,476	3,514	2,952	1.1904

Table A-5. Vehicle Occupancy Data for Freeways During Midday Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Julia Tuttle CY	Biscayne Bd and N Bay Rd	3/16/2006	360	268	2,946	2,195	1.3423
2	SR 826 EX	W 63rd St and W 52nd St	4/6/2006	817	702	3,687	3,191	1.1553
3	SR 826 EX	NW 17th St and NW 15th St	5/23/2006	614	537	3,785	3,308	1.1442
4	SR 826 EX	NW 48th St and NW 43rd St	6/8/2006	633	523	4,234	3,502	1.2091
5	SR 836 EX	NW 36th Ave and NW 31st Ave	7/13/2006	454	357	3,506	2,753	1.2733
6	SR 826 EX	SW 75th St and SW 85th St	8/10/2006	290	229	2,058	1,626	1.2654
7	SR 836 EX	NW 57th Ave and Perimeter Rd.	9/28/2006	358	304	1,678	1,421	1.1807
8	SR 826 EX	NW 41st St and NW 36th St	10/18/2006	670	613	4,188	3,891	1.0765
9	SR 836 EX	NW 111th Pl. and NW 107th Ave	11/14/2006	443	422	3,564	3,388	1.0519
10	I-95	NW 5th Ct and SR 836 EX	12/28/2006	563	393	3,505	2,467	1.4205
11	SR 826 EX	NW 35th Te and NW 34th St	1/24/2007	926	779	5,510	4,635	1.1888
12	SR 826 EX	NW 12th St and NW 7th St	2/20/2007	532	512	2,996	2,882	1.0393

Table A-6. Vehicle Occupancy Data for Toll Facilities During Midday Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	SR 821 EX	SW 154th St and SW 180th St	3/22/2006	654	505	1,820	1,411	1.2899
2	SR 821 ET	SW 134th St and Louis St	4/25/2006	422	367	1,266	1,101	1.1499
3	SR 821 HY	SW 24th St and SW 35th Te	5/11/2006	1,685	1,346	5,055	4,038	1.2519
4	Florida TP	NW 183rd St and NW 170th St	6/22/2006	264	225	779	664	1.1734
5	Florida TP	NW 202nd St and W 194th St	7/27/2006	269	216	861	691	1.2454
6	SR 821 ET	SW 106th Ave and SW 112th Te	8/24/2006	727	566	2,150	1,674	1.2839
7	SR 874 EX	SW 117th St and SW 120th St	9/21/2006	-	-	-	-	-
8	SR 874 EX	SW 56th St and SW 66th St	10/12/2006	2,202	1,767	4,333	3,482	1.2444
9	Florida TP	NW 194th St and NW 186th St	11/22/2006	3,376	3,168	5,239	4,926	1.0635
10	Opa Locka EX	NW 135th St and NW128th St	12/9/2006	1,195	1,101	1,793	1,652	1.0854
11	Florida TP	NW 186th Te and NW 183rd St	1/10/2007	263	237	395	356	1.1097
12	Florida TP	Near NW 27th Ave	2/7/2007	487	425	925	808	1.1459

