ABSTRACT

SWIDAN, HASSAN MOHAMED. Integrating AIMSUN Micro Simulation Model with Portable Emissions Measurement System (PEMS): Calibration and Validation Case Study. (Under the direction of Dr. Nagui Rouphail).

The growing state of the art micro simulation models has enabled researchers to evaluate many traffic and environmental strategies. Micro simulation models do not typically describe actual driver acceleration behavior as observed in the field; rather they mostly describe the maximum vehicle acceleration capabilities. Users of micro simulation models will often accept these acceleration rates in estimating vehicle fuel consumption and emissions. Therefore, there is a need to contrast the vehicle activity profiles inferred from traffic simulation models with real-world speed profiles for the same road type, same route and the same running time. The benefits of the research in this thesis accrue from linking state-of-the-art traffic models and vehicle Fuel Use and Emissions (FU&E) models as derived from Portable Emissions Measurement Systems (PEMS) using second-by-second Vehicle Specific Power (VSP) and speed.

The thesis has two main objectives. The first is to calibrate a micro simulation emission model (AIMSUN) with real world emissions data collected by PEMS. The purpose is to investigate how AIMSUN internal emissions model work and if PEMS data would produce an adequate fit in calibrating the AIMSUN emissions model. The second objective is to validate AIMSUN micro-scale vehicle activity model against real world traffic data. AIMSUN speed, acceleration and VSP distributions are contrasted against PEMS activity distributions in order to validate AIMSUN activity algorithms.

The thesis investigated two case studies. The first is for a small test network in Victoria City in Spain. The objective of this study was to verify how AIMSUN micro simulator and environmental models work. The first case study demonstrated that AIMSUN fuel consumption and emissions models utilize individual vehicles speed and acceleration, and that the PEMS based models did not provide a good fit to the AIMSUN specific emission models. This conclusion leads to the second case study which is aimed at validating AIMSUN individual vehicles speed and acceleration distributions.

The second case study demonstrates the vehicle activity calibration and validation procedures. Part of Research Triangle Area was modeled in AIMSUN and tested with PEMS field operational data. AIMSUN traffic volumes were calibrated by point sensors that are installed in the area. AIMSUN outputs were validated against real world traffic data on different scales. First, AIMSUN results were validated at the macro scale. AIMSUN route travel time was compared with route travel time measured from field. Second, AIMSUN individual vehicles speed and VSP distributions were validated against vehicles tested by PEMS and this is the micro scale validation. It was found from this case study that calibrating large network demand using sparse traffic sensors is not sufficient. This type of calibration produced demands that were statistically different from actual field counts. In addition, the speed and VSP distributions for AIMSUN vehicles were found to be statistically different from PEMS vehicles speed and VSP distributions. Even though the extracted vehicles from AIMSUN experience the same travel time as PEMS vehicles on the same routes, AIMSUN vehicles VSP distributions were statistically different from real world PEMS VSP distributions. The resulting estimates of average emission rates were also found to be somewhat different, although the differences were much more pronounced on the arterial portion of the route, and less so on the freeway portion. The differences in both activity and emission rates are beyond the expected range of uncertainties in such experiments on arterials. The large difference between AIMSUN and PEMS arterials speed profiles yielded large variation in fuel consumption and emissions estimates.

Integrating AIMSUN Micro Simulation Model with Portable Emissions Measurement System (PEMS): Calibration and Validation Case Study

by
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DEDICATION

To my mother and my brother

BIOGRAPHY

The author was born and raised in Cairo, Egypt. He graduated from Cairo University in 2007 with a Bachelor of Science in Civil Engineering. After graduation, the author worked at Dar Group consulting engineering firm for 2 years. Dar Group is ranked among the top ten international engineering consulting firms. He travelled to Raleigh, NC in August 2009 to attend North Carolina State University and pursue a Master of Science degree in Civil Engineering with a concentration in transportation engineering.

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Chapter1 Introduction

1.1 Background

Transportation accounts for 28% of the U.S. energy use (1). Surface transportation alone accounts for 40% of the national annual emissions of nitrogen oxides (NOx), 56% of CO, and 28% of volatile organic compounds (VOC) (2) while NOx, CO, and VOC are known precursors to tropospheric ozone formation (3). Vehicle Fuel Use and Emissions (FU&E) have substantial national energy and environmental implications**.** The steady increase in traffic volumes along many US road facilities requires a sustained effort to reduce vehicle emissions along with fuel consumption. In the meantime, the growing state of the art of traffic micro simulation models allows simulating different networks at different spatial and temporal resolutions. Furthermore, the increase in accuracy of micro-scale vehicle specific fuel use and emissions estimation has led to improved emission inventory development based on real world data (3).

Transportation models are used to evaluate traffic flow and demand management strategies. Some transportation models have some emissions estimation capabilities through their own internal emissions models. Those models vary with respect to temporal scales and level of detail of traffic representation. Microscopic models simulate second by second trajectories of individual vehicles on each link. These vehicle specific speed trajectories are estimated using algorithms based on car following, gap acceptance and lane changing behavior.

Microscopic models such as VISSIM and AIMSUN (4, 5) provide more detail regarding the trajectories (driving cycles) of individual vehicles, but become computationally intractable if applied to large networks. The micro simulation models outputs are activity data on second by second. The outputs contain instantaneous vehicle trajectories on second by second bases. The results can be represented at various spatial scales, namely at the link, path, origin-destination OD (with multiple paths connecting them) and network-wide levels. Based on vehicles location information, the vehicles can be aggregated on different links and ODs.

Some alternative traffic strategies such as traveler information systems are available only at the microscopic simulation level. Furthermore, micro simulation models can be very effective in analyzing the environmental impacts of Intelligent Transportation Systems (ITS) (6). These high resolution models can analyze future vehicles, control or network design scenarios; and quantify the relative contribution of vehicle type, vehicle activity and traffic control measures on the magnitude and variability in regional emission estimates (6).

Furthermore, Fuel Use and Emissions Models (FU&E) (3) can be used in combination with micro-scale transportation simulation models to assess the impact of traffic control measures on fuel consumption and emissions. (FU&E) models can be coupled with real-time sensor information to enable real time estimation for fuel consumption and emissions (3).

Some activity data sources, such as micro-scale transportation models and real-time traffic detection, can estimate vehicle-specific micro-scale data (e.g., second-by second speed). The interface of these models with transportation models need to be evaluated for use with real-time vehicle detection. In addition, the advanced technology in traffic detection provides real time data sets which are very useful in the calibration and validation of transportation models.

1.2 Problem statement

We hypothesize that the majority of traffic micro simulation models do not properly describe observed driver acceleration and deceleration behavior in the real-world environment; rather they have tended to focus on the maximum acceleration behavior that a vehicle can sustain. Therefore, there is a need to compare simulated speed / acceleration profiles extracted from calibrated traffic simulation models with real-world speed profiles for the same road type and similar average speed in order to assess the ability of these models to estimate speed profiles, and subsequently their impact on energy and emission use, when they cannot be directly measured (Silva et al. 2006) (7).

The proposed calibration process should be carried out at various spatial (i.e. link and route) levels. The objective is to calibrate and validate micro scale vehicle activity against high quality micro scale empirical traffic data. At the link level, the estimated speed trajectories from micro simulation models should be compared with point or segment speed on the same link.

Furthermore, the challenge in linking transportation and vehicle Fuel Use and Emissions (FU&E) models (3) is to obtain a proper interface regarding vehicle activity in terms of speed, acceleration, and road grade on a second-by-second basis. For example, the model AIMSUN (4) provides a very flexible Application Programming Interface (API) environment, which allows users to interact with AIMSUN internal simulator using user-customized simulation tools. In addition, transportation models differ with respect to time scale and level of vehicle aggregation. Therefore, input data representative of the study routes should be developed consistent with the outputs of such models and used for comparative case studies. Generally, there is a need for linking state-of-the-art traffic models and vehicle FU&E models and the traffic detection data in order to use the calibrated micro simulation models to study the environmental impacts of traffic management strategies with degree of confidence (3).

1.3 Research Objectives

This thesis aims to produce a framework to calibrate micro simulation models such as AIMSUN with real world traffic detection data, and to test the model's own emission estimation procedures. In addition the micro simulation will be validated with real-world second by second activity data. This activity data can be obtained from any filed measurement devices such as GPS or PEMS. PEMS is the Portable Emissions Measurement System (16) which is a unit installed in the vehicle that can collect data on second by second basis based on a real world driving environment. PEMS generates both emissions and vehicle activity data such as speed and acceleration on second by second basis. PEMS activity data can be a valuable source for validating micro simulation models against real world traffic data. The objectives of the thesis can be summarized as follows:

1- Develop a calibration process of micro simulation emissions models with real world emissions data (e.g. PEMS)
2- Develop a calibration process of micro simulation models using real traffic sensing techniques (e.g.Traffic.com)

3- Validate micro simulation acceleration and speed profiles against real-world second by second activity data.

1.4 Motivation and Thesis Contribution

The key benefits of this research accrue from linking state-of-the-art traffic models and vehicle FU&E models using second-by-second vehicle activity data. The thesis integrates a micro simulation model with real world fuel consumption and emissions into a framework. The thesis also validates a micro simulation model with real world activity data and recalibrates the model if necessary. Thus, the thesis contribution can be summarized in the following items:

1.4.1 Calibration of Micro Simulation Emissions Models

Micro simulation models have their own embedded internal emissions models. These models need to be calibrated with real-world emissions data which is measured from field. Emissions models outcomes depend on both emission factors and fuel consumption algorithms. PEMS emissions data can be a valuable source for calibrating AIMSUN both emissions model factors and fuel consumption algorithms. The thesis first contribution will be to calibrate AIMSUN internal emissions model with PEMS emissions data. The resulting fuel and emissions calibrated model in AIMSUN can then be used to quantify different environmental simulation scenarios.

1.4.2 Macro Scale Calibration of Micro Simulation Models

Micro simulation models have traffic demand models and traffic assignment algorithms. Meanwhile, traffic detection technologies are a good source for traffic counts based on real world traffic sensing. Traffic detection data could be used in calibrating the micro simulation traffic demand models. A sub-network of the Research Triangle area was modeled in the AIMSUN micro simulation model. Some network links were covered by traffic detection sensors. Traffic counts obtained from those sensors on every link will be matched with AIMSUN estimates on the same link. The objective is to calibrate AIMSUN traffic demand model by matching traffic counts on the same links.

1.4.3 Macro Scale Validation of Micro Simulation Models

The thesis approach is to match the output of a simulation model for a given link of roadway to a library of real world data. The validation process consists of two scales: macro scale and micro scale. Macro scale validation based on matching route travel time. Real-world speed and travel time data are available for this part of the triangle which was measured using vehicle probe technology (e.g. INRIX) (13). Real world measured travel times were used to validate AIMSUN model estimates at the macro level. Therefore, travel time was aggregated on every route. AIMSUN travel time was compared with INRIX travel time on a route basis.

1.4.4 Micro Scale Validation of Micro Simulation Models

PEMS micro-scale data were used to validate AIMSUN micro simulation model at the highest temporal resolution. AIMSUN can produce speed profiles similar to those gathered with PEMS. Freeways such as: I-40 and I-540 were modeled in the micro simulation model and were tested by PEMS also. Therefore, sub-routes such as I-40 and I-540 were used to validate AIMSUN in this study on the micro scale. The activity data were extracted from AIMSUN by using the Application Program Interface (API) code (3). This extracted activity data was used in micro validation of AIMSUN model with PEMS activity data. Vehicle trajectories were extracted from AIMSUN output and from PEMS database. VSP distributions were generated from PEMS activity data and out of AIMSUN activity output for these extracted samples of vehicles. The micro scale validation process depends mainly on comparisons between AIMSUN and PEMS VSP distributions. In addition, speed and acceleration cumulative distributions were generated in order to gain insights about AIMSUN individual vehicles behavior on freeway and arterial segments. Finally, implications of these distributions on estimated fuel consumption and emissions on selected routes are provided.

1.5 Thesis Outline

The remainder of the thesis is organized as follows. Chapter 2 introduces the literature review for studies concerning the integration of micro simulation models with emissions models, in addition to calibration and validation studies for microscopic traffic simulation models. Chapter 3 explains the two model applications conducted in the thesis's research work. A description of Portable Emissions and Measurement System (PEMS) empirical studies, test experiments in addition to empirical traffic data are presented in Chapter 4. AIMSUN fuel consumption and emissions models calibration methodology and results are presented in Chapter 5. Chapter 6 illustrates AIMSUN activity models calibration and validation methodology and results. The conclusions and recommendations are discussed in Chapter 7. Chapter 8 presents the references used.

Chapter 2 Literature Review

The following technical literature review covers four main areas: (1) the Portable Emissions Measurement System (PEMS); (2) integration of micro simulation models with real world emissions models; (3) Calibration and Validation of micro simulation models.

2.1 The Portable Emissions Measurement System (PEMS)

The increasing concern regarding near-roadway air quality motivates the need for accurate micro scale vehicle fuel consumption and emissions data. The ability to measure such data with Portable Emission Measurement Systems (PEMS) offers the opportunity to address several key scientific challenges. NC State University is a national leader in the real-time data collection of second-by-second vehicle dynamics, road grade and associated fuel consumption and emissions from PEMS for a variety of transportation and environmental applications. These have included before and after studies of the effectiveness of improved signalization on emission reductions (9), emission comparison for alternative-fueled vehicles (10), estimation of emissions inventories (11), and calibration of traffic simulation models fuel and emission modules (12), among many others. The available data sets are over one million quality-controlled data points at 1-sec resolution, each providing instantaneous measurements of speed, accelerations/ decelerations, fuel use, NO, HC, CO and CO2 emissions for a host of vehicles (light duty, buses, trucks, locomotives) that use a variety of fuels. The equipped vehicle position is geo-coded using an integrated GPS unit within PEMS, thus allowing positional data, which can identify locations with high fuel consumption and emission rates.

Since micro simulation models such as VISSIM and AIMSUN (5) (3) can produce speed profiles similar to those gathered with PEMS. The existing PEMS data collected by the team at NC State University can be used to calibrate a representative fleet-wide fuel and emission model. The resulting fuel and emissions fleet coded in AIMSUN or VISSIM can then be used to quantify different environmental simulation scenarios. The micro simulation output can be aggregated with PEMS fleet emissions factors to produce fuel consumption an emissions for every vehicle. After this aggregation, the emissions on g/sec for every vehicle can be calculated on second by second bases. The emissions results can be aggregated on different spatial levels (link, OD, network).

There are different ways for measuring the tailpipe emissions. The portable onboard tailpipe emissions measurement systems enable data collection under real world driving conditions. The Portable Emissions Measurement System PEMS is used to capture real world fuel consumption and emissions on second by second bases. One key advantage of PEMS is that it can reflect variations in traffic and ambient conditions (15). Models which depend on dynamometer laboratory tests may not adequately represent real word driving conditions (15). Frey et al. (2003) (16) emphasized an empirical approach to on-road vehicle emissions measurement by using PEMS. Key considerations of the experimental design of PEMS and data collection procedures were introduced. Furthermore, Frey et al. (2003) provided an approach for PEMS data processing and screening and applied quality assurance steps to correct the measurement errors.

Vehicles emissions can be characterized through different vehicle parameters such as speed, acceleration, and vehicle power and fuel rate. There are some nonparametric approaches for modeling emissions such as vehicle specific power (VSP). VSP is estimated based on second-by-second speed, acceleration, and road grade and is given in units of kW/ton of vehicle weight (Jimenez-Palacios, 1999) (17). VSP is the instantaneous attractive power per unit vehicle mass. The VSP can be calculated based on filed measurement from the road side by using instrument such as PEMS. Therefore, VSP can reflect the effects of driving conditions on light duty vehicle emissions. There are no assumptions need to be made in the VSP equations, in contrast to many emission models that depend non-roadside measurable parameters (17). The dependence of NO_x, HC and CO_2 on the specific power makes the VSP reasonable indication for vehicle emissions. In addition, using VSP allows comparing between emissions data from different sources such as dynamometer driving cycles and emission models (17).

Frey et al. (2002) (18) used VSP bins approach to estimate emission factors for a tested vehicle. Frey et al. (2002) estimated VSP from PEMS second by second measurements and vehicle location GPS. Vehicle Specific Power (VSP) was estimated using an equation given (18), which is:

$$\text{VSP (kW/ton)} = v\,[1.1a + 9.81(a \tan(\sin(\text{grade}))) + 0.132] + 0.000302v^3$$

Where:

VSP: vehicle specific power (kW/metric ton)

v: vehicle speed (m/sec) on second by second basis

a: acceleration or deceleration (m/s^2) on second by second basis

VSP was executed by second by second speed profile and GPS data for road grade. Frey et al. (2002) categorized the VSP and corresponding fuel consumption and emissions into fourteen VSP bins. The use of VSP binning approach enables comparisons between vehicles for a given VSP mode. In addition, the VSP modes can be weighted in order to represent different driving cycles.

PEMS used in many studies to assess the environmental impacts of many traffic management strategies and to quantify the impacts of vehicle and fuel types on emissions and fuel consumption. Unal et al. 2003 conducted before and after studies of the effectiveness of improved signalization on emission reductions (19). Zhai et al. 2009 conducted emissions comparison for alternative-fueled vehicles (20). Frey et al. 2009 integrated tailpipe emissions models with link-based vehicle activity data for estimating emissions inventories for different fuel types and different vehicles technologies (21). Frey et al. 2006 used PEMS to measure emissions for trucks that were tested on petroleum diesel and B20 biodiesel (22). Zhai et al. 2008 used VSP approach to estimate emissions for diesel transit bus (23). Frey et al. 2007 compared real-world fuel Consumption for Diesel- and Hydrogen-fueled transit buses (24).

2.2 Integration of Micro Simulation Models with Real World Emissions Models

In previous years, many researchers have tried to integrate micro simulation emissions models with real world emissions models and modal emissions models. The integrated microscopic emissions simulation models were used to study the effects of traffic operations on emissions and fuel consumptions. The mobile emissions models like MOBILE and MOVES developed by the US Environmental Protection Agency (EPA) have the ability to estimate the emissions on large scale levels but on the operational levels, its estimates for emission are not accurate (25). On the other hand, microscopic simulation models can give accurate estimates for emissions and fuel consumption on operational level projects (25). Many studies used modal emissions data base such as MODEM and CMEM to calibrate the micro simulation models and used these models to study the effect of ITS strategies.