Table A-7. Vehicle Occupancy Data for Surface Streets During P.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	NW 72nd Ave	NW 36th St and NW 31st St	2/28/2006	1,544	1,297	4,632	3,891	1.1904
2	NW 116th Wy	NW South River Dr and NW 100th Rd	3/7/2006	926	828	2,778	2,484	1.1184
3	SW 82nd Ave	SW 24th St and SW 28th St	3/24/2006	591	484	1,773	1,452	1.2211
4	NW 58th St	NW 87th Ave and NW 97th Ave	3/29/2006	1,344	1,219	4,032	3,657	1.1025
5	S Dixie Hwy	SW 24th Ave and SW 22nd Ave	4/12/2006	3,014	2,363	9,042	7,089	1.2755
6	SW 184th St	SW 132nd Ave and SW 127th Ave	4/18/2006	1,373	1,148	4,119	3,444	1.1960
7	W 29th St	W 8th Ave and W 11th Ave	5/3/2006	941	728	2,823	2,184	1.2926
8	SW 152nd St	SW 152nd Ave and SW 148th Ct	5/16/2006	1,777	1,501	5,331	4,503	1.1839
9	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	2,270	1,797	6,810	5,391	1.2632
10	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	588	457	1,764	1,371	1.2867
11	SW 88th St	SW 79th Ave and SW 77th Ave	7/11/2006	1,315	1,093	3,945	3,279	1.2031
12	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	626	508	1,945	1,578	1.2325
13	NW 37th Ave	NW 3rd St and W Flagler St	8/4/2006	917	722	2,776	2,185	1.2703
14	Old Cutler Rd	SW 157th Te and SW 168th St	8/15/2006	968	802	2,904	2,406	1.2070
15	Granada Bd	SW 8th St and Venetia Te	9/14/2006	410	339	738	610	1.2094
16	NW 20th St	NW 10th Ave and NW 11th Ave	10/4/2006	1,978	1,416	3,956	2,832	1.3969
17	NE 2nd Ave	NE 95th St and NE 90th St	10/26/2006	1,737	1,452	2,749	2,290	1.2004
18	S Dixie Hwy	SW 380th St and SW 384th St	11/2/2006	1,268	964	2,725	2,080	1.3100
19	SW 127th Ave	SW 76th St and SW 80th St	11/8/2006	2,437	2,023	3,656	3,035	1.2046
20	NE 190th St	NE 29th Ave and Country Club Dr	12/6/2006	1,282	1,002	1,923	1,503	1.2794
21	NE 2nd Ave	NE 117th St and NE 114th St	12/14/2006	1,748	1,350	2,622	2,025	1.2948
22	NW 215th St	Florida TP and NW 7th Ave	1/4/2007	2,043	1,637	3,173	2,541	1.2487
23	W 37th St	W 14th Ave and W 16th Ave	1/17/2007	1,419	1,099	2,129	1,649	1.2912
24	SW 117th Ave	SW 64th St and SW 72nd St	2/15/2007	1,879	1,584	2,819	2,376	1.1862

Table A-8. Vehicle Occupancy Data for Freeways During P.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Julia Tuttle CY	Biscayne Bd and N Bay Rd	3/16/2006	406	307	2,992	2,257	1.3255
2	SR 826 EX	W 63rd St and W 52nd St	4/6/2006	794	662	5,949	4,991	1.1921
3	SR 826 EX	NW 17th St and NW 15th St	5/23/2006	485	401	2,245	1,852	1.2125
4	SR 826 EX	NW 48th St and NW 43rd St	6/8/2006	735	652	3,858	3,489	1.1058
5	SR 836 EX	NW 36th Ave and NW 31st Ave	7/13/2006	416	343	2,902	2,387	1.2159
6	SR 826 EX	SW 75th St and SW 85th St	8/10/2006	163	138	1,557	1,318	1.1817
7	SR 836 EX	NW 57th Ave and Perimeter Rd.	9/28/2006	669	540	2,908	2,350	1.2371
8	SR 826 EX	NW 41st St and NW 36th St	10/18/2006	650	558	2,528	2,162	1.1691
9	SR 836 EX	NW 111th Pl. and NW 107th Ave	11/14/2006	216	198	1,447	1,327	1.0909
10	I-95	NW 5th Ct and SR 836 EX	12/28/2006	479	367	3,331	2,556	1.3035
11	SR 826 EX	NW 35th Te and NW 34th St	1/24/2007	827	764	3,958	3,644	1.0861
12	SR 826 EX	NW 12th St and NW 7th St	2/20/2007	550	468	2,316	1,947	1.1897

Table A-9. Vehicle Occupancy Data for Toll Facilities During P.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	SR 821 EX	SW 154th St and SW 180th St	3/22/2006	834	640	2,461	1,885	1.3054
2	SR 821 ET	SW 134th St and Louis St	4/25/2006	1,049	762	2,937	2,134	1.3766
3	SR 821 HY	SW 24th St and SW 35th Te	5/11/2006	1,554	1,224	5,019	3,949	1.2711
4	Florida TP	NW 183rd St and NW 170th St	6/22/2006	498	452	1,483	1,348	1.0997
5	Florida TP	NW 202nd St and W 194th St	7/27/2006	717	598	2,151	1,794	1.1990
6	SR 821 ET	SW 106th Ave and SW 112th Te	8/24/2006	-	-	-	-	-
7	SR 874 EX	SW 117th St and SW 120th St	9/21/2006	4,037	3,367	5,847	4,881	1.1978
8	SR 874 EX	SW 56th St and SW 66th St	10/12/2006	1,033	868	2,996	2,517	1.1903
9	Florida TP	NW 194th St and NW 186th St	11/22/2006	3,360	2,532	6,498	4,908	1.3240
10	Opa Locka EX	NW 135th St and NW128th St	12/9/2006	1,688	1,438	5,053	4,304	1.1739
11	Florida TP	NW 186th Te and NW 183rd St	1/10/2007	653	570	1,331	1,158	1.1491
12	Florida TP	Near NW 27th Ave	2/7/2007	1,009	918	1,757	1,591	1.1044

Table A-10. Vehicle Occupancy Data for Surface Streets During Off-Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	NW 72nd Ave	NW 36th St and NW 31st St	2/28/2006	2,902	2,482	9,107	7,781	1.1704
2	NW 116th Wy	NW South River Dr and NW 100th Rd	3/7/2006	1,632	1,390	5,283	4,498	1.1745
3	SW 82nd Ave	SW 24th St and SW 28th St	3/24/2006	1,058	853	3,174	2,559	1.2403
4	NW 58th St	NW 87th Ave and NW 97th Ave	3/29/2006	3,266	2,856	9,798	8,568	1.1436
5	S Dixie Hwy	SW 24th Ave and SW 22nd Ave	4/12/2006	8,745	7,108	26,235	21,324	1.2303
6	SW 184th St	SW 132nd Ave and SW 127th Ave	4/18/2006	2,379	1,933	7,401	6,010	1.2315
7	W 29th St	W 8th Ave and W 11th Ave	5/3/2006	1,774	1,427	5,459	4,392	1.2429
8	SW 152nd St	SW 152nd Ave and SW 148th Ct	5/16/2006	2,451	2,063	7,353	6,189	1.1881
9	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	5,462	4,221	16,872	13,023	1.2956
10	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	2,401	1,985	11,256	9,409	1.1963
11	SW 88th St	SW 79th Ave and SW 77th Ave	7/11/2006	3,372	2,737	10,116	8,211	1.2320
12	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	1,262	999	3,835	3,034	1.2638
13	NW 37th Ave	NW 3rd St and W Flagler St	8/4/2006	1,503	1,219	5,958	4,828	1.2340
14	Old Cutler Rd	SW 157th Te and SW 168th St	8/15/2006	1,556	1,288	4,668	3,864	1.2081
15	Granada Bd	SW 8th St and Venetia Te	9/14/2006	1,603	1,286	3,339	2,678	1.2469
16	NW 20th St	NW 10th Ave and NW 11th Ave	10/4/2006	4,058	3,006	8,031	5,913	1.3581
17	NE 2nd Ave	NE 95th St and NE 90th St	10/26/2006	3,312	2,702	4,968	4,053	1.2258
18	S Dixie Hwy	SW 380th St and SW 384th St	11/2/2006	3,451	2,496	5,177	3,744	1.3826
19	SW 127th Ave	SW 76th St and SW 80th St	11/8/2006	4,305	3,762	6,536	5,719	1.1428
20	NE 190th St	NE 29th Ave and Country Club Dr	12/6/2006	3,202	2,783	4,983	4,339	1.1483
21	NE 2nd Ave	NE 117th St and NE 114th St	12/14/2006	3,996	3,446	5,994	5,169	1.1596
22	NW 215th St	Florida TP and NW 7th Ave	1/4/2007	3,993	3,213	6,117	4,919	1.2435
23	W 37th St	W 14th Ave and W 16th Ave	1/17/2007	2,879	2,313	4,319	3,470	1.2447
24	SW 117th Ave	SW 64th St and SW 72nd St	2/15/2007	4,134	3,443	8,002	6,669	1.2000

Table A-11. Vehicle Occupancy Data for Freeways During Off-Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Julia Tuttle CY	Biscayne Bd and N Bay Rd	3/16/2006	1,389	1,076	8,458	6,533	1.2946
2	SR 826 EX	W 63rd St and W 52nd St	4/6/2006	2,063	1,811	11,236	9,652	1.1641
3	SR 826 EX	NW 17th St and NW 15th St	5/23/2006	1,339	1,137	7,016	5,960	1.1772
4	SR 826 EX	NW 48th St and NW 43rd St	6/8/2006	1,552	1,343	9,156	7,939	1.1532
5	SR 836 EX	NW 36th Ave and NW 31st Ave	7/13/2006	1,029	843	7,434	6,126	1.2135
6	SR 826 EX	SW 75th St and SW 85th St	8/10/2006	533	432	4,255	3,445	1.2352
7	SR 836 EX	NW 57th Ave and Perimeter Rd.	9/28/2006	1,010	854	5,542	4,663	1.1885
8	SR 826 EX	NW 41st St and NW 36th St	10/18/2006	1,789	1,603	12,066	10,848	1.1122
9	SR 836 EX	NW 111th Pl. and NW 107th Ave	11/14/2006	1,456	1,357	7,860	7,272	1.0808
10	I-95	NW 5th Ct and SR 836 EX	12/28/2006	1,162	893	7,105	5,480	1.2967
11	SR 826 EX	NW 35th Te and NW 34th St	1/24/2007	1,704	1,551	9,622	8,758	1.0987
12	SR 826 EX	NW 12th St and NW 7th St	2/20/2007	1,120	1,034	6,353	5,819	1.0918