The MODEM is a microscopic modal emissions database that was developed based on empirical dynamometer driving cycle measurements. The MODEM was developed by the European Commission's DRIVE II research program (26). Park et al. (2001) combined the VISSIM micro simulation model developed by PTV with the MODEM microscopic emissions database to estimate emissions under different traffic operations scenarios (26). The output results were compared with the Design Manual for Roads and Bridges (DMRB) UK emissions standards. The results were not significantly different from the DMRB model at different levels. One key limitation of MODEM model is that it doesn't represent the real world emissions data because its data depends mainly on dynamometer measurements.

The Comprehensive Modal Emissions Model (CMEM) was developed at the University of California, Riverside based on 1997 vehicle data (An et al., 1997; Jost et al., 1992) (27, 28 and 29). Nam et al. (2003) integrated the VISSIM micro simulation model and the modified version of CMEM model (30). In addition, CHEN et al. (2007) integrated VISSIM model with CMEM to study the effect of some traffic management strategies on emissions for a specified case study (31). Noland et al. (2006) used the integration between VISSIM and CMEM to study the effects of capacity increase on vehicles emissions (32).

H. Rakha et al. (2004) developed a microscopic emissions model called (VT-Micro model version 2.0). The VT micro model was developed based on dynamometer data from

60 light duty vehicles and trucks. Laboratory measurements were used to validate the VT micro model. The CMEM model and the VT micro model were combined to study the effects of microscopic vehicle behaviors on emissions (33). Ahn et al. (2008) combined the VT micro simulation model, the CMEM model and the macroscopic emission estimation model MOBILE6 that was developed by the EPA (34). The Ahn et al. study illustrated the insufficiency of the macroscopic models in estimating the emissions of the operational level projects. In addition, the microscopic models can simulate real world driving conditions, so these micro simulation models are adequate for the operational level projects (34). The TransModeler micro simulation package was used by Lee et al. (2009) to study the emissions of a freight corridor (35). The output from TransModeler was changed to the CMEM format and they were combined for the case study.

Boriboonsomsin et al. (2008) combined the microscopic modal emissions model CMEM with the micro simulation model PARAMICS (parallel microscopic simulator) (38). PARAMICS model is capable to work with external programming interfaces, so specific simulation scenarios can be modeled using integrated modules under PARAMICS. The output results from PARAMICS were classified into different vehicle categories to synchronize with the CMEM ones. CMEM model limitation is that it is based on dynamometer laboratory tests and it doesn’t reflect the real word data (32). In addition, CMEM is unable to estimate the emissions of buses and trucks (32). When VISSIM model was integrated with CMEM, it gave accurate estimates for the aggregate measurements but for the simulated vehicle, VISSIM didn’t give accurate estimates (30).

However MODEM and CMEM models were widely used to calibrate the micro simulation models, other modal emissions models were coupled with micro simulation models. Marsden et al. (2001) used data from the SCOOT demand-responsive traffic control system, and this data was used as inputs to a micro simulation model called SIGSIM to model traffic emissions (36). The emissions results from the micro simulation model were not significantly different compared to the field measured in the study. The DRACULA (Dynamic Route Assignment Combining User Learning and micro simulation) model is a micro simulation tool. Panis et al. (2006) combined The DRACULA with a microscopic emission model (37). The emissions model was developed based on different field measurements using different tested vehicles. The simulation outputs from the DRACULA model, which are the instantaneous speed and acceleration, were used to develop the emissions functions from the microscopic simulation model. Calibration and validation of these models need more efforts before it can be reliably used in different methodologies (37).

2.3 Calibration and Validation of Micro Simulation Models

Chu et al. (2004) presented multi stage procedures for calibration and validation of PARAMICS micro simulation model (41). In this study, four steps of calibration were done: 1- Driving behavior model calibration 2- Route choice model calibration 3-OD estimation 4-Model fine tuning. However, various components of the PARAMICS model were addressed in the calibration process; the default route choice model in PARAMICS was used.

Dowling et al 2004 presented a methodological top down approach to calibrate CORSIM micro simulation model (42). The calibration process consisted of three steps. The first step was capacity calibration; the model was calibrated at the key bottlenecks in the system. In the second step, the route choice model was calibrated by calibrating the traffic flow at non bottleneck locations. The third step demonstrated a comparison between the predicted traffic results by the model and traffic filed measurement such as travel time. The model results satisfied the calibration criteria.

Park et al 2006 used CORSIM and VISSIM micro simulation models to conduct calibration and validation procedures on case study of 12 actuated signalized intersections (43). The calibration procedures were done by travel time and the validation process was done by queue length. The simulation results were compared with average value for field measurements in order to calibrate and validate the micro simulation model. Park et al indicated that the VISSIM default parameters have failed to reproduce results similar to field measurements. The calibrated and validated models generated results similar to field data.

Toledo et al 2003 applied MITSIMLAB micro simulation model to a case study that contains freeways and urban arterials (44). The objective was to apply calibration and validation tools to MITSIMLAB micro simulation model. Two models were calibrated in this study: driving behavior model and travel behavior model. The aggregated flow speed data at sensors locations were used to calibrate and validate the micro simulation model. In addition, point to point travel time field measurements were used in the validation process. Toledo et al suggested that the aggregate data is not effective in validating micro simulation models since the simulation model outputs are result of interaction between model components. Toledo et al also recommended that the sensors used in calibration and validation process should have efficient spatial coverage.

Balakrishna et al 2007 presented a methodology for calibrating MITSimLab microscopic simulation model parameters by using general traffic field measurements (45). The driver behavior model parameters were calibrated by using traffic sensors counts. Balakrishna et al 2007 used SPSA algorithm in the optimization of model parameters. One of the advantages of this application was its use of multiclass OD matrix to simulate parkway access restrictions for heavy vehicles.

Toledo et al 2004 presented iterative framework for MITSIMLab micro simulation model calibration by estimating origin destination (OD) mutually with behavioral parameters (46). This enabled the framework to consider the interactions between different model parameters. The framework applied in this study assumed that the network has multiple paths and depended on optimization algorithm. This approach was tested against traffic field observations for two case studies. However, the model replicate similar results in the two case studies, the OD estimation algorithm performance need to be improved.

Chapter 3 Model Applications

Microscopic models simulate second by second trajectories of individual vehicles on each link. These vehicle specific speed trajectories are estimated using algorithms based on car following, gap acceptance and lane change rules. Microscopic simulation models use default values for traffic assignment models and car following models. Therefore, micro simulation models tend to maximize acceleration and deceleration rates and may not reflect the real traffic conditions.

This thesis' approach is to match the output of a simulation model for a given link of roadway to a library of real world traffic data. The objective is to evaluate the utility microscopic transportation models to predict vehicle emissions and activity at sufficient resolution and to quantify the relative contribution of vehicle activity data obtained from micro simulation models on estimation of regional emissions. Therefore, the approach covers two parts: first part is the emissions side and the second part is the activity side. First part (Application I) integrates PEMS emissions data with AIMSUN micro simulation emissions model. The second part (Application II) uses PEMS activity data in AIMSUN activity data validation.

PEMS data consists of activity data which contains speed, acceleration and VSP on a second by second bases. The second part is the emissions and fuel consumption based on second by second measurements. The two case studies presented in the thesis explained two methods of using PEMS data. The first case study relies on PEMS emissions data. The second case study relies on PEMS activity data.

3.1 Calibrating AIMSUN Emissions Model with PEMS Data

The first case study depends on the emissions side of PEMS data. PEMS emissions data was used to calibrate AIMSUN internal emissions model. Then AIMSUN emissions output were verified against AIMSUN given emissions algorithms in order to check how AIMSUN emissions model works. The calibrated AIMSUN emissions model can be used for assessing environmental impacts of different scenarios.

A micro simulation model such as AIMSUN has its internal emissions model which is integrated in its platform, and calculates the emissions simultaneously with activity data modeling. Here we use PEMS emissions data in calibrating AIMSUN internal emissions and fuel consumption models. This is focused on extracting a sample of vehicles on the network from AIMSUN in order to estimate the emissions externally. AIMSUN fuel consumption and emissions equations were used to estimate emissions for the same set of activity data. The objective is to evaluate and verify how AIMSUN works and estimate the emissions and to understand AIMSUN method of estimating emissions.

As a first step PEMS data were extracted and modified to be compatible with AIMSUN required inputs for fuel consumption and emissions models. It is assumed that the fleet consists of one vehicle which is a Ford Taurus 2006 tested in PEMS. The second step was calibration of AIMSUN fuel consumption equations and emissions by extracting PEMS emissions data. The third step was to calculate the fuel consumption and emissions externally out of AIMSUN model and compare the results to AIMSUN estimates in order to verify AIMSUN results.

3.2 Calibrating and Validating AIMSUN Micro Simulation Model against PEMS Activity Data

The second portion of the research focused on the activity side of PEMS data. PEMS activity data was used to validate AIMSUN micro simulation outputs on micro scale level. Individual vehicles speed and VSP distributions obtained from AIMSUN were compared with PEMS vehicles speed and VSP distributions. The objective is to validate AIMSUN speed and acceleration distributions of individual vehicles and to check if these distributions reflect the real world driving behaviors.

Part of the Research Triangle area network was traveled and data collected using a Portable Emissions Measurement System (PEMS) on different days. PEMS data consists of vehicle activity which includes speed and acceleration on second by second basis. The second part is fuel consumption and emissions also based on second by second. In addition, the Triangle regional network is covered by the Traffic.com fixed sensor data collection system.

The approach was to model a portion of the Research Triangle Region in AIMSUN micro simulation model. AIMSUN was calibrated with Traffic.com demands. In particular, the traffic assignment model and traffic demand matrix were calibrated with Traffic.com vehicle counts. After calibration selected PEMS test were used in AIMSUN validation. PEMS runs were selected to coincide with the same date that Traffic.com data were gathered. AIMSUN micro simulation outputs were validated with PEMS activity data which include travel time, speed and acceleration. Figure 1 summarizes the thesis conceptual approach.

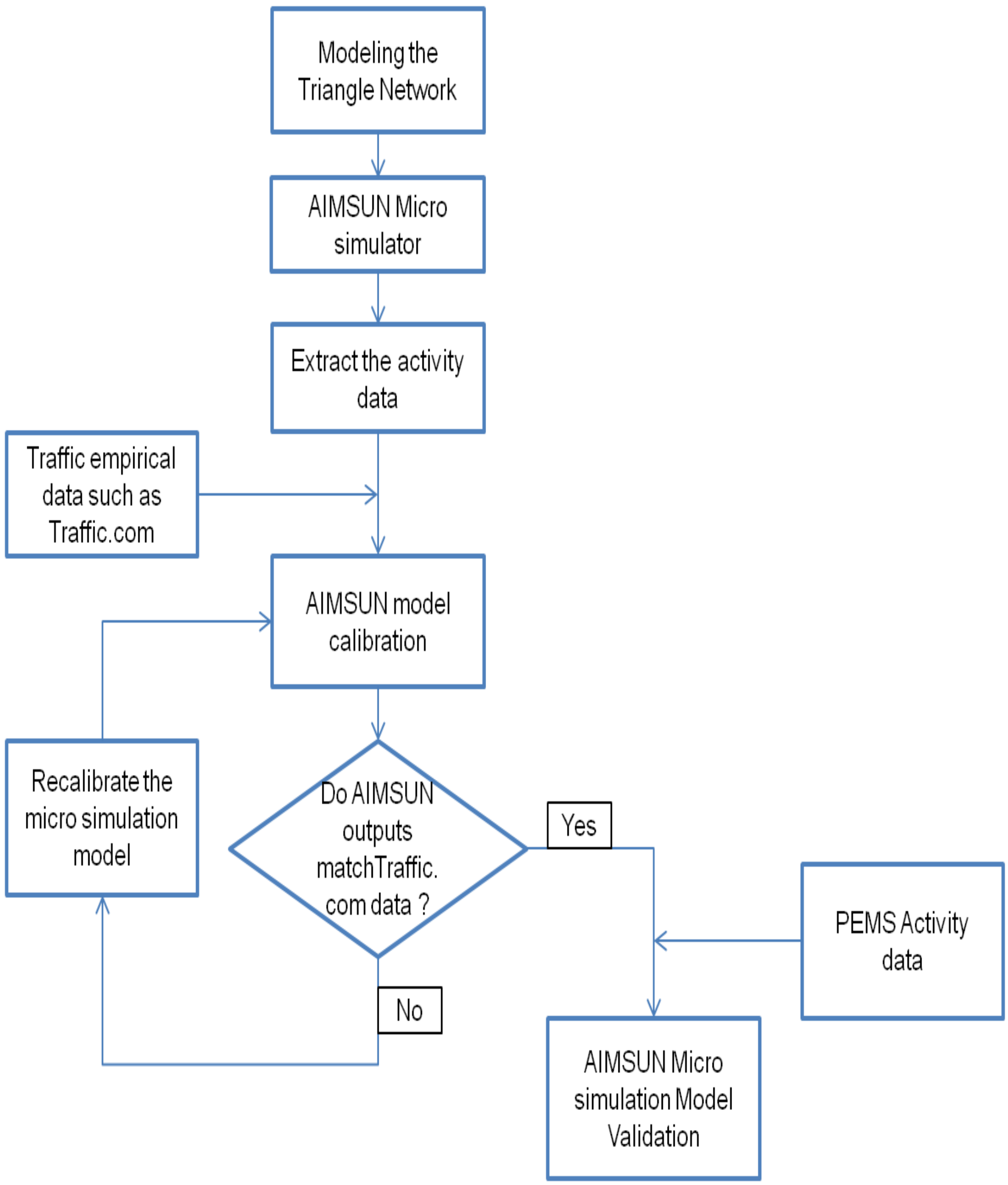


Figure 1 Conceptual Approach Chart

3.3 AIMSUN Micro simulation Model

AIMSUN (Advanced Interactive Microscopic Simulator for Urban and Non-urban Networks) is an integrated traffic modeling software, developed and marketed by TSS -

Transport Simulation Systems in Barcelona, Spain (3). AIMSUN core component is the micro simulator which simulates real traffic conditions for different types of traffic networks. AIMSUN micro simulator models the behavior of every individual vehicle in the system through the simulation step. AIMSUN is using driver operational algorithms to simulate the movement of every single vehicle. Car following, lane changing, and gap-acceptance models are used in AIMSUN micro simulator. AIMSUN provides detailed capabilities for modeling traffic networks, which can handle different vehicle types such as cars and trucks. Different road types can be modeled in AIMSUN such as arterials and freeways, and a wide range of traffic control types including fixed-time signal controls and actuated signalized controls. The traffic demands could be entered into AIMSUN in two forms: the first is origin-destination (OD) trip matrices; the second is link traffic flows and turning proportions on each road section.

AIMSUN can also model impact of incidents and Variable Message Signs (VMS) and collect traffic operations statistics at different spatial scales such as links and OD levels. In addition to its very detailed modeling capabilities, AIMSUN offers great flexibility through providing an Application Programming Interface (API) for interfacing with user-defined applications to allow them to interact with its internal micro-simulator. The user API can be written in python or C++ and it collect data from AIMSUN internal micro simulator and it also has the ability to change variables while the simulation is running.

Chapter4 Empirical Studies and Traffic Data

This chapter demonstrates the different types of data that have been used in the thesis. The first part presents information about PEMS empirical studies. The second part illustrates the type of empirical traffic data that were used in the calibration and validation process. Definitions and detailed description of traffic sensing data is also provided in this section. The purpose is to highlight the real world emissions and traffic data that have been used in the calibration and validation process of the micro-simulation model.

4.1 Empirical Studies

This section discusses the empirical data measured by PEMS. Description of EPMS components and PEMS background is also provided. In addition, details about PESM tests and data processing are demonstrated.

4.1.1 Portable Emission Measurement System (PEMS) Description

The Portable Emission Measurement System (PEMS) used in the thesis research is a third generation Axion PEMS, the Montana system PEMS was manufactured by Clean Air Technologies International, Inc. The Montana system is comprised mainly of two parallel five-gas analyzers which are used in emissions measurements during the test. In addition PEMS main unit contains the following parts: particulate matter (PM) measurement system, an engine sensor array, a global positioning system (GPS), and an onboard computer (16). The two parallel gas analyzers instantaneously measure the volume percentage of carbon monoxide (CO), carbon dioxide (CO2), hydrocarbons (HC), nitrogen oxide (NO), and oxygen (O2) in the vehicle exhaust (tailpipe exhaust). A temporarily connected OBD engine scanner is connected to vehicle engine. The OBD scanner measures Manifold Absolute Pressure (MAP), intake air temperature, and engine RPM. The OBD measures are used in estimate air and fuel use. The GPS system measures vehicle position. The Montana system is designed to measure emissions during the actual use of the vehicle on real world driving conditions (11).

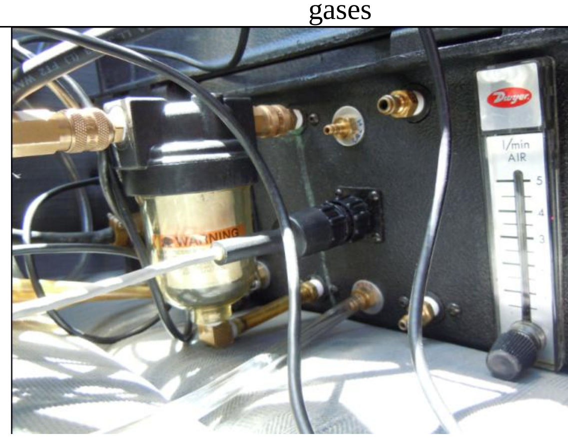
The pollutants measured by PEMS include O2, HC, CO, CO2 and NO using different detection techniques (10). The HC, CO and CO_2 are detected by using non-dispersive infrared (NDIR). The CO and CO_2 detection have a good accuracy; however HC detection accuracy depends on fuel type. On the other hand, NO_x which is comprised of approximately 95 volumes percent NO is detected by using electrochemical cell. Software codes were used to convert the On Board Diagnostics data and the GPS data into second by second bases and to carry out the modal analysis of the data. Road grade was calculated from GPS data. The components of PEMS system are indicated in Figure 2.

Figure 2 Illustration of PEMS Components and Connections

(a) PEMS main unit

(b) Tailpipe intake for sampling exhaust gases

(c) PEMS tubes and thermal unit



(d) PEMS tubes and emissions filter

(e) OBD connection to vehicle engine

(f) GPS unites

4.1.2 Description of test routes

The field experiment from which was intended to gather recent PEMS data took into account several factors: choice of network and route; choice of vehicles; choice of driver; and scheduling. Based on statistical analysis of six routes for which data was previously collected in the Research Triangle Park, NC, the analyst determined that data collection should focus on one primary route between North Raleigh and Research Triangle Park, NC via I-540, which produces over 95 percent of the variability in fuel use and emissions that is observed compared to any of the other routes. Hence, by collecting at least 3 hours of second-by-second data under a range of variability in speed, acceleration, and road grade, we are able to develop "emissions fingerprints" for an individual vehicle. Figure 3 and Figure 4 illustrates the test routes for data collection experiments.

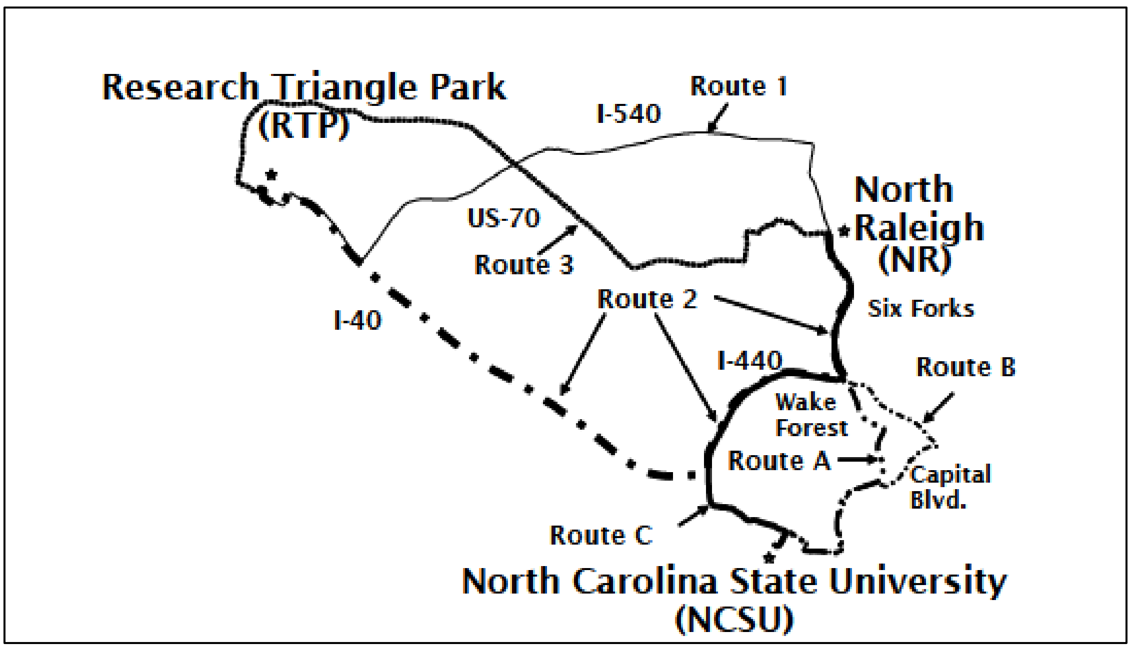


Figure 3 Data Collection Routes for Fuel Consumption and Emissions

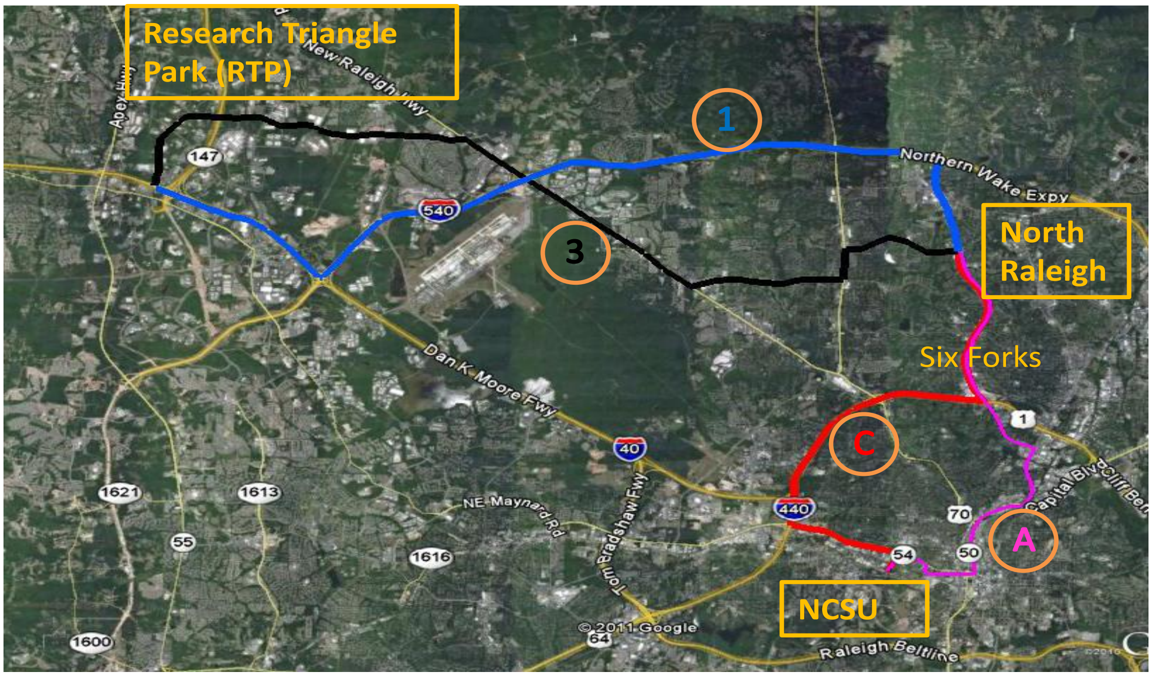


Figure 4 Map for PEMS test routs from NCSU to RTP through North Raleigh

The routes are based on two main origins and destination (O/D) pairs: (1) North Carolina State University (NCSU) to North Raleigh (NR); and (2) North Raleigh (NR) to Research Triangle Park (RTP). The routes from NCSU to NR are comprised primarily of signalized minor and major arterial roads. The routes from NR to RTP consists primary from highways. Since route conations mix of major arterials and interstate highways, it represents variation in tested road types. In addition, some routes have a mix of feeder/collector, minor and major arterial and freeway. The study area covers the variation in road types and road grades.

Route 1 and 2 represent the highways in PEMS experiment. Route 1 is comprised mainly from interstate highway I-540. Route 2 is comprised mainly of I-40. Route A consists of minor arterials and collectors. There are common segments between Route A and Route C.

The I-440 in Route C differentiates it from Route A. Route C is mainly consisted of minor arterial and interstate highway which has higher average speed. Table 1 summarizes some routes attributes.

Table 1 Summary of Route Attributes Cited

	Mileage (miles)		Intersection Control (number)		
Routes	Freeway	Arterial	Signal	Stop Sign	Roundabout
A Inbound	0	11	43	26	3
A Outbound	0	11	43	26	3
C Inbound	5	6	29	16	2
C Outbound	5	6	29	16	2
1 Inbound	13	3	4	3	0
1 Outbound	13	3	4	3	0
3 Inbound	0	18	26	31	0
3 Outbound	0	18	26	31	0

4.1.3 Description of quality assurance steps

There are three sources of raw data: the data logger, GPS with altimeter and PEMS. We have developed quality assurance procedures that include the following main steps: (a) convert data to a second-by-second basis, (b) synchronize the data from multiple instruments into a single database; and (c) screen and evaluate the data for possible errors, correct errors where possible, and remove invalid data that cannot be corrected (d) modal analysis of the data.

The research team developed LabVIEW-based quality assurance algorithms to deal with: identifying and imputing missing values of MAP (manifold absolute pressure); identifying unusual engine RPM and imputing correct values; identifying situations in which the gas analyzer data were “frozen” because of failure of the instrument to provide updated readings; loss of precisions of exhaust concentration measurements because of high oxygen levels in the exhaust possibly associated with air leakage in the sampling line; identification of unusual values of IAT, and identification and removal of negative emissions concentrations that were statistically different from zero.

The team developed detailed modal fuel use and emissions models based on vehicle specific power VSP for every tested vehicle. We have used a 14-mode approach to estimating average fuel use and emissions rates for specific ranges of VSP (11). VSP is estimated based on second-by-second speed, acceleration, and road grade and is given in units of kW/ton of vehicle weight. VSP modes are defined for 14 ranges of VSP, including two modes for negative VSP and 12 modes for positive VSP (18). In addition, we have developed “engine-based” modal models for each vehicle; in which average fuel use and emission rates are estimated for 10 modes equally divided between the minimum and maximum observed values of MAP. For both types of models, we have compared the empirical modal emissions models for units of g/sec and g/gallon. New platform was developed using LabView software for calculating VSP and MAP modal emissions for each tested vehicles.

4.1.4 Data Analysis

The results from PEMS are emissions and fuel consumption measurements on a second by second basis, in addition to the vehicle activity data (speed and acceleration) also on a second by second basis for every vehicle tested. The research team had mined the high-resolution PEMS data to develop real-world, empirically-based fuel consumption and emission models. These include micro-scale models using the Vehicle Specific Power (VSP) binning approach, which is essentially the approach that has been adopted in the recently released EPA MOVES model. These PEMS data sets were used in the research in this thesis for calibration and validation of AIMSUN micro simulation models. Figure 5 depicts an example of micro-scale raw data acquired by PEMS showing second-by-second vehicle speed and CO2 emission rate time traces.

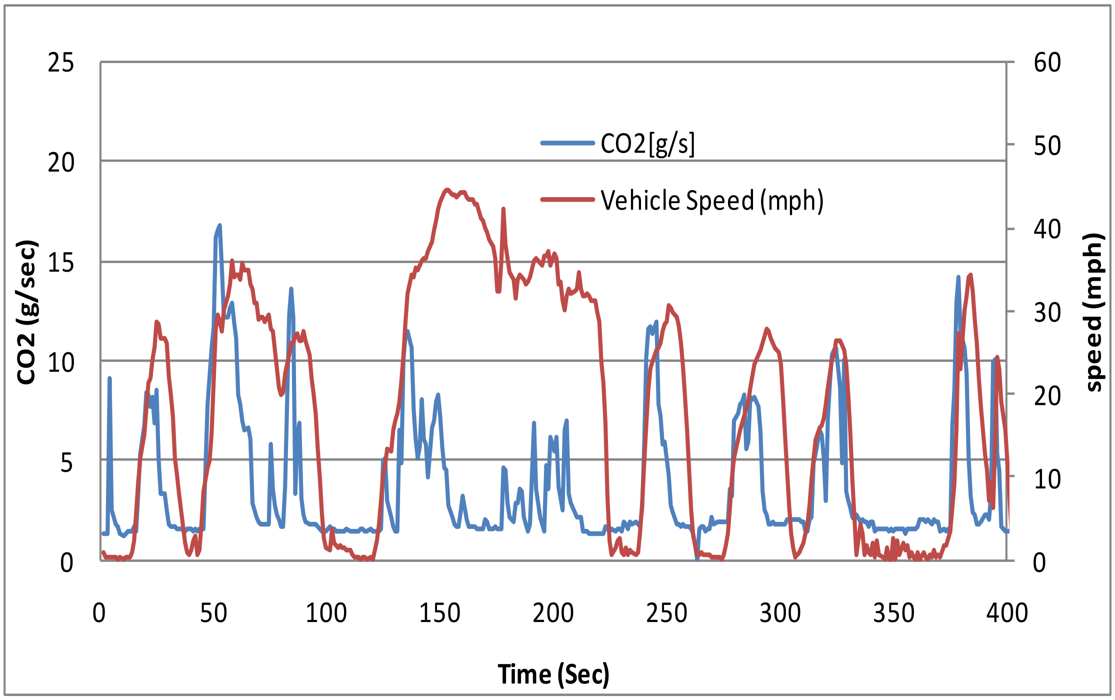


Figure 5 Sample of PEMS Data: Second by Second Speed and CO_2 Traces

The PEMS data base at NC State contains about 35 vehicles; every vehicle was tested on the routes for four hours driving based on real world driving conditions. Quality assurance algorithms were applied on these data sets for all the 35 vehicles. PEMS data base covers tests for many vehicles with different models and year makes with different drivers. About 95 % of those vehicles were used in the calibration and validation process of AIMSUN. The author also carried out conducted detailed quality assurance tests for different vehicles; the following results in Table 2 are sample of quality assurance output.

Table 2 Data Quality Assurance Sample Results

Sample Tested Vehicles	Raw Data (seconds)	Quality Assured Data (seconds)
Ford Taurus 2006	11,760	11,600
Pontiac Grand Prix	13,117	12,832
2005 Toyota Prius	19,677	18,140
2008 Honda Civic	11,855	11,508

The VSP bins approach was used to bin the VSP distribution into VSP bins defined according to Frey at el 2002. The fuel consumption and emissions were aggregated into the VSP bins for every VSP mode. Figure 6 illustrates Toyota Camry vehicle results tested at October 20, 2010 that will be used later in the thesis research.

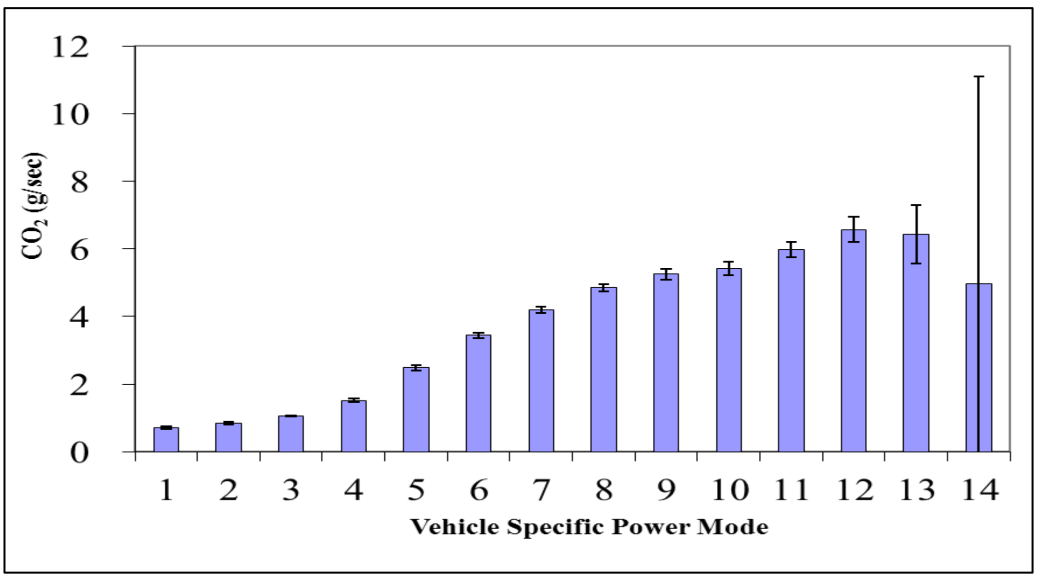


Figure 6 CO2 Emission Binned into VSP Bins Distribution

PEMS data analysis yields VSP modal emissions factors calculated based on time weighted average for every VSP mode. The fuel consumption and emissions are binned into the 14 VSP bins with respect to percentage of time under every VSP bin. These VSP modal emissions values can be used in estimating total emissions based on number of seconds of every VSP modes. Table 3 shows fuel consumption and emissions results based on the VSP bin for a Toyota Camry vehicle (used in the validation process).

Table 3 Average fuel use and emission rates for each VSP mode

VSP Mode	VSP Range (kW/ton)	Sample Size	Fuel (g/s)	NO as NO_2 (mg/s)	HC (mg/s)	CO (mg/s)	CO_2 (g/s)
1	Below -2	1852	0.227	0.441	0.385	2.416	0.713
2	-2 – 0	1100	0.270	0.511	0.442	2.682	0.848
3	0 – 1	3178	0.337	0.697	0.612	3.068	1.059
4	1 – 4	1700	0.484	1.494	0.801	4.629	1.523
5	4 – 7	1456	0.790	2.420	1.152	8.772	2.483
6	7 – 10	1306	1.094	3.150	1.723	12.238	3.440
7	10 – 13	999	1.336	3.687	1.894	15.226	4.200
8	13 – 16	760	1.545	4.707	2.183	18.427	4.858
9	16 – 19	424	1.671	4.851	2.427	22.260	5.249
10	19 – 23	307	1.729	5.355	2.564	27.866	5.423
11	23 – 28	143	1.909	6.453	2.500	37.696	5.980
12	28 – 33	51	2.102	8.310	2.495	44.744	6.578
13	33 – 39	16	2.066	7.084	3.765	64.345	6.427
14	Over 39	2	1.616	9.445	1.430	87.230	4.975

4.2 Empirical Traffic Data

The key research needs are to evaluate and validate the micro simulation activity outputs with the real-time vehicle data, and integrate the vehicle data from traffic detection with micro simulation emission models to demonstrate the feasibility of real-time emission estimation. A framework for calibrating the micro simulation models with the traffic detection data need to be developed. The research efforts should demonstrate the applicability of the framework and its benefits with respect to interface with transportation models and improved real-time based traffic detection. These include point sensors (Traffic.com) and link-based sensors (INRIX) as described next.

4.2.1 Traffic.com

There are many traffic detection systems that can be used for such purpose such as the Traffic.com data collection system (Traffic.com, 2009) operated by the NC Department of Transportation (47). Many of the freeway facilities in the Research Triangle region have lane sensors and detectors that provide: data timestamp, sensor ID; sensor lane ID; type of lane, average speed (mph); total counts; percent time sensor is occupied; count of non-commercial vehicles, Count of single unit CV's, count of single-trailer CV's, and count of multi-trailer CV's. The data in Traffic.com may be aggregated in 1 min intervals. Traffic.com maintains strict Quality Assurance (QA) checks and tests on the data reported by the sensors.

4.2.2 INRIX

The I-95 Monitoring Site operated by INRIX Inc (I95 Corridor coalition, 2010) can be another source of traffic data for the project (13). It provides real-time traffic speeds and travel time information using vehicle probe technology for more than 5,000 miles of roads along the I-95 corridor. It has broader coverage but less detail information than Traffic.com.

The traffic data include location, average speed, reference speed, confidence Score (based on data type, age, density), travel time (in minutes), length, and road direction for a specific section of road.

Chapter 5 AIMSUN Fuel and Emissions Models Calibration

The objective of this application is to calibrate AIMSUN fuel consumption and emission models and to evaluate and verify the input data and algorithms used in AIMSUM for estimating fuel use and emissions. The AIMSUN version 6.0.5 fuel consumption and emissions model was calibrated with PEMS based data. The sample road network coded in the AIMSUN traffic simulator was used to both calibrate the AIMSUN modal fuel consumption and emission models and to verify its results.

5.1 AIMSUN Model Calibration and Verification

This chapter approach was to calibrate AIMSUN fuel and emissions model with PEMS based emissions and fuel consumptions. The AIMSUN version 6.0.5 fuel consumption and emissions model was calibrated with PEMS based data. The sample road network coded in the AIMSUN traffic simulator was used to both calibrate the AIMSUN modal fuel consumption and emission models and to verify its results. This enables the analyst to check how AIMSUN model works and to evaluate and verify the input data and algorithms used in AIMSUM for estimating fuel use and emissions.