Table 12. Vehicle Occupancy Data for Toll Facilities During Off-Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	SR 821 EX	SW 154th St and SW 180th St	3/22/2006	1,499	1,202	4,090	3,258	1.2554
2	SR 821 ET	SW 134th St and Louis St	4/25/2006	1,405	1,116	4,215	3,348	1.2590
3	SR 821 HY	SW 24th St and SW 35th Te	5/11/2006	3,803	3,012	11,339	8,987	1.2618
4	Florida TP	NW 183rd St and NW 170th St	6/22/2006	777	653	2,302	1,935	1.1896
5	Florida TP	NW 202nd St and W 194th St	7/27/2006	973	764	3,034	2,384	1.2730
6	SR 821 ET	SW 106th Ave and SW 112th Te	8/24/2006	1,456	1,217	4,826	4,043	1.1936
7	SR 874 EX	SW 117th St and SW 120th St	9/21/2006	2,157	1,758	3,988	3,255	1.2250
8	SR 874 EX	SW 56th St and SW 66th St	10/12/2006	4,481	3,647	11,120	9,074	1.2255
9	Florida TP	NW 194th St and NW 186th St	11/22/2006	8,494	7,100	14,782	12,484	1.1841
10	Opa Locka EX	NW 135th St and NW128th St	12/9/2006	3,366	2,929	6,563	5,653	1.1610
11	Florida TP	NW 186th Te and NW 183rd St	1/10/2007	976	851	1,526	1,335	1.1432
12	Florida TP	Near NW 27th Ave	2/7/2007	1,676	1,482	4,431	3,833	1.1561

Table A-13. Vehicle Occupancy Data for Surface Streets During Daylight Hours.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	NW 72nd Ave	NW 36th St and NW 31st St	2/28/2006	7,046	6,030	21,539	18,425	1.1690
2	NW 116th Wy	NW South River Dr and NW 100th Rd	3/7/2006	4,321	3,719	13,350	11,485	1.1624
3	SW 82nd Ave	SW 24th St and SW 28th St	3/24/2006	2,438	2,021	7,314	6,063	1.2063
4	NW 58th St	NW 87th Ave and NW 97th Ave	3/29/2006	6,942	6,119	20,489	18,041	1.1357
5	S Dixie Hwy	SW 24th Ave and SW 22nd Ave	4/12/2006	20,004	16,416	59,478	48,812	1.2185
6	SW 184th St	SW 132nd Ave and SW 127th Ave	4/18/2006	5,664	4,628	17,349	14,178	1.2237
7	W 29th St	W 8th Ave and W 11th Ave	5/3/2006	4,093	3,299	13,022	10,514	1.2386
8	SW 152nd St	SW 152nd Ave and SW 148th Ct	5/16/2006	5,920	4,899	18,235	15,060	1.2108
9	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	9,792	7,683	33,305	26,293	1.2667
10	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	4,780	3,941	24,760	20,638	1.1997
11	SW 88th St	SW 79th Ave and SW 77th Ave	7/11/2006	8,673	7,181	26,264	21,759	1.2071
12	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	3,010	2,440	9,646	7,834	1.2312
13	NW 37th Ave	NW 3rd St and W Flagler St	8/4/2006	4,065	3,350	14,241	11,726	1.2146
14	Old Cutler Rd	SW 157th Te and SW 168th St	8/15/2006	3,634	2,969	11,222	9,156	1.2256
15	Granada Bd	SW 8th St and Venetia Te	9/14/2006	3,604	2,941	7,111	5,795	1.2271
16	NW 20th St	NW 10th Ave and NW 11th Ave	10/4/2006	9,707	7,234	17,539	13,016	1.3475
17	NE 2nd Ave	NE 95th St and NE 90th St	10/26/2006	8,306	6,895	12,602	10,454	1.2055
18	S Dixie Hwy	SW 380th St and SW 384th St	11/2/2006	7,048	5,312	11,488	8,688	1.3222
19	SW 127th Ave	SW 76th St and SW 80th St	11/8/2006	9,801	8,610	15,993	14,115	1.1331
20	NE 190th St	NE 29th Ave and Country Club Dr	12/6/2006	7,482	6,575	11,734	10,330	1.1359
21	NE 2nd Ave	NE 117th St and NE 114th St	12/14/2006	9,659	8,618	15,081	13,505	1.1167
22	NW 215th St	Florida TP and NW 7th Ave	1/4/2007	9,294	7,650	14,990	12,384	1.2104
23	W 37th St	W 14th Ave and W 16th Ave	1/17/2007	5,970	4,785	9,850	7,913	1.2448
24	SW 117th Ave	SW 64th St and SW 72nd St	2/15/2007	9,521	8,052	17,136	14,475	1.1838