This task aims mainly to calibrate AIMSUN fuel and emissions models, and to establish correlations between the PEMS-based data and micro simulation model. This process is best described in the following six step-processes.

1) Extracted PEMS empirical model data
2) Calibrated both the fuel and emission models for AIMSUN using PEMS data

3) Extracted the instantaneous vehicle activity data (speed, acceleration) on a second by second basis for a random sample of vehicles traveling the simulated network at AIMSUN
4) Inputted the calibrated model parameters into AIMSUN and extract the emissions and fuel consumption results from AIMSUN
5) Estimated link, Origin/ Destination and network wide emissions with the empirical model using the tracked vehicle sample
6) Compared the empirical estimates with those automatically generated from AIMSUN as part of its fuel and emissions output

Step 1: Extract PEMS data

The Portable Emission Measurement System (PEMS) used to acquire the fuel and emissions data is the OEM-2100 Montana system manufactured by Clean Air Technologies International, Inc. The PEMS is comprised of two parallel five-gas analyzers, an engine scanner, a global position system (GPS), and an on-board computer. The Montana system is designed to measure emissions of NO_x, CO, and HC during the actual use of the vehicle or equipment in its regular operation. The results from PEMS are emissions and fuel consumption rates on a second by second basis, in conjunction with vehicle activity data (speed and acceleration).

Step 2: Calibrate AIMSUN

In this initial effort, it was assumed that the vehicle fleet consisted entirely of 2006 Ford Taurus vehicles. The vehicle was driven for four hours on a specified network. The experimental design was developed taking into account the following factors: choice of network and route; choice of vehicles; choice of driver; and time-of-day traffic effects.

The AIMSUN fuel consumption and emission models assume that each vehicle is operating in one of four possible modes: idling, cruising, acceleration or deceleration. All AIMSUN emission rates and fuel consumption equations are defined based on these four modes. PEMS-based modeling provides emission and fuel consumption on a second by second basis that can be binned into modes. The four modes are characterized based on Frey et al. (2003). The idle mode was defined at zero speed and zero acceleration. The acceleration mode was defined based on a minimum acceleration of two mph/sec along with an average sustained acceleration rate of at least one mph/sec in the last three seconds. Deceleration was defined in a similar fashion, as a minimum deceleration rate of -2 mph/sec along with an average sustained deceleration rate of -1 mph/sec in the last 3 seconds. All other data was considered to be in cruise mode (16). The PEMS data were stratified into the four modes based on these definitions. The data for each mode was used in calibrating the AIMSUN fuel consumption and emission models.

The AIMSUN fuel consumption model defines specific formulas for calculating fuel consumption for each mode; the following equations show these formulas:

Idle fuel consumption

$$F_u = F_i \times \Delta \mathrm{t} \qquad (1)$$

Acceleration Fuel Consumption

$$F_u = (C_1 + C_2 \times a \times v) \times \Delta t \qquad (2)$$

Cruise fuel Consumption

$$F_u = (K_1 \times (1 + (v \div 2V_m)^3) + K_2 \times V) \times \Delta t \qquad (3)$$

Deceleration fuel Consumption

$$F_u = F_d \times \Delta t \quad (4)$$

The following parameters must be specified for the above models:

- F_u : fuel consumption for every vehicle mode in (ml)
- F_i : the fuel consumption rate for idling vehicles in ml/s
- C_1 and C_2: two constants in the model for the fuel consumption rate for accelerating vehicles
- K_1 is constant defined based on the fuel consumption rate, in liters per 100 km, for vehicles travelling at constant speed v_1 90 km/h
- K_2 is constant defined based on the fuel consumption rate, in liters per 100 km, for vehicles travelling at constant speed v_2 120 km/h
- V_m: the speed at which the fuel consumption rate, in ml/s, is at minimum for a vehicle cruising at constant speed
- F_d: the fuel consumption rate for decelerating vehicles in ml/sec
- a: vehicle acceleration (m/s/s)
- v: vehicle speed (m/sec)
- Δt : simulation time step

F_i and F_d *Calculation*

After defining the operational modes for the 2006 Ford Taurus, idling, cruise, acceleration and deceleration data were extracted from the PEMS data. These data include fuel consumption in (g/sec) for every second of operation for the Ford Taurus. F_i and F_d were calculated simply by taking the average of all *Fu* (ml/sec) at idle and deceleration modes, respectively.

C_1 and C_2 Constants Estimations

For the acceleration mode, the C_1 and C_2 constants were calibrated by statistical linear regression based on the extracted acceleration data. The equation for regression model was Y = C1 +C2 *X where X = a*v and Y is Fu (ml)

Statistical linear regression was used to calibrate this model. The regression output is: y = 3.18 + 0.0520 X. Figure 7 shows the predicted fuel consumption (predicted Y) versus the original fuel consumption. So C1 = 3.18 and C2=0.0520

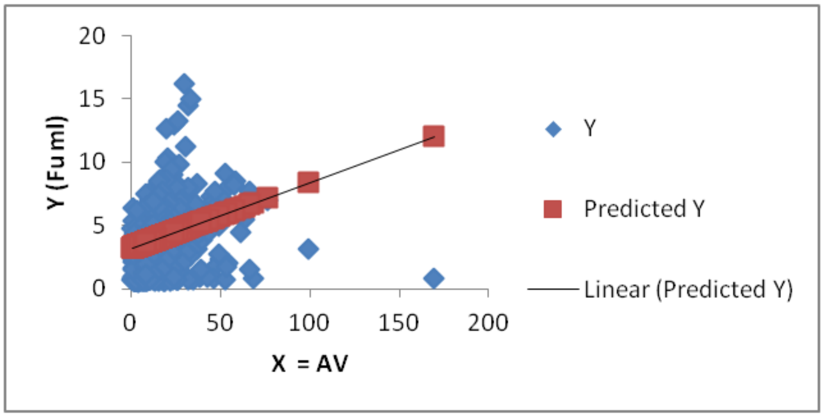


Figure 7 Calibrating Acceleration Fuel Consumption Equation Constants

K_1 and K_2 Factors Estimation

Statistical linear regression was used also to calibrate the cruise mode constants K_1 and K_2 using extracted cruise data. The equation was modified in the following form:

Fu (ml/sec) = A + B * V^3 + C * V,

Fu (ml/sec) = A + B * X_1 + C * X_2, Where A = K1, C= K2, B= K1/ (2 V_m) ^{3}, X_1= V ^{3} and X_2= V

AIMSUN fuel consumption model inputs form two parameters F1 and F2, which are the fuel consumption rates in liters per 100 km/hr for vehicle traveling at constant speed V_1 and V_2 respectively. We used the following equations provided in AIMSUN 6.0 user manual (TSS 2008) to calibrate the F1 and F2 factors.

$$k_1 = \frac{(F_1 - F_2)v_1 v_2 v_m^3}{180(2v_2 v_m^3 - 2v_1 v_m^3 + v_2 v_1^3 - v_1 v_2^3)}$$

$$k_2 = \frac{2F_2 v_2 v_m^3 - 2F_1 v_1 v_m^3 + F_2 v_2 v_1^3 - F_1 v_1 v_2^3}{360(2v_2 v_m^3 - 2v_1 v_m^3 + v_2 v_1^3 - v_1 v_2^3)}$$

Where F1 is the fuel consumption in (l/100km) for vehicles traveling at speed 90km/hr and F2 is the fuel consumption in (l/100km) for vehicles traveling at speed 120 km/hr. In addition, the V_1 = 90 km/hr and V_2= 120 km/hr by definition in these equations. Figure 8 and Figure 9 show the linear regression estimates for variables X_1 and X_2. V_m was calculated based on the speed at the min cruise fuel rate (ml/sec).

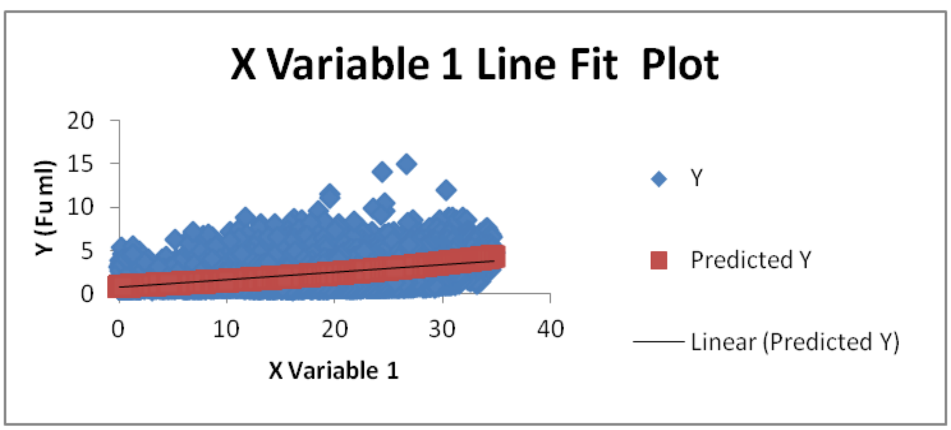


Figure 8 Calibrating Fuel Consumption Model for Cruise Mode (X1=V^3)

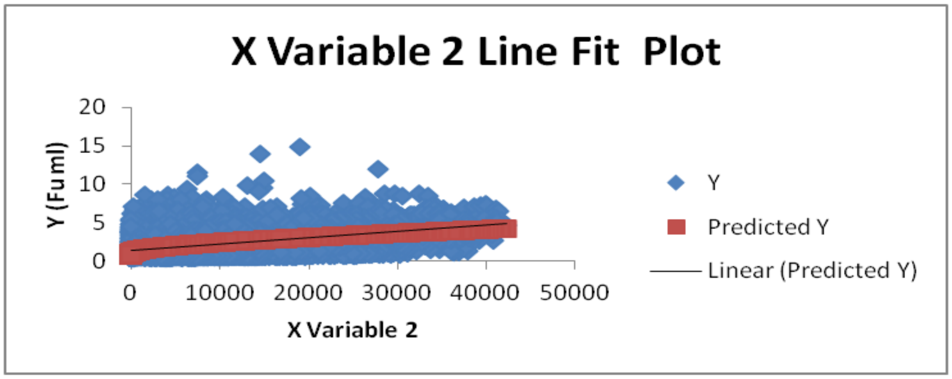


Figure 9 Calibrating Fuel Consumption Model for Cruise Mode (X2=V)

The regression model after calibration is:

$y = 0.862 + 0.000030\ X_1 + 0.0624\ X_2$; thus K1= 0.862, K2= 0.0624 and V_m= 55 km/hr.

AIMSUN Emissions Factors Estimation

The AIMSUN emissions model calculates the emissions based on emission factors defined for the same four modes discussed earlier. These emission factors are expressed in (g/sec). The emission rates were calibrated using PEMS-based emissions data for the Ford Taurus. The emission factors for idle, acceleration, and deceleration were calibrated for each pollutant by taking the average of the emissions data from PEMS for idling, accelerating and decelerating modes respectively. These emissions factors are inputs to the AIMSUN emissions model.

The AIMSUN emissions model requires that input cruise mode emission factors be stratified with respect to speed ranges. The PEMS data for the cruise mode were used to estimate average emission rates for each needed speed range. Average emission rates for a given speed or speed range were estimated based on each of a linear model and an exponential model that were fit to the PEMS data for each pollutant. The two models were compared for each pollutant based on relative R^2 performance. The exponential models gave the best calibration for the emission rates for all three pollutants. The different emission factors were calibrated using the exponential equations by estimating the emission factors for different speed break points from 10 km/hr to 120 km/hr in increments of 10 km/hr and for every speed range, a central estimate was used. Figure 10, Figure 11 and Figure 12 show emissions model calibration.

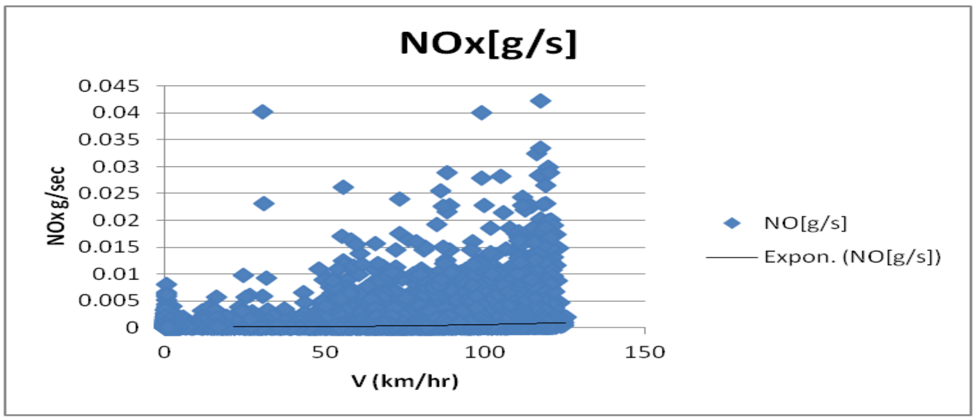


Figure 10 Calibrated AIMSUN Emission Model for Cruising Mode for NO

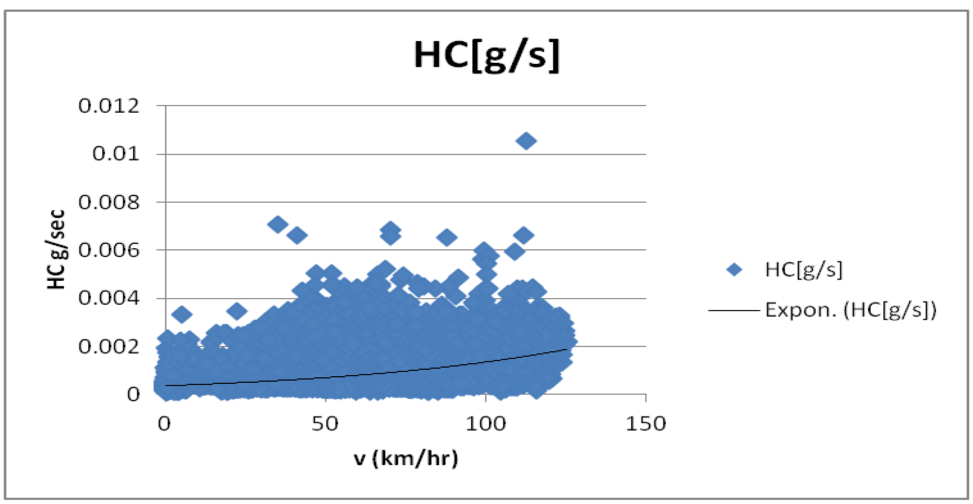


Figure 11 Calibrated AIMSUN Emission Model for Cruising Mode for HC

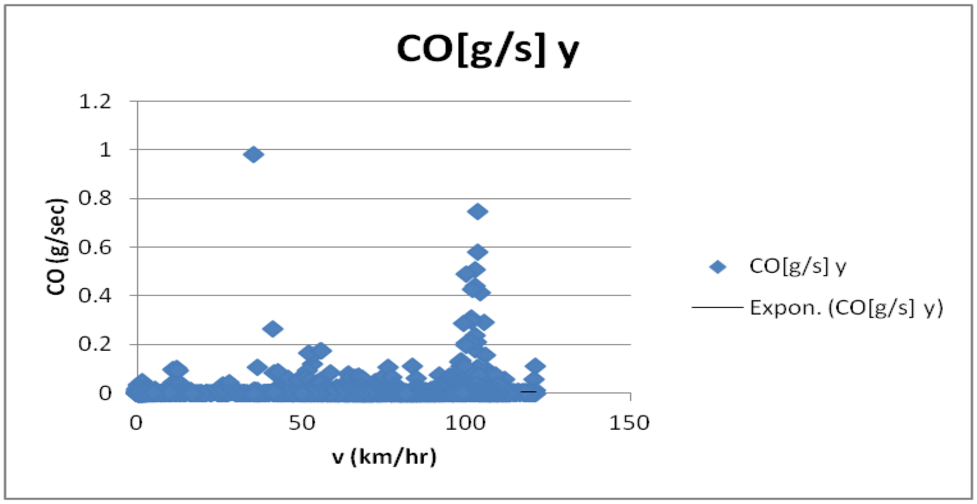


Figure 12 Calibrated AIMSUN Emission Model for Cruising Mode for CO

Step 3: Estimate a Sample of Vehicle Activity Data for Use in Model Verification

In order to verify the correct implementation of the fuel use and emissions inputs to AIMSUM, a separate "External Model" was created in order to compare estimated fuel use and emissions based on the same set of vehicle activity data. The External Model was created in order to verify our understanding of the input data and algorithms used in AIMSUM, since the documentation of these in the AIMSUM manual was very cursory. The External Model is based on the same fuel use and emissions parameters and algorithms as appear to be used in AIMSUM. In order to compare fuel use and emissions estimates generated by AIMSUM with those of the External Model, a common set of vehicle activity data are needed. The activity data were generated by running AIMSUM for ten replicated runs of the test network for the baseline scenario.

Each run was based on a different random sequence of simulated vehicles, leading to random fluctuation in traffic flow. Because each run generates a large amount of second-by-second data, only a random sample of 10% of the network-wide vehicle flow activity data was extracted from AIMSUM for input to the External Model. The activity data include second-by-second speed, from which acceleration is estimated. In the External Model, these data stratified by operating mode (idling, cruising, acceleration and deceleration) were defined and the emissions and fuel consumption are calculated on a second by second basis for every sampled vehicle.

The results of the External Model and from AIMSUM were compared to determine whether the External Model closely mimics the fuel use and emissions results reported by AIMSUM model. High concordance in the comparative results, in turn, verifies a thorough understanding of the data and algorithms used in AIMSUM. Because the External Model was executed based on a random subset of activity data generated in the AIMSUM model runs, there is expected to be some random error in the comparison.

Step 4: Run AIMSUN

The calibrated fuel consumption model parameters and emission factors were input to AIMSUN. Simulated values of fuel use of emissions were extracted from the ten AIMSUM model runs for entire population of vehicles in the network. The objective here was to verify AIMSUN output estimates, by comparing it with the external model.

Step 5: External model development

After calibrating the AIMSUN fuel consumption and emissions model, the calibrated equations and factors were used to develop an external model for fuel consumption and emissions in order to simulate what AIMSUN should be estimating in terms of the fuel and emissions output at different spatial levels and verify its results. The external model was used to estimate link, Origin/ Destination and network wide emissions using the tracked vehicle sample.

Step 6: Comparison between external model estimates and AIMUSN output

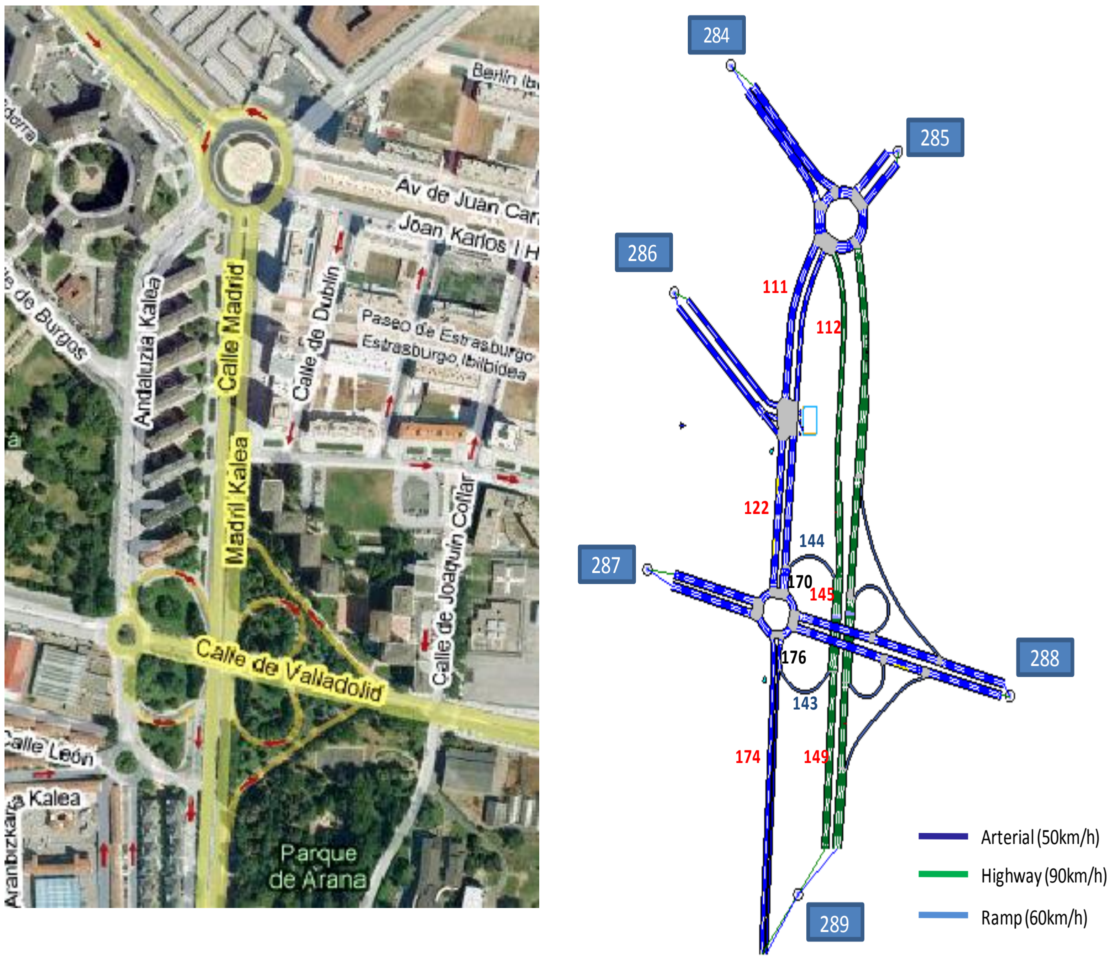
The external model estimates were compared with those automatically generated from AIMSUN as part of its fuel and emissions output. Comparisons were established at various spatial scales, namely at the link, path, origin-destination OD (with multiple paths connecting them) and network-wide levels. The AIMSUN model reports total fuel consumptions in liters and total emissions in kg. The author calculated and compared fuel consumption and emissions on a per vehicle basis in order to normalize the results across different scenarios. The total fuel consumption and emissions were divided by total number of vehicles to get per vehicle estimates on different spatial levels.

5.2 Numerical Application

A simulation fuel consumption and emissions models were calibrated using real-world data available from PEMS. This work was done initially using one vehicle sample (a 2006 Ford Taurus) in order to ensure that the model output matched external set of fuel and emission computations.

5.3 Network Description

A small portion of the transportation network of Victoria City, Spain, was selected, which is presented in Figure 13 with the modeled network in AIMSUN. The simulation network had been calibrated and validated under a baseline condition by the developer and has been distributed with the AIMSUN simulation software package. The size of the network is about 1000 meters from north to south and 450 meters from east to west. There are three major arterials with one corridor in the east-west directions (Calle de Valladolid) and two parallel corridors (Calle Madrid and Madrid Kalea) in the north-south directions.



(a) (b)

Figure 13 The study area with the Modeled Network in AIMSUN

The simulation time for this study is 15 min, during which about 1900 vehicles were processed. The size of the network is about 1000 meters from north to south and 450 meters from east to west. Since the highways including sections (links) 112, 145, and 149 typically have short travel times, the route constituting these links is considered to be the primary route for southbound traffic.

5.4 Results

The author has assessed the variability in fuel use and emissions estimates when aggregated at various spatial and temporal scales. On the spatial level, the analyst estimated emissions at the network link, path, origin-destination (multiple paths connecting them) and network-wide levels. The source of the vehicle activity data was also varied, from instantaneous vehicle trajectories (speed, acceleration, deceleration, idling, and VSP mode) to average speed on the link, O/D and the network. The purpose of this analysis is to assess the loss in fuel and emission estimation accuracy as a result of aggregating at the various temporal and spatial levels.

After calibrating the AIMSUN fuel consumption and emissions model, the calibrated equations and factors were to develop an independent model for fuel consumption and emissions in order to simulate what AIMSUN is estimating in terms of the fuel and emissions output. This model was called the external model, the objective of establishing this external model is to verify AIMSUN emissions model estimates.

The results are divided into two sections, the first section is for the calibration results and the second part is for the verification results.

5.4.1 AIMSUN Model Calibration

Table 4 shows the AIMSUN fuel consumption and emission calibration parameters of AIMSUN internal models. These factors were calibrated with PEMS fuel consumption and emissions data sets. Table 5 statistical measurements for the calibrated factors.

Table 4 Calibrated AIMSUN fuel consumption and emissions model parameters

Calibrated Modal AIMSUN Fuel Consumption Parameters			
Idling	F_i = 0.6957 ml /sec		
Accelerating	C_1= 3.18		
	C_2= 0.0520		
Cruising	K_1= 0.862 (at speed 90 km/hr)		
	K_2= 0.0624 (at speed 120 km/hr)		
	V_m=55 km/hr		
Decelerating	F_d = 0.9833 ml /sec		
Emission Factors for: Idling, Acceleration and Deceleration Modes			
Emission rates (mg/sec)	NO_x [mg/s]	HC [mg/s]	CO [mg/s]
Idle emission rate (mg/sec)	0.056	0.292	0.752
Acceleration emission rate (mg/sec)	0.924	2.039	4.124
Deceleration emission rate (mg/sec)	0.403	0.494	0.813

Table 4 Continued

Emissions Rates for Cruising Mode			
V(km/hr)	NO_x[mg/s]	HC[mg/s]	CO[mg/s]
10 km/hr	0.098	0.456	0.568
20 km/hr	0.120	0.521	0.646
30 km/hr	0.146	0.594	0.734
40 km/hr	0.179	0.678	0.834
50 km/hr	0.219	0.774	0.948
60 km/hr	0.267	0.883	1.078
70 km/hr	0.327	1.008	1.225
80 km/hr	0.399	1.150	1.392
90 km/hr	0.488	1.312	1.582
100 km/hr	0.597	1.497	1.798
110 km/hr	0.730	1.709	2.044
120 km/hr	0.893	1.950	2.323

Table 5 Statistical Measurements for the Calibrated Factors

Calibrated Modal AIMSUN Fuel Consumption Parameters	
Accelerating	R^2 = 7.5 %
Cruising	R^2 = 30 %
Calibrated Modal Emissions Rates for Cruising Mode	
NO_x	R^2 = 18 %
HC	R^2 = 37 %
CO	R^2 = 10 %

5.4.2 AIMSUN Model Verification

Using the average of ten simulation replications, model's estimates that use a 10% vehicle activity sample from AIMSUN (hereafter called the *External Model*) for fuel consumption and emissions were developed. Then, the External Model estimates were compared with AIMSUN's direct outputs on a link by link basis and also for trips between key OD pairs. The following depict that comparison, in which each point represents a single link. As expected, there was no significant difference between the external model estimate and the AIMSUN output at link level, yielding an R^2 of 98.8 % for fuel consumption estimates. R^2 values for the emissions are 98.6%, 98% and 97% for NO_x, HC and CO emissions respectively.

In addition, the external model estimate and AIMSUN output gave comparable results when data were aggregated at the OD level. There is no significant difference between the external model and AIMSUN model for most ODs, although there is a slight difference at OD 284-289. Some of the differences at some links and ODs are likely attributable to the fact that the comparison was made between the entire population estimate in AIMSUN and a 10% random sample used to estimate the external model. The objective was to verify how AIMSUN estimates the emissions and fuel consumption at different spatial levels. Figure 14 to Figure 17 show the comparison on links level.

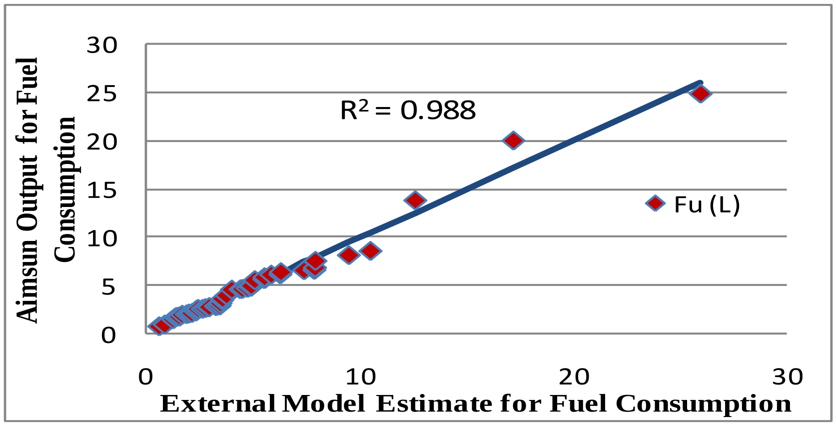


Figure 14 Fuel Consumption Comparisons at Link Level

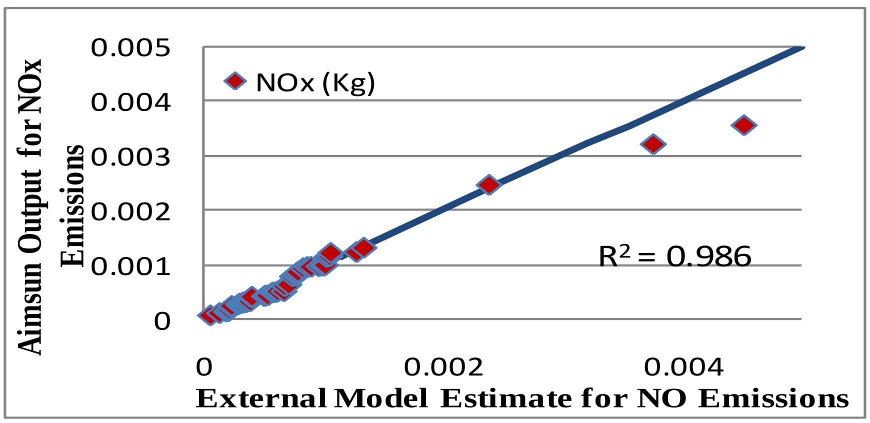


Figure 15 NOx Emissions Comparison at Links Level

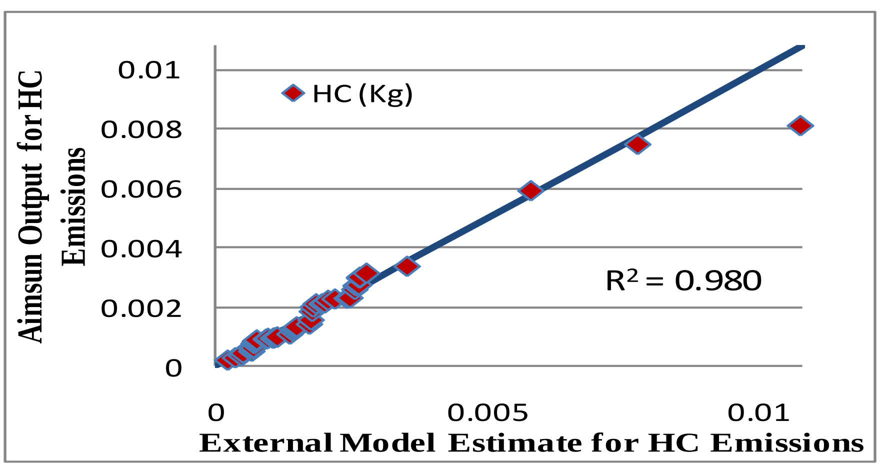


Figure 16 HC Emissions Comparison at Link Level

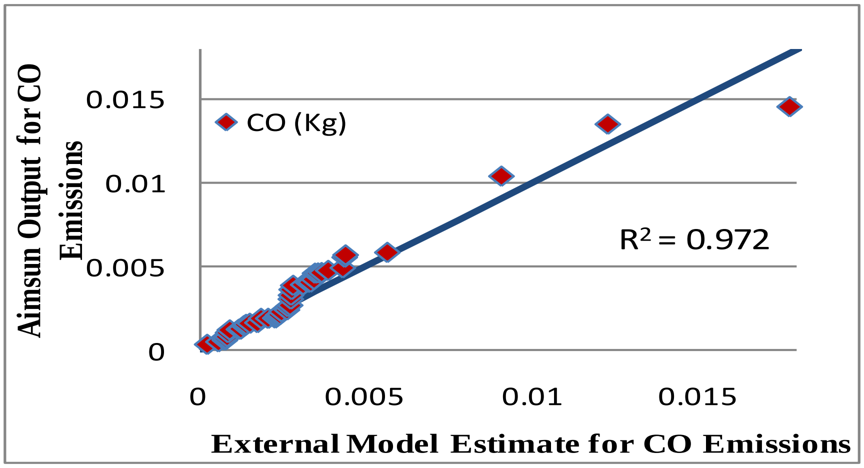


Figure 17 CO Emissions Comparison at Link Level

Figure 18 to Figure 21 show the comparison between the external model and AIMSUN model on OD levels. The emissions and fuel consumption for all vehicles were aggregated on the different ODs based on different vehicles paths.

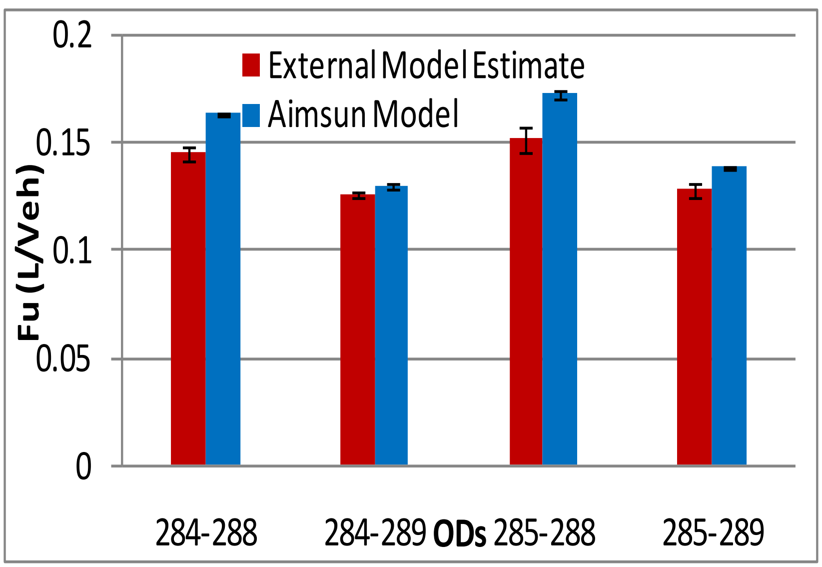


Figure 18 Fuel Consumption Comparisons at ODs Level

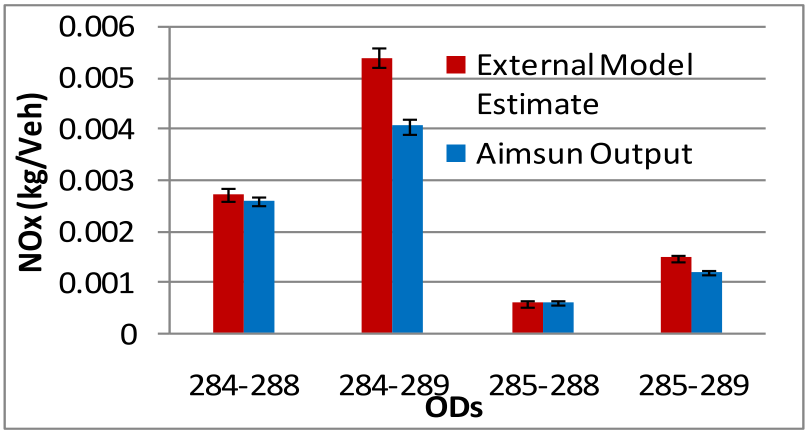


Figure 19 NO_x Emissions Comparison at ODs Level

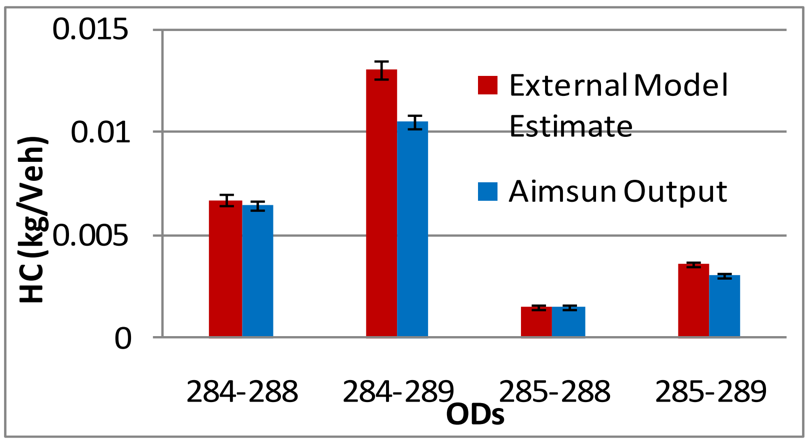


Figure 20 HC Emissions Comparison at ODs Level

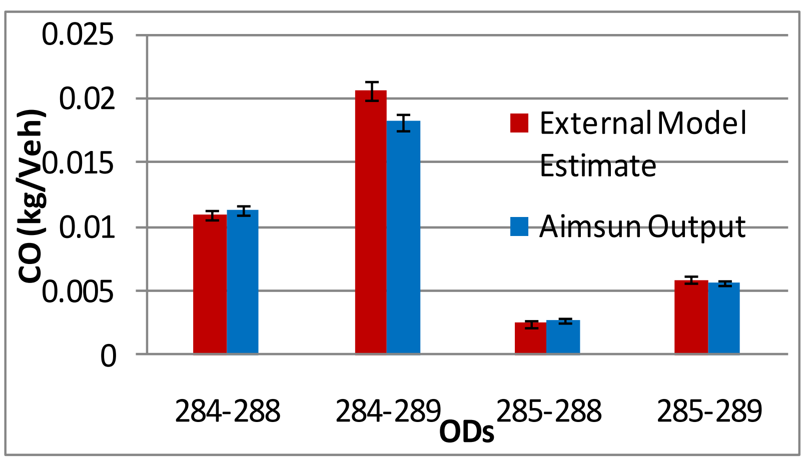


Figure 21 CO Emissions Comparison at ODs Level

The external model estimates and AIMSUN model outputs were found to be highly comparable at all spatial levels (R^2 based on link by link comparison ~ 98%) for fuel consumption and emissions. This was critical to understand how AIMSUN algorithms estimate fuel consumption and emissions, since it was not clear in AIMSUN documentation. Therefore, AIMSUN can be trusted to produce accurate results in this case study.