Table A-14. Vehicle Occupancy Data for Freeways During Daylight Hours.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Julia Tuttle CY	Biscayne Bd and N Bay Rd	3/16/2006	2,692	2,108	18,140	14,173	1.2799
2	SR 826 EX	W 63rd St and W 52nd St	4/6/2006	4,277	3,757	22,801	19,698	1.1575
3	SR 826 EX	NW 17th St and NW 15th St	5/23/2006	3,111	2,660	16,500	14,106	1.1697
4	SR 826 EX	NW 48th St and NW 43rd St	6/8/2006	3,781	3,252	21,574	18,609	1.1593
5	SR 836 EX	NW 36th Ave and NW 31st Ave	7/13/2006	2,382	1,966	17,586	14,536	1.2098
6	SR 826 EX	SW 75th St and SW 85th St	8/10/2006	1,312	1,099	10,202	8,537	1.1950
7	SR 836 EX	NW 57th Ave and Perimeter Rd.	9/28/2006	2,543	2,133	12,654	10,601	1.1936
8	SR 826 EX	NW 41st St and NW 36th St	10/18/2006	4,054	3,681	25,355	23,204	1.0927
9	SR 836 EX	NW 111th Pl. and NW 107th Ave	11/14/2006	2,447	2,307	15,592	14,697	1.0609
10	I-95	NW 5th Ct and SR 836 EX	12/28/2006	2,717	2,093	16,407	12,609	1.3013
11	SR 826 EX	NW 35th Te and NW 34th St	1/24/2007	4,293	3,888	24,255	21,934	1.1059
12	SR 826 EX	NW 12th St and NW 7th St	2/20/2007	2,840	2,637	15,152	14,049	1.0785

Table A-15. Vehicle Occupancy Data for Toll Facilities During Daylight Hours.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	SR 821 EX	SW 154th St and SW 180th St	3/22/2006	4,139	3,248	11,626	9,111	1.2761
2	SR 821 ET	SW 134th St and Louis St	4/25/2006	3,598	2,843	10,798	8,548	1.2631
3	SR 821 HY	SW 24th St and SW 35th Te	5/11/2006	8,900	7,147	26,987	21,668	1.2455
4	Florida TP	NW 183rd St and NW 170th St	6/22/2006	2,398	2,104	7,046	6,186	1.1391
5	Florida TP	NW 202nd St and W 194th St	7/27/2006	2,581	2,128	7,912	6,519	1.2137
6	SR 821 ET	SW 106th Ave and SW 112th Te	8/24/2006	3,301	2,715	10,263	8,458	1.2134
7	SR 874 EX	SW 117th St and SW 120th St	9/21/2006	9,396	7,827	16,923	14,095	1.2006
8	SR 874 EX	SW 56th St and SW 66th St	10/12/2006	8,118	6,596	17,239	14,029	1.2289
9	Florida TP	NW 194th St and NW 186th St	11/22/2006	17,271	14,753	35,832	31,342	1.1433
10	Opa Locka EX	NW 135th St and NW128th St	12/9/2006	8,468	7,608	16,737	14,819	1.1294
11	Florida TP	NW 186th Te and NW 183rd St	1/10/2007	2,679	2,411	4,511	4,053	1.1128
12	Florida TP	Near NW 27th Ave	2/7/2007	4,253	3,820	9,161	8,112	1.1293

Table A-16. Vehicle Occupancy Data for Moving and Stopped Vehicles on Surface Streets During A.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	Vehicles	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	314	271	3,337	2,861	1.1665
				Stopped	48	41	691	589	1.1743
2	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	713	620	4,124	3,592	1.1481
				Stopped	131	104	887	691	1.2835
3	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	733	620	2,699	2,283	1.1821
				Stopped	271	225	1,018	843	1.2066

Table A-17. Vehicle Occupancy Data for Moving and Stopped Vehicles on Surface Streets During Midday Period.

Index	Survey Roadway	Intersecting Roadways	Date	Vehicles	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	1,746	1,394	6,286	5,019	1.2525
				Stopped	696	520	2,201	1,644	1.3386
2	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	1,078	879	7,616	6,266	1.2155
				Stopped	142	108	717	536	1.3359
3	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	389	313	1,167	939	1.2428
				Stopped	346	281	1,087	882	1.2329

Table A-18. Vehicle Occupancy Data for Moving and Stopped Vehicles on Surface Streets During P.M. Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	Vehicles	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	2,270	1,797	6,810	5,391	1.2632
				Stopped	652	516	2,297	1,819	1.2628
2	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	-	-	-	-	-
				Stopped	273	240	1,035	915	1.1312
4	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	626	508	1,945	1,578	1.2325
				Stopped	532	419	1,596	1,257	1.2697

Table A-19. Vehicle Occupancy Data for Moving and Stopped Vehicles on Surface Streets During Off-Peak Period.

Index	Survey Roadway	Intersecting Roadways	Date	Vehicles	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	Biscayne Bd	NE 143rd St and NE 146th St	6/1/2006	Moving	5,462	4,221	16,872	13,023	1.2956
				Stopped	1,375	1,065	4,451	3,448	1.2910
2	SW 37th Ave	SW 28th St and Bird Rd	6/28/2006	Moving	2,401	1,985	11,256	9,409	1.1963
				Stopped	586	476	1,987	1,612	1.2322
3	SW 112th St	SW 97th Ave and SW 94th Ave	7/20/2006	Moving	1,262	999	3,835	3,034	1.2638
				Stopped	1,052	831	3,165	2,500	1.2660

Table A-21. Vehicle Occupancy Data for Flagler Street During Off-Peak Period.

Index	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	4/2/2007	1,076	850	3,336	2,635	1.2659
2	4/3/2007	1,708	1,315	4,908	3,793	1.2939
3	4/4/2007	1,413	1,163	4,158	3,424	1.2142
4	4/5/2007	1,534	1,254	4,602	3,762	1.2233
5	4/6/2007	1,610	1,305	5,290	4,288	1.2337
6	4/7/2007	2,594	1,664	7,782	4,992	1.5589
7	4/8/2007	2,457	1,441	7,759	4,549	1.7058

Table A-22. Vehicle Occupancy Data for Flagler Street During P.M. Peak Period.

Index	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	4/2/2007	1,314	1,017	4,154	3,214	1.2923
2	4/3/2007	2,063	1,621	6,363	5,004	1.2715
3	4/4/2007	1,507	1,255	4,576	3,812	1.2004
4	4/5/2007	2,249	1,718	8,337	6,345	1.3140
5	4/6/2007	1,733	1,333	5,525	4,247	1.3009
6	4/7/2007	2,453	1,530	7,640	4,759	1.6055
7	4/8/2007	2,247	1,290	6,806	3,898	1.7460

Table A-23. Vehicle Occupancy Data for Flagler Street During P.M. Period.

Index	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
1	4/2/2007	2,390	1,867	7,490	5,849	1.2804
2	4/3/2007	3,771	2,936	11,270	8,797	1.2812
3	4/4/2007	2,920	2,418	8,734	7,237	1.2069
4	4/5/2007	3,783	2,972	12,939	10,107	1.2802
5	4/6/2007	3,343	2,638	10,815	8,535	1.2671
6	4/7/2007	5,047	3,194	15,422	9,751	1.5816
7	4/8/2007	4,704	2,731	14,565	8,447	1.7244

Table A-24. Vehicle Occupancy Data for Three Observation Locations on Flagler Street.

Index	Survey Roadway	Intersecting Roadways	Date	P_{ri}	V_{ri}	P_i	V_i	AVO_i
Off-Peak Period (2:00 p.m. – 4:00 p.m.)								
1	Flagler Street	Near 82 Ave	4/4/2007	2,400	1,769	7,200	5,307	1.3567
2	Flagler Street	Near 90 Ave	4/4/2007	1,413	1,163	4,158	3,424	1.2142
3	Flagler Street	Near 108 Ave	4/4/2007	1,282	1,036	3,908	3,161	1.2363
P.M. Peak Period (4:00 p.m. – 6:00 p.m.)								
4	Flagler Street	Near 82 Ave	4/4/2007	2,603	1,986	7,809	5,958	1.3107
5	Flagler Street	Near 90 Ave	4/4/2007	1,507	1,255	4,576	3,812	1.2004
6	Flagler Street	Near 108 Ave	4/4/2007	1,457	1,223	4,371	3,669	1.1913
P.M. Period (2:00 p.m. – 6:00 p.m.)								
7	Flagler Street	Near 82 Ave	4/4/2007	5,003	3,755	15,009	11,265	1.3324
8	Flagler Street	Near 90 Ave	4/4/2007	2,920	2,418	8,734	7,237	1.2069
9	Flagler Street	Near 108 Ave	4/4/2007	2,739	2,259	8,279	6,830	1.2121

APPENDIX B:

WEIGHTING FACTORS FOR DRIVER'S AGE BIAS ADJUSTMENT

Table B-1 Weighting Coefficients for Age Groups.