5.4.3 Conclusions

The objective of this application was to understand how AIMSUN emissions and fuel consumption model works and how it estimates vehicle emissions at different temporal and spatial scales. AIMSUN emissions model was calibrated by PEMS single vehicle emissions data as an initial step in order to understand AIMSUN methodology in estimating emissions. Furthermore, AIMSUN uses algorithms and specific equations in estimating vehicle fuel consumption and emissions. The objective was to check whether PEMS data would be fitted in AIMSUN equations. In addition to check how good or bad was the model calibration with PEMS real world emissions data.

The results showed that PEMS emissions data didn’t fit very well statistically using AIMSUN emissions and fuel consumption equations. In addition, it is inferred from this application that AIMSUN emissions model depends mainly on the acceleration and speed for estimating emissions. This conclusion led to the next application in this thesis which is concerned with validating AIMSUN estimates for speed and acceleration.

Chapter 6 AIMSUN Activity Model Calibration and Validation

6.1 Objective

The second focus area was to evaluate the vehicle activity from AIMSUN with PEMS activity data. PEMS activity data was collected in the field and can be valuable source for evaluating AIMSUN activity data on macro and micro scale. AIMSUN activity contains speed and acceleration on second by second basis. AIMSUN micro simulator estimates the speed and acceleration. These speed and acceleration estimates were validated against real traffic data on macro and micro levels. The macro level validation was based on route travel time comparisons between AIMSUN and INRIX. Comparing VSP distributions for individual AIMSUN vehicles with PEMS VSP distributions and their implications on vehicle fuel consumption and emissions comprised the micro scale validation.

6.2 Scope

The scope of this effort is to validate AIMSUN micro simulation model with PEMS activity data sets and real traffic detection data. In particular, real traffic detection data will be used to calibrate AIMSUN model and PEMS activity data will be used to validate AIMSUN model outputs. The scope is to model part of the routes that was tested by PEMS under real world driving conditions in AIMSUN micro simulation model. Furthermore, these routes cover some of Traffic.com detectors for the calibration purposes.

6.3 Study Site

The case study network is a part of the Research Triangle Area in North Carolina. The network includes I-40, I-440, I-540 and NC-70 carrying heavy through commuter traffic in the Triangle region. In addition, the study area includes major arterials such as Glenwood Ave and Six Forks Rd. The selected area is an appropriate location for evaluating the effect of various control measures. This study area was covered by PEMS routes and also by many Traffic.com detectors. The study area covers I-540 starting from its interchange with Capital Blvd. to the interchange of I-540 and I-40. I-40 is included in the study area from its intersection with I-440 till the interchange of I-40 and Davis Drive in the RTP. The study area also covers the I-440 from the interchange with I-54 to the intersection between I-440 and Capital Blvd. Furthermore, Capital Blvd and Six Forks Rd between I-440 and I-540 are included in the study area. The advantage of this study area is the coverage of different types of roads and many highways. Figure 22 shows the map of the study area that was coded in the micro simulator.

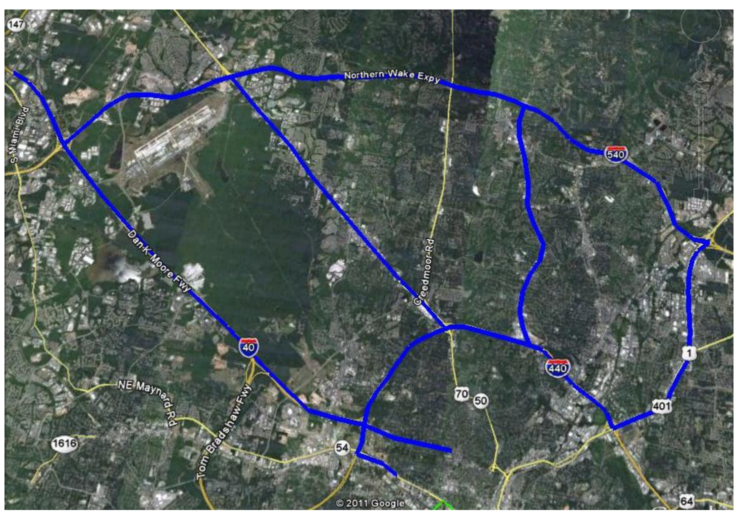


Figure 22 Study Area Showing Modeled Routes

6.4 Modeling the Network in AIMSUN

Step 1: Modeling Geometric Details in AIMSUN:

The first step is to model the roads and intersections with all its geometric details in AIMSUN. AIMSUN micro simulation model provides the capability to put image or a map as background in the network in order to code the geometric details of roads. Image for research triangle map was installed in the background of AIMSUN platform. As first step, single lane road was drawn on every road center line for all roads in the network. Afterwards, every part of the network was matched with the map in terms of geometric details. Every road segment was assigned number of lanes such as the background map.

The long road segment was divided into sub road segment in order to model the geometric details such as lane drop or road widening. Every sub segment was connected to the other segments by AIMSUN nodes and junctions. The study area contained a lot of geometric details in terms of number of lane drops and lane added. The second stage was to model the intersections and interchanges between roads and highways. This included modeling the different directions in the intersection according to the real map. AIMSUN allows the user to define junction for every intersection with multiple lane details and different movement's directions. For every intersection, number of lanes, turning movements and lane directions were matched with the real background map. In addition, the on ramps and off ramps for the highways were connected to highways segment by using AIMSUN junction. After connected all the roads, every road were assigned specified road type whether arterial or freeway.

Step 2: Modeling Signalized Intersection Control Plans

The second step was to model the signalized control plans in AIMSUN with the actual signal plans. The North Carolina Department of Transportation (NC DOT) provided actual signal plans for the study area. All signals have actuated signal control plans. AIMSUN has the ability to simulate actuated signalized control. As a first step, the detectors were installed in AIMSUN network with the same numbers and geometry as showed in NC DOT drawings. Then, the signal timing details were entered in AIMSUN for every intersection which includes min, max green time, red and yellow time and passenger recall time. All phases timing plans were entered in AIMSUN according the NC DOT signal details. Every detector was assigned to signal movement according the NC DOT drawing details and maps. The phases followed NEMA control plan in all the signalized intersection.

Step 3: Network Demand Modeling

There are two ways to enter traffic demand in AIMSUN; the first is to model trip origin destination (OD) matrix and second is to model link based trips (number of trips per link). The first approach was chosen because of two reasons. First, there are available models that can provide traffic demand matrix for this study area. Second, by entering the demand OD matrix, the demand on links can be compared with Traffic.com data and the AIMSUN traffic assignment model can also be evaluated. One of thesis objectives is to check AIMSUN traffic assignment by comparing link volumes to actual traffic counts from Traffic.com.

The required input data for AIMSUN are time-dependent origin-destination (OD) matrices. These input data can be transferred from the corresponding regional travel demand model (TDM). For this study area, we also have “legacy” data from previous studies describing transportation activity. We have an existing representation of the transportation network that is modeled under the existing Trans CAD-based Triangle Regional Model

(TRM). The 2005 Triangle TRM Model has 9,534 nodes, 20,342 links, and 2,389 zones (TAZs). For a typical weekday simulation, there are an estimated 876,953 trips in the four hour morning peak period, 1,521,434 trips for the four hour afternoon peak period, and 2,294,266 for the remaining 16 hours (48).

This existing Trans CAD-based Triangle Regional Model (TRM) was used for this thesis research. The model produces network data including zone, node, link, and origin-destination demand data for the regional network. The OD matrix is defined in the TRM model in Trans CAD. Therefore, the OD matrix was extracted from Trans CAD and entered in AIMSUN for this study. Trans CAD has its tool for subarea analysis. The subarea tool in Trans CAD enable the user to extract specific study area from the overall the model and this helps to reduce the complexity of model. Since, the TRM Model covers the overall triangle region, it is not effective to model the total TRM model in AIMSUN because this will make AIMSUN model very large and complicated. Therefore, we have decided to use the subarea tool in Trans Cad in order to extract the study area from the TRM model.

The subarea extracted the study area demand matrix from the overall TRM model matrix. The extracted traffic demand matrix had 200 OD pairs. The resulted demand matrix was extracted from the TRM pm matrix which is from 3:30 pm to 7:30 pm. Therefore, the initial traffic demand matrix entered in AIMSUN was for 4 hour from 3:30 to 7:30 pm which contains the PM peak hour. The pm period was chosen because there are available PEMS tests for the weekdays only for PM peak. The thesis objective is to validate AIMSUN model against PEMS real world driving data, so the model in AIMSUN was constructed for the pm peak period.

The ODs were defined in AIMSUN according to the Trans CAD TRM network. AIMSUN allows the user to define the ODs as centroid and after that; each centroid can be defined as origin or destination. Each centroid can contain different origins or different destinations. Then, the centroids were connected to each section, and connected to each other. At this stage, AIMSUN defined the matrix based on the modeled number of centroids without values. The subarea matrix values were copied from Trans CAD into AIMSUN matrix. The initial matrix time was from 3:30 pm to 7:30 pm.

Step 4: Check Network Connectivity

This step focused on debugging the network and checks its connectivity. The network in the study area contains a lot of geometric details which makes checking connectivity is vital. Every segment was divided into small sub segments in order to include the change in lane numbers along the segment. The connection between segments was done in AIMSUN by adding node to connect the segments. If this node is not found, there will be a problem in network connectivity and the vehicle will not pass from segment to another. In order to check the network connectivity, initial run was done in AIMSUN.

In this initial run, the following checks were done: (1) vehicles that had lost its paths (2) traffic flows that don't have available paths in the network due to error in ODs connectivity (3) problems in on ramps and off ramps for the highways (4) errors due conflict in lane directions (5) unconnected links. After debugging the model to solve these problems, the network was eligible to carry off any traffic demands and any simulation scenarios. Figure 23 shows the study area as it is modeled in AIMSUN micro simulator with the total ODs.

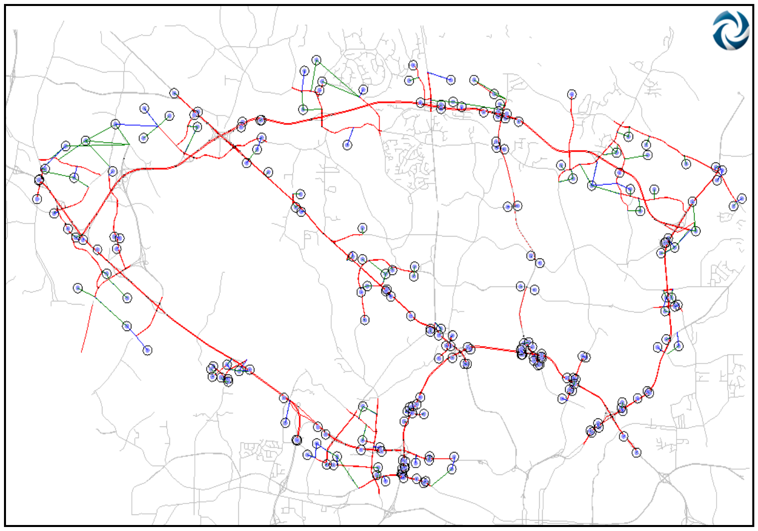


Figure 23 Final Modeled Network in AIMSUN Micro Simulator

The modeled network details are:

- Number of links = 1000
- OD Pairs= 200
- Nodes= 509 nodes
- Signals= 54 (signal plans were modeled according to NC DOT signal plans)
- Detectors= 681
- Length of the simulated network=112 center line miles

Step 5: Check AIMSUN Network Visualization by Animated simulation:

AIMSUN model has animation tools that allow user to run simulation with different visualization capabilities. One of AIMUN outputs are graphical animation of the simulation in 2D and in 3D if it runs under interactive simulation. As a first step for model use is to run the simulation with the animation tool in AIMSUN. Visualization is very important tool in order to identify any problems in the network. As example, sometimes intersection blockage happens in micro simulation models. This intersection blockage is not realistic compared to the actual conditions in the field. However, the model inputs might be correct statistically but the animation simulation is not acceptable according to the actual field conditions. Hence, the visualization check is very important for microscopic simulation models. The visualization check were done for a base run with the 4 hour demand with only one replication to check if there is any network blockage or sections connectivity problem.

6.5 Calibration Methodology

The objective of calibration stage is to obtain the best match between model estimates and filed measurements and recalibrate model parameters if there is a gap between model estimates and filed counts. The calibration process in this thesis focused on the OD estimation and traffic assignment model in AIMSUN. The OD matrix was estimated from TRM model in Trans CAD and was entered into AIMSUN. Then AIMSUN generated links traffic flow based on its traffic assignment model. The estimated links traffic flow in AIMSUN need to be compared against traffic counts based on actual field conditions. The traffic detection technologies allow collecting traffic counts from field detection with acceptable degree of confidence. Traffic.com detection was chosen to compare AIMSUN traffic counts against its counts. Figure 24 explains the calibration process.

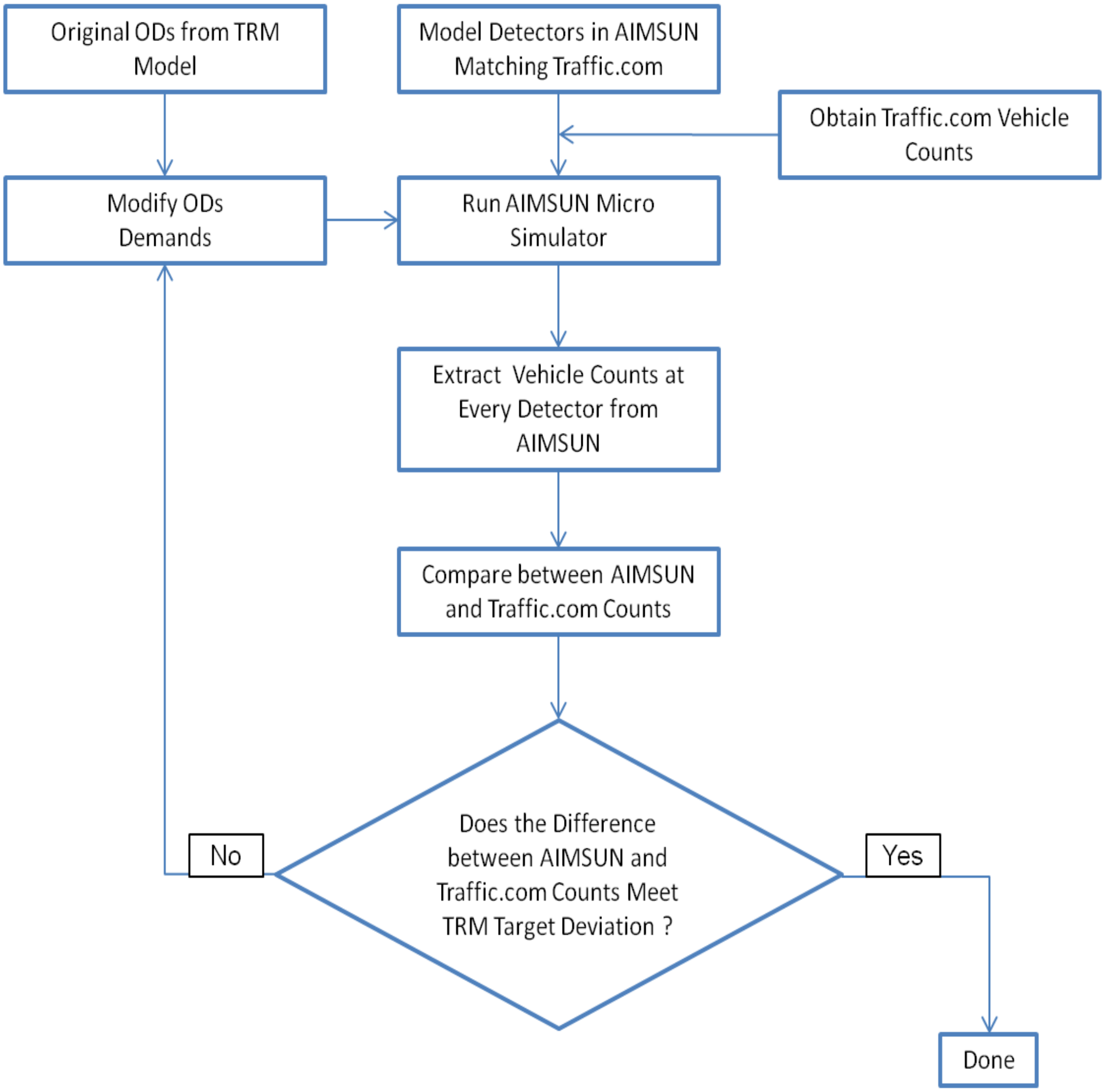


Figure 24 Calibration Process for the Traffic Demand Matrix in AIMSUN

The start of the calibration process was to define Traffic.com detectors that will be used as a base for comparison. Traffic.com detectors should cover the simulated study area in AIMSUN. In addition, the detectors should provide effective spatial coverage for the study area. Traffic.com detectors are providing these characteristics with many different detectors at the triangle area. Traffic.com detectors cover I-40, I-540, I-440 and Wade Ave on both directions west and east and cover also all its lanes. The detectors which located in the study area were chosen to compare its counts to AIMSUN estimates. Figure 25 shows Traffic.com detectors locations which included in the study area.