County Name	16-19	20-24	25-29	30-39	40-49	50-59	60-69	70-79	>=80
Charlotte	0.0396	0.0345	0.0396	0.1108	0.1341	0.1489	0.1953	0.1990	0.0982
Citrus	0.0440	0.0352	0.0408	0.1138	0.1399	0.1553	0.1938	0.1881	0.0891
Collier	0.0511	0.0566	0.0645	0.1550	0.1499	0.1463	0.1653	0.1480	0.0634
DeSoto	0.0764	0.0985	0.0963	0.1610	0.1430	0.1248	0.1315	0.1166	0.0519
Glades	0.0592	0.0672	0.0813	0.1673	0.1596	0.1504	0.1614	0.1117	0.0419
Hardee	0.0869	0.1013	0.1014	0.1870	0.1598	0.1270	0.1036	0.0958	0.0372
Hendry	0.1021	0.1274	0.1016	0.1974	0.1601	0.1236	0.0941	0.0650	0.0286
Hernando	0.0487	0.0439	0.0457	0.1240	0.1443	0.1457	0.1707	0.1936	0.0834
Highlands	0.0533	0.0506	0.0505	0.1161	0.1280	0.1271	0.1738	0.2048	0.0958
Hillsborough	0.0699	0.0856	0.0950	0.2104	0.1952	0.1411	0.0908	0.0732	0.0389
Lake	0.0494	0.0480	0.0569	0.1509	0.1543	0.1396	0.1659	0.1600	0.0750
Lee	0.0489	0.0517	0.0599	0.1489	0.1568	0.1492	0.1588	0.1533	0.0725
Manatee	0.0516	0.0553	0.0632	0.1546	0.1624	0.1408	0.1399	0.1500	0.0821
Pasco	0.0501	0.0478	0.0567	0.1548	0.1568	0.1402	0.1416	0.1601	0.0919
Pinellas	0.0491	0.0542	0.0663	0.1685	0.1826	0.1486	0.1202	0.1258	0.0847
Polk	0.0684	0.0720	0.0760	0.1717	0.1705	0.1434	0.1277	0.1148	0.0553
Sarasota	0.0405	0.0401	0.0472	0.1284	0.1531	0.1477	0.1597	0.1789	0.1044
Sumter	0.0424	0.0498	0.0609	0.1391	0.1350	0.1473	0.2226	0.1516	0.0513
Alachua	0.1103	0.2010	0.0985	0.1566	0.1619	0.1179	0.0686	0.0542	0.0310
Baker	0.0862	0.0883	0.0895	0.2086	0.2041	0.1486	0.0960	0.0539	0.0248
Bradford	0.0668	0.0848	0.0895	0.2005	0.1989	0.1447	0.1014	0.0746	0.0388
Columbia	0.0763	0.0795	0.0762	0.1769	0.1935	0.1561	0.1168	0.0859	0.0388
Dixie	0.0643	0.0693	0.0723	0.1638	0.1757	0.1635	0.1507	0.1033	0.0372
Gilchrist	0.0826	0.1366	0.0667	0.1568	0.1741	0.1479	0.1159	0.0810	0.0384
Hamilton	0.0684	0.1040	0.0947	0.2056	0.1941	0.1405	0.0979	0.0603	0.0344
Lafayette	0.0689	0.0963	0.1130	0.2147	0.1654	0.1324	0.1058	0.0680	0.0353
Levy	0.0671	0.0570	0.0641	0.1598	0.1782	0.1685	0.1467	0.1110	0.0476
Madison	0.0799	0.0828	0.0892	0.1804	0.1791	0.1408	0.1119	0.0844	0.0516
Marion	0.0577	0.0521	0.0588	0.1494	0.1608	0.1444	0.1569	0.1542	0.0657
Suwannee	0.0759	0.0704	0.0691	0.1572	0.1769	0.1626	0.1352	0.0996	0.0531
Taylor	0.0721	0.0712	0.0848	0.1786	0.1916	0.1626	0.1165	0.0831	0.0394
Union	0.0666	0.0756	0.1017	0.2639	0.2286	0.1326	0.0724	0.0413	0.0173
Bay	0.0689	0.0767	0.0828	0.1943	0.1972	0.1511	0.1123	0.0822	0.0345
Calhoun	0.0665	0.0832	0.0992	0.1982	0.1823	0.1379	0.1044	0.0791	0.0493
Escambia	0.0869	0.1007	0.0877	0.1819	0.1811	0.1401	0.1015	0.0793	0.0408
Franklin	0.0494	0.0658	0.0831	0.1874	0.1856	0.1652	0.1330	0.0837	0.0468
Gadsden	0.0822	0.0825	0.0859	0.1878	0.2025	0.1462	0.1017	0.0707	0.0405
Gulf	0.0590	0.0581	0.0765	0.1834	0.1939	0.1588	0.1343	0.0937	0.0423
Holmes	0.0687	0.0774	0.0864	0.1920	0.1701	0.1540	0.1197	0.0813	0.0504
Jackson	0.0748	0.0829	0.0848	0.1861	0.1871	0.1477	0.1075	0.0800	0.0491
Jefferson	0.0678	0.0710	0.0730	0.1773	0.2088	0.1689	0.1032	0.0842	0.0458
Leon	0.1114	0.1826	0.0995	0.1683	0.1749	0.1257	0.0632	0.0471	0.0272
Liberty	0.0637	0.0867	0.1182	0.2330	0.1922	0.1285	0.0928	0.0607	0.0243
Okaloosa	0.0718	0.0887	0.0879	0.2024	0.1950	0.1424	0.1113	0.0718	0.0287
Santa Rosa	0.0728	0.0625	0.0766	0.2128	0.2166	0.1550	0.1103	0.0675	0.0259
Wakulla	0.0756	0.0641	0.0778	0.2105	0.2227	0.1598	0.1013	0.0628	0.0254
Walton	0.0592	0.0607	0.0739	0.1772	0.1937	0.1665	0.1366	0.0939	0.0383

Washington	0.0656	0.0680	0.0756	0.1853	0.1811	0.1626	0.1225	0.0860	0.0533
Brevard	0.0600	0.0560	0.0592	0.1735	0.1904	0.1479	0.1364	0.1200	0.0566
Clay	0.0802	0.0692	0.0769	0.2108	0.2167	0.1628	0.0944	0.0596	0.0294
Duval	0.0728	0.0896	0.1001	0.2157	0.2009	0.1390	0.0828	0.0649	0.0343
Flagler	0.0464	0.0371	0.0419	0.1224	0.1538	0.1637	0.1990	0.1759	0.0599
Nassau	0.0662	0.0637	0.0729	0.1906	0.2063	0.1731	0.1211	0.0763	0.0298
Orange	0.0740	0.1020	0.1065	0.2239	0.1939	0.1278	0.0799	0.0607	0.0314
Putnam	0.0693	0.0648	0.0637	0.1532	0.1781	0.1624	0.1444	0.1172	0.0471
Seminole	0.0690	0.0762	0.0857	0.2124	0.2168	0.1559	0.0871	0.0645	0.0324
St. Johns	0.0641	0.0576	0.0611	0.1755	0.2138	0.1689	0.1151	0.0982	0.0456
Volusia	0.0611	0.0679	0.0625	0.1556	0.1731	0.1464	0.1327	0.1301	0.0706
Broward	0.0585	0.0647	0.0826	0.2097	0.1957	0.1375	0.0918	0.0909	0.0685
Miami-Dade	0.0702	0.0824	0.0932	0.2079	0.1827	0.1372	0.1035	0.0783	0.0446
Indian River	0.0534	0.0472	0.0511	0.1348	0.1566	0.1372	0.1516	0.1758	0.0924
Martin	0.0452	0.0437	0.0471	0.1403	0.1658	0.1489	0.1526	0.1682	0.0881
Monroe	0.0432	0.0539	0.0689	0.1857	0.2229	0.1887	0.1172	0.0832	0.0363
Okeechobee	0.0799	0.0831	0.0816	0.1752	0.1649	0.1387	0.1296	0.1045	0.0425
Osceola	0.0751	0.0860	0.0928	0.2095	0.1927	0.1432	0.0965	0.0695	0.0347
Palm Beach	0.0533	0.0560	0.0661	0.1734	0.1744	0.1348	0.1181	0.1385	0.0854
St. Lucie	0.0589	0.0552	0.0604	0.1624	0.1717	0.1396	0.1432	0.1439	0.0647