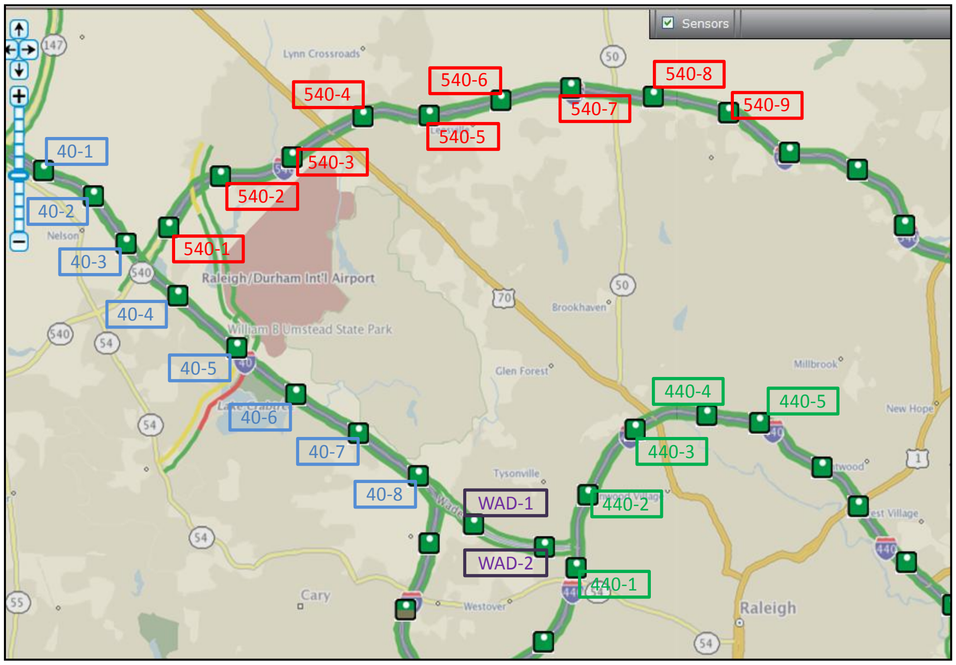


Figure 25 Selected Detectors from Traffic.com Covering the Study Area (47)

Traffic.com provides complete details about every detector location. These details contain X, Y coordinates for detector location, length of detector, the direction of the detectors (west or east direction), the distance between every two consecutive detectors and number of lane covered by every detector. In addition, Traffic.com provides distance from major roads and land marks for every sensors and every sensor have unique ID defined in Traffic.com (47). Appendix A contains more details about Traffic.com detectors and sensors.

The next step was to model these detectors in AIMSUN with the exact field locations according to Traffic.com details. AIMSUN has the ability to model different detectors on the same road with the exact defined coordinates. AIMSUN can record and store detectors collected data and executed in later simulation replications. The collected traffic data from detectors include vehicle counts which will be compared to Traffic.com counts. The detectors were defined in AIMSUN based on Traffic.com details about every sensor locations. Every sensor in AIMSUN was assigned name and ID same as its name and ID on Traffic.com data sets. The objective is to have the same detectors locations and names in AIMSUN and Traffic.com in order to establish the comparisons easily. The comparisons are between AIMSUN detectors vehicle counts and Traffic.com vehicle counts for the same detector and the same time period.

The next stage is to choose the days form Traffic.com data sets that will be compared with AIMSUN estimates. The objective is to calibrate AIMSUN with Traffic.com, and then the calibrated AIMSUN model will be validated with PEMS filed measurements in order to make sure that AIMSUN can replicate outputs that match field data. This validation process will depend mainly on available PEMS data sets. Therefore, Traffic.com days that will be used in AIMSUN calibration should match PEMS days. The Traffic.com data sets must be chosen from days that contain PEMS filed data sets as well.

Furthermore, the chosen days should be in normal weekdays with normal traffic and weather conditions. The author selected the PEMS test held on 20 October to be the base field test to be used in the calibration process with AIMSUN. For the demand values, three days from Traffic.com were extracted for the calibration process. These three days include the day before PEMS date, day after PEMS date and the day with PEMS filed measurement.

The average vehicle counts for these three days were used to compare against AIMSUN estimates.

The analyst acquired vehicle counts from Traffic.com for the selected three days; the data is aggregated for 15 minutes interval along the pm 4 hours from 3:30 pm to 7:30 pm. The average traffic counts will be calculated from these three days data. The original demand matrix in AIMSUN is representing the demand for the pm 4 hours from 3:30 pm to 7:30 pm. This demand matrix entered in AIMSUN was obtained from Trans CAD total TRM matrix; the TRM demand matrix was also for the 4 hour pm peak from 3:30 to 7:30 pm.

Since, the calibration process contains many OD modifications and runs, the analyst decide to execute the calibration process for one hour demand matrix. One hour matrix in AIMSUN will increase the simulation speed and efficiency compared to 4 hours demand matrix. In addition, this will help in doing many modifications and trials in order to modify the OD matrix and calibrate it against Traffic.com. The 4 hour demand matrix was divided by 4 to convert it to one demand matrix. This demand matrix is representing the demand for one hour for base line scenario without any change in the original demand obtained from Trans CAD.

The resulted traffic counts estimated from AIMSUN at every detector will be compared with Traffic.com detectors counts for one hour. The comparison is based on one hour vehicle counts in AIMSUN and Traffic.com. The Traffic.com counts were acquired for 15 min interval for the three days. The data was aggregated for one hour interval for traffic detectors on the different highways on east and west direction. The comparisons were done on every direction, on east direction and on the west direction.

The difference between AIMSUN counts and Traffic.com field counts need to be evaluated according to predefined target deviation. The target deviation is the acceptable percentage of difference compared to Traffic.com as a base counts. The target deviation is the acceptable deviation for AIMSUN estimates from Traffic.com counts. The target deviation should be varied depending on link volume. If link volume is high, the target deviation percentage should be smaller because it will count based in the large volume and will return bigger difference in volume.

The TRM model has its target deviation compared to other daily vehicle counts. The TRM model compares its vehicle estimates to these daily counts according its target deviation. The TRM target deviation is also based on volumes. The analyst decided to use the TRM target deviation as target deviation for the calibration process since the TRM used to establish the base AIMSUN subarea matrix. Using the TRM target deviation in the calibration process of AIMSUN is more reasonable compared with defining a new target deviation based on other criteria (49). We think that TRM deviation is the best criteria also since the TRM contains our study area in AIMSUN. Table 6 shows the chosen target deviations.

Table 6 Target Percent Difference of AIMSUN Estimates (Target Deviation) (49)

Volume Group (veh/hr)	Target Deviation from Traffic.com
1-1000	55%
1001-2500	50%
2501-5000	30%
5001-10000	25%
10001-25000	20%
25001-50000	15%

Table 6 Continued

>=50001	10%

The calibration process started with only one run in order to make the simulation run fast and not to consume a lot of time in every trial. This was the initial trial and then after matching the target deviations, final runs were made with 20 replications in order to check the final demand matrix. The initial run in AIMSUN is for one hour demand. After doing the first run, there were differences between Traffic.com actual counts and AIMSUN estimates at different detectors. The differences didn't satisfy the target deviations. Therefore, there was a need to modify the OD demand matrix in order to match Traffic.com counts for every detector.

AIMSUN has the ability to show different paths for specific OD on the network. The selected ODs which need modifications were defined by using this tool. For every detector which its estimates didn't match Traffic.com, different paths that pass through these detectors was defined. By using these defined passes, ODs were selected for modifications, so these OD modifications can impact the detectors. By changing these selected ODs, we can modify the demand of the detectors in order to match Traffic.com according to the target deviation.

In every trial, the demand in the selected ODs was changed manually and then a test simulation run was done in AIMSUN. After every trial, the demand in each detector was checked against Traffic.com to be sure that the demand was sensitive to the change in ODs. The check was done on every Traffic.com detector on the freeways on the study area and on both sides. During this calibration process, many improvements for the network were done in order to improve network mobility and connectivity. For example, when the demand of specific of ODs was increased and the detectors didn't detect this change which means a problem in network connectivity such as lane blockage or unconnected sections. These errors were corrected during the calibration process.

A total number of 35 trials were carried out in AIMSUN in order to match traffic counts in AIMSUN with Traffic.com. Multiple replications and different seed numbers were used in AIMSUN in order to make sure that AIMSUN can repeat the demand output with acceptable degree of variation. The comparison was for AIMSUN average of 16 replications with the Traffic.com average of the three days counts.

6.5.1 Establish Time Dependent Demand Matrix

The thesis approach is to compare AIMSUN simulation results with the real world driving data. In particular, we want to compare vehicles tested by PEMS with AIMSUN on the same routes and on the same running time. Therefore, the demand matrix in AIMSUN model need to be modified according the PEMS test time. For example, if Route 1 was tested by PEMS from 3:30 pm to 4:00 pm, the AIMSUN demand matrix for Route 1 need to be modified to match the demand from 3:30 pm to 4:00 pm. The total demand matrix will be separated to many time dependent matrixes based on the test time for every route.

In order to establish the time dependent matrix, the times of PEMS tests on different routes need to be defined. For the chosen tested vehicle (Toyota Camry), the start testing time and end time of every route need to be extracted. The demand matrixes will be redefined to match these times. Traffic.com data was used to establish the demand distribution within the four hours (from 3 pm to 7 pm). Traffic.com data was acquired on aggregated bases for every 15 min within the chosen three days. Since, PEMS test on every route continued for about 30 min approximately, the Traffic.com data was aggregated for average 30 min counts. The traffic demand distribution was calculated for four hours period based on 30 min interval by using Traffic.com data. Table 7 contains start and end time for every route.

Table 7 Time Interval for every Route

Route	PEMS Test Duration	Simulated Time
R1 OUT	3.01 to 3.25	3:00 to 3:30
R1 IN	3.25 to 3.47	3:30 to 4:30
RC IN	5.56 to 6.21	5:00 to 5:30
RC OUT	4.14 to 4.37	4:15 to 4:45

Figure 26 and Figure 27 show the demand percentages for every half an hour for the 4 hours (from 3:00 pm to 7:00 pm). By using these demand percentage, four time dependent matrixes were defined in AIMSUN for different simulated time.

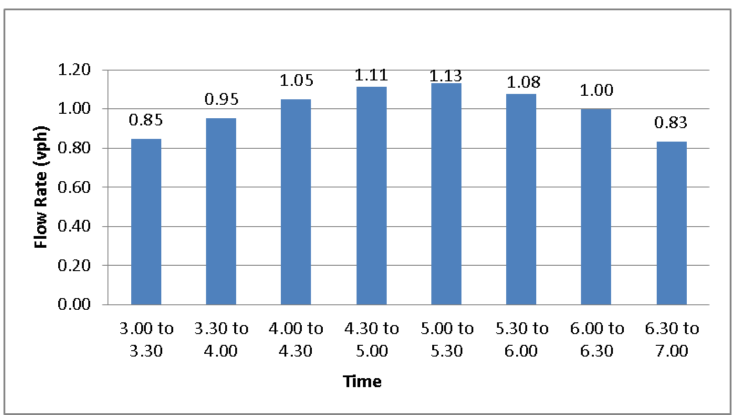


Figure 26 PM Peak Travel Demand Distributions in East Direction

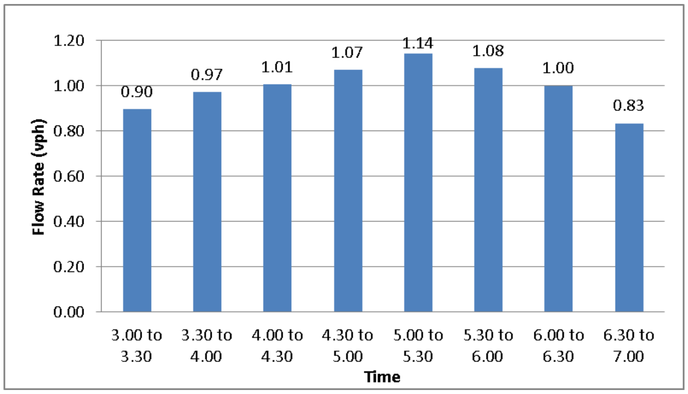


Figure 27 PM Peak Travel Demand Distributions in West Direction

6.5.2 AIMSUN Model Modifications and Recalibration

The objective of this task is to recalibrate AIMSUN model so it can produce reliable results that can be compared to INRIX and PEMS travel times. The validation process indicated that there is a problem in the model. The problem at the end of validation process was that AIMSUN travel time was higher than PEMS and INRIX. As a first step, the author checked the animated simulation runs and checked if there is any problem in the simulations or network geometric configuration. Trial simulation run with full animation properties was done in AIMSUN. The animated simulation check has shown that there was a problem on off and on ramp entrance to highways, vehicles were slowing down at every entrance to highway or at highways exits. This problem caused vehicles to slow down to very speed at every entrance and exit and increased route travel time significantly.

This problem was solved by modifying the acceleration and deceleration lane configuration and lengths. In addition, the distance taken by every vehicle to change lanes was increased. This increased the time and distance available for every vehicle to change lanes at entrances and exits. Figure 28 shows screen shot for AIMSUN animation depicting the problem at I-540 off ramp causing the speed to drop travel time to increase.

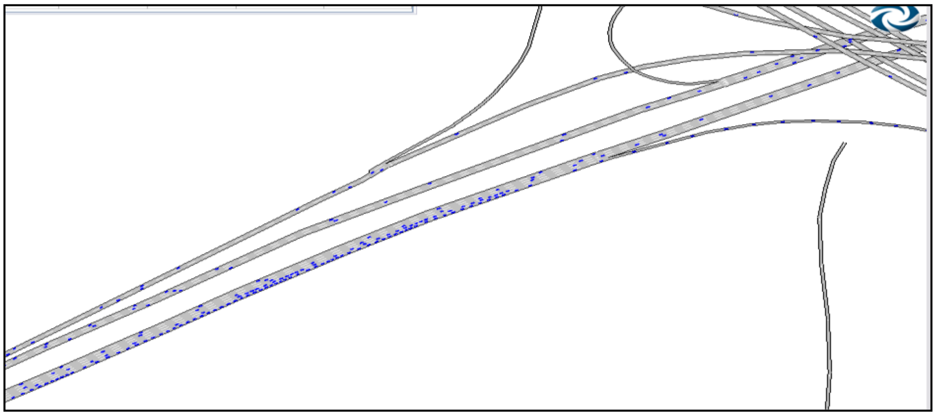


Figure 28 AIMSUN Animated Simulation Problem

These changes in AIMSUN geometric configurations and vehicle simulation parameters were applied to the entire network. Initial runs done in AIMSUN checked the effectiveness of these changes. Although, these changes reduced travel time, route travel time remained higher in AIMSUN compared to PEMS and there were bottlenecks at highways entrances and exits. This means that there is a problem with the demand levels. In order to check the demands generated by AIMSUN, the demands at every detector on route simulated time were extracted from AIMSUN and compared with Traffic.com detectors vehicle counts at the same time. For example, Route 1 IN started at 3:30 pm and ended at 4:00 pm, so the Traffic.com detectors vehicle counts were obtained from 3:30 pm to 4:00 pm and were compared with AIMSUN vehicle counts on the same detectors on the same time.

The demand generated in AIMSUN was found to be much higher compared to Traffic.com. Therefore, the demand matrix in AIMSUN was reduced by 30% for Route 1 IN and Route 1 OUT. Afterwards, AIMSUN vehicle counts on detectors were compared with

Traffic.com again to check AIMSUN traffic assignment model. At this stage, the demand of AIMSUN was comparable with Traffic.com counts and was below the TRM Target deviation. It was inferred that demand percentiles through sensors over the network were nor effective. The final demand results at each detector will be presented later in this chapter.

6.6 AIMSUN Micro Simulation Model Validation Methodology

After calibrating the demand model in AIMSUN, the next step was to validate this calibrated model with real world traffic performance data. The objective is to assure that AIMSUN can repeat the results and simulate the real world traffic movements at an acceptable degree of confidence. The real traffic data that will be used in the validation process is PEMS activity data and INRIX traffic detection data for different routes.

The validation was done on a macro scale and micro scale. The macro scale consisted of comparing travel time and space mean speed on routes. AIMSUN travel time and space mean speed values were compared with PEMS and INRIX travel time and space mean speed. During the validation process, some of model parameters and geometric elements were modified in order to match the field measurements. After matching the values on macro scale, the validation was done on the micro scale.

The validation process was done on the micro scale level by using individual vehicle trajectories. The objective of micro scale validation is to check that the distribution of individual vehicles speed, acceleration and VSP distributions match the distribution of real world driving conditions. The micro scale validation was done using PEMS speed, acceleration and VSP distributions. The chosen vehicle that was tested by PEMS on October 20, 2010 was used to be the base test. Vehicles were chosen from PEMS data base by using the October 20 Toyota Camry travel times within specific ranges. These extracted PEMS vehicles were used to generate VSP distribution for different routes. PEMS VSP distribution was compared with AIMSUN VSP distribution. The speed, acceleration and VSP distribution were extracted from AIMSUN by using the API written by the author. The output of the API was all vehicles run on AIMSUN network. Sample of vehicles were extracted from API output based on Toyota Camry travel times (within specified range). These vehicles were used to generate AIMSUN VSP distribution.

The validation process was done on two spatial scales: Macro scale and Micro scale. Macro scale validation was conducted on the route level, with AIMSUN travel time on different routes compared with INRIX travel times. Micro scale validation focused on comparing AIMSUN VSP, speed and acceleration for individual vehicles with PEMS activity data. The following sketch in Figure 29 summarizes the validation process.

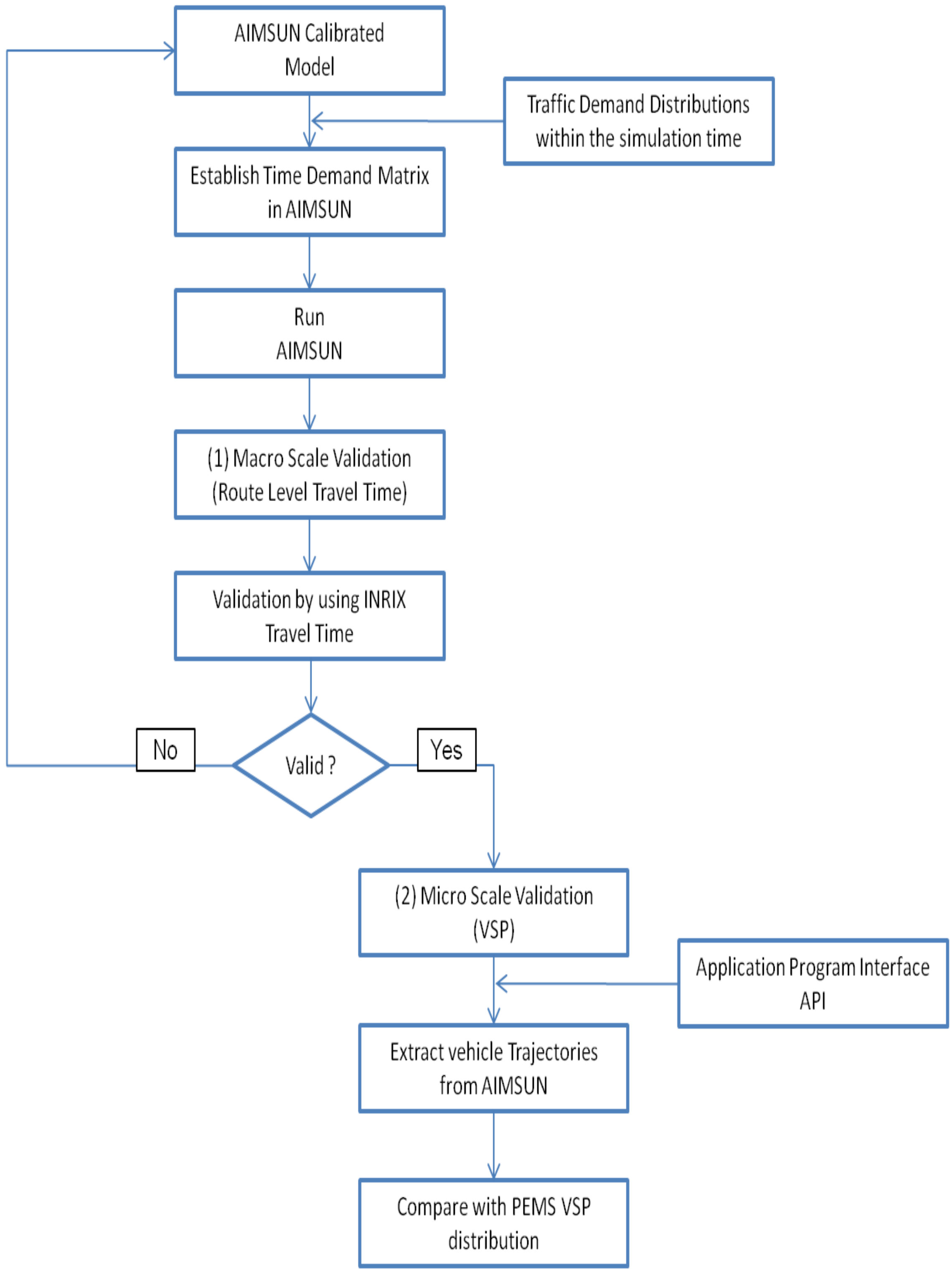


Figure 29 Validation Process Approach

6.6.1 Macro Scale, or Route-Based Validation

The objective of this stage is to compare AIMSUN output with INRIX travel time in order to make sure that the difference between PEMS and AIMSUN values is due to AIMSUN model problem. In addition, the advantage of this stage is that AIMUSN was compared with INRIX average values of travel time. However in the case of comparing AIMSUN with PEMS, multiple vehicles from PEMS were compared with average vehicles travel times. INRIX values are the average travel times based on three days counts from 19 October to 21 October.

AIMSUN simulated 20 replications for every route. The average travel time, standard deviation, max travel time, min travel time and 95th percentiles were reported based on the twenty replications. Routes were sub-divided based on road types: freeway or arterial. For example, Route 1 passes through Six Forks Rd., I-540 and I-40 and was thus divided into three sub routes: Six Forks, I-540 and I-40. In addition, PEMS route was divided into the same sub routes. The coordinates (latitude and longitude) were used to check the start and end of every route in AIMSUN and PEMS in order to make sure that all sub routes have the same starts and same ends. The comparison was done on Route 1 as the initial step since Route 1 contains a mix of freeways and arterials (I-40, I-540 and Six Forks). Route 1 was divided into 3 sub routes: I-40, I-540 and Six Forks, and the comparison were done on the three separated routes. Route 1 IN is the inbound direction which starts at RTP and end at north Raleigh (Six Forks). Route 1 OUT is the outbound direction which starts at Six Forks (north Raleigh) and end at RTP.

6.6.2 Micro Scale Validation

The objective of this task is to check AIMSUN model at the micro scale level. This task aims to check individual vehicles behavior in AIMSUN. In other words, this task objective is to check individual vehicles speed, acceleration and VSP distribution. Individual vehicles that have the same travel time as PEMS vehicle was extracted from AIMSUN. For those extracted vehicles that have the same travel time as PEMS tested vehicle, our objective is to check whether the speed distribution was the same. In addition, the VSP distribution need to be checked and see if vehicles that have the same travel time will maintain the same VSP distribution or not.

The initial validation process used a sample of PEMS vehicles that experienced travel time equal to the Toyota Camry vehicle tested by PEMS at 20 October 2010 within a specific range. The Toyota Camry vehicle was the basis for choosing PEMS vehicles which was used in comparison with AIMSUN. This vehicle was chosen because the model was established based on the three days data from Traffic.com (from 19 October to 21 October) and the demand in AIMSUN was defined based on those three days demand percentiles.

6.6.3 API Development and Extracting Vehicle Trajectories

The application interface program in AIMSUN provided the opportunity to extract second by second data from the simulator. The AIMSUN API module is the extension of AIMSUN environment which enables the user to define his/ her own applications that can interact with AIMSUN. The API can collect information from AIMSUN micro simulator and exchange information with it. In addition, API can modify simulation parameters which AIMSUN is working and change it dynamically.

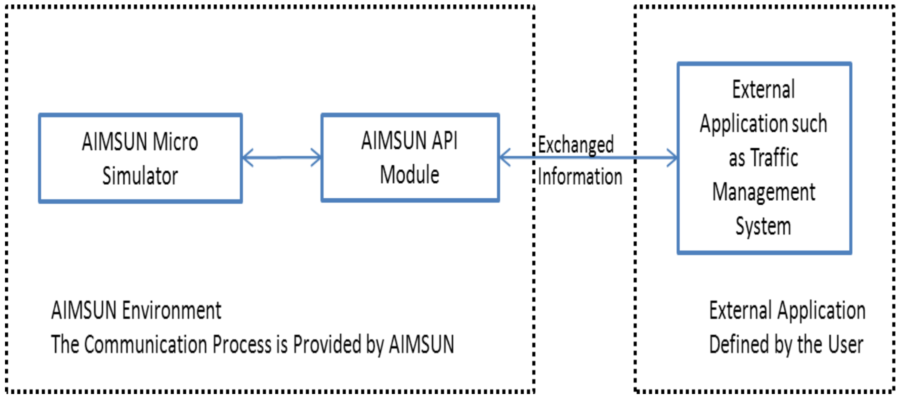


Figure 30 Interaction of AIMSUN Environment with API External Application

Figure 30 shows AIMSUN environment and its interaction with API external module. The communication process between the API module and AIMSUN micro simulator is defined in AIMSUN model via different high level functions. On the other hand, the communication process between the external API and AIMSUN API module is defined by the user to meet user's requirements. The external program can be written in Python or C++.

6.7 Results

The following sections summarize the results. These consist of 3 main parts. First is AIMSUN activity model calibration results. The second is the macro scale validation for the AIMSUN activity model. Finally, the micro scale validation results of AIMSUN using PEMS activity data are discussed.

6.7.1 AIMSUN Micro Simulation Model Calibration

The following tables and graphs indicate the comparison between Traffic.com and AIMSUN average of 20 replications. The comparisons were done in both east and west directions. Table 8 to Table 13 and Figure 31 to Figure 36 illustrate the comparison between AIMSUN and Traffic.com for every detector. Please note the following definitions:

- Traffic.com results are the average one hour counts in three data collection days, (veh/hr)
- Max: is the max hourly vehicle counts during the three days, (veh/hr)
- Min: is the max hourly vehicle counts during the three days, (veh/hr),
- AIMSUN: average AIMSUN hourly volume based on average of 16 replications
- St Dev: is the standard deviation of the 16 replications of AIMSUN outputs. (Note: standard deviations of the individual runs, not of the mean)
- Percentage Difference: the percentage difference compared to Traffic.com, (Traffic.com – AIMSUN)/Traffic.com
- Number of lanes are the number of lanes that are covered by Traffic.com detectors
- Error bars on Traffic.com on bar charts are representing max and min counts

Table 8 Vehicle Counts Comparison on I-40 East Direction Detectors

East Sensors	Traffic.com	Max	Min	AIMSUN	St Dev	Percentage Difference	TRM Target Deviation	Number of lanes
40-4	5065	6142	3932	3942	111	22	25	4
40-5	5181	5477	4860	5041	74	3	25	5
40-6	5739	5910	5477	4670	86	19	25	4
40-7	4935	5058	4740	4635	61	6	30	4
40-8	4422	4523	4230	3519	64	20	30	4
WAD-1	3243	3494	2964	3202	63	1	30	3
WAD-2	2631	2979	2330	2422	45	8	30	2

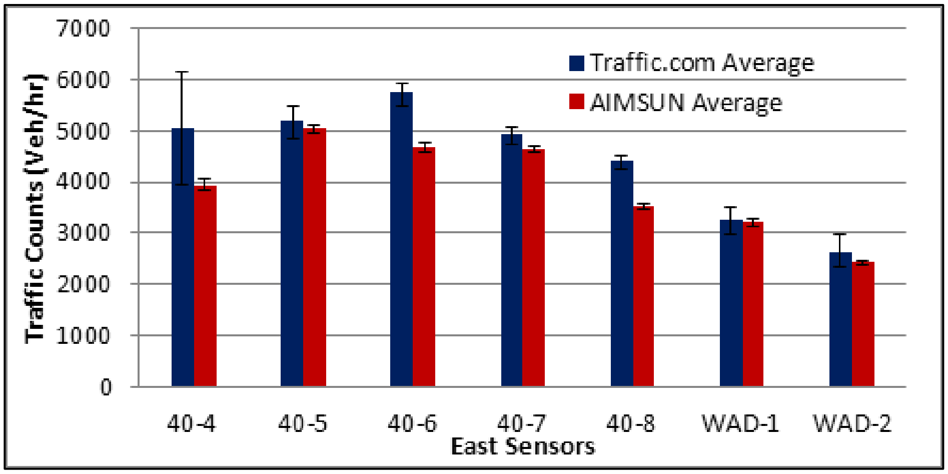


Figure 31 Vehicle Counts Comparison on I-40 East Direction Detector

Table 9 Vehicle Counts Comparison on I-40 West Direction Detectors

West Sensors	Traffic.com	Max	Min	AIMSUN	St Dev	Percentage Difference	TRM Target Deviation	Number of lanes
40-4	5260	6007	4749	5157	124	2	25	4
40-5	4502	5068	4068	5268	145	-17	30	5
40-6	5545	6311	4848	4894	126	12	25	4
40-7	4100	4378	3709	4290	112	-5	30	4
40-8	6002	6667	5332	4836	98	19	25	4
WAD-1	3234	3807	2792	3390	94	-5	30	3
WAD-2	2277	2613	2031	2252	50	1	50	2

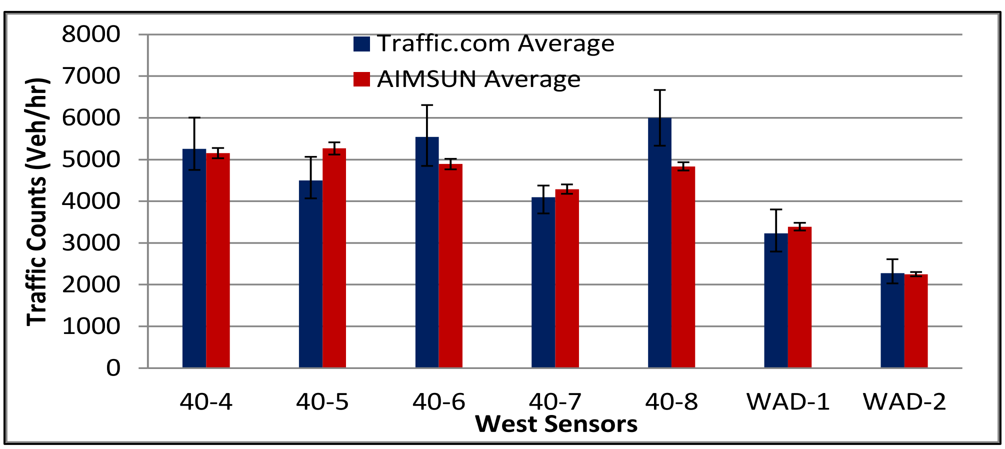


Figure 32 Vehicle Counts Comparison on I-40 West Direction Detectors

Table 10 Vehicle Counts Comparison on I-540 East Direction Detectors

East Sensors	Traffic.com	Max	Min	AIMSUN	St Dev	Percentage Difference	TRM Target Deviation	Number of lanes
540-1	4483	5607	3312	5923	47	-32	30	4
540-2	4962	6233	3512	5187	108	-5	30	5
540-3	4371	5409	2873	5089	218	-16	30	3
540-4	5165	6059	4281	4439	114	14	25	5
540-5	4562	5481	3413	4946	56	-8	30	3
540-6	4568	5466	3775	5107	41	-12	30	3
540-7	4529	5276	3347	4892	58	-8	30	3
540-8	4749	5831	3555	5071	49	-7	30	3
540-9	4280	5370	3274	4178	81	2	30	4

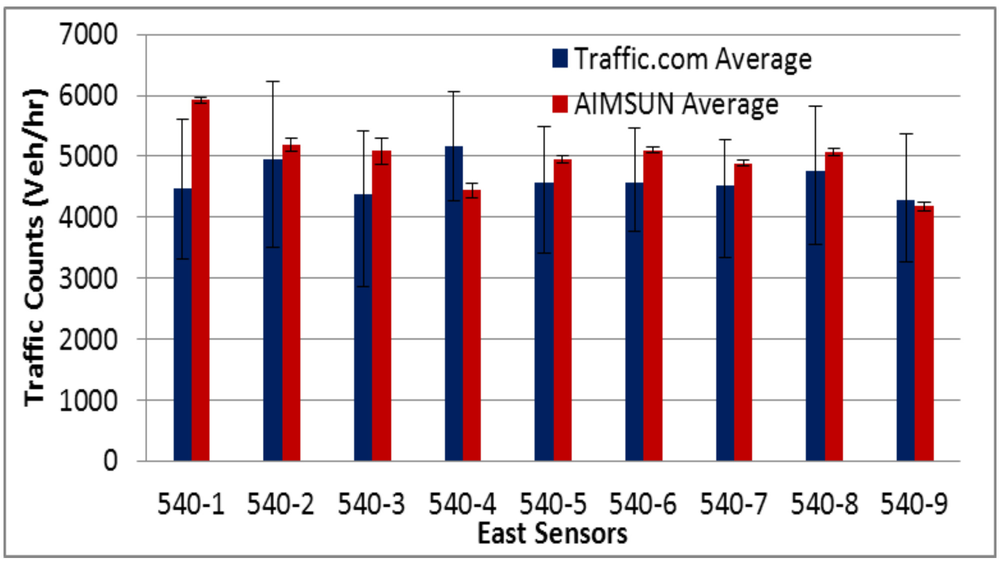


Figure 33 Vehicle Counts Comparison on I-540 East Direction Detectors

Table 11 Vehicle Counts Comparison on I-540 West Direction Detectors

West Sensors	Traffic.com	Max	Min	AIMSUN	St Dev	Percentage Difference	TRM Target Deviation	Number of lanes
540-1	2037	2398	1844	1975	96	3	50	4
540-2	2533	2954	2290	2294	127	9	30	5
540-3	2177	2490	2009	2007	55	8	50	5
540-4	2467	2887	2226	2444	49	1	50	3
540-5	2601	3014	2345	2496	50	4	30	3

Table 11 Continued

540-6	2674	3093	2337	2895	35	-8	30	3
540-7	2535	2860	2269	2949	36	-16	30	3
540-8	2938	3502	2589	2708	196	8	30	3
540-9	2810	3249	2586	3377	99	-20	30	4

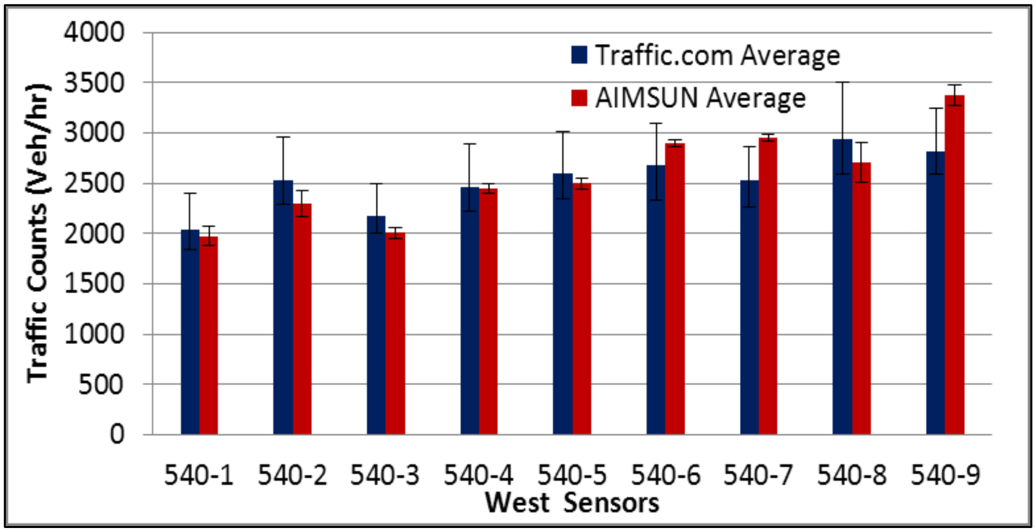


Figure 34 Vehicle Counts Comparison on I-540 West Direction Detectors

Table 12 Vehicle Counts Comparison on I-440 West Direction Detectors

East Sensors	Traffic.com	Max	Min	AIMSUN	St Dev	Percentage Difference	TRM Target Deviation	Number of lanes
440-1	3861	4200	3391	2684	74	30	30	3
440-2	4178	4556	3570	3671	116	12	30	3
440-3	4980	5513	4176	4326	215	13	30	3
440-4	5829	6549	4857	5905	107	-1	25	4
440-5	4572	5142	3716	3765	57	18	30	3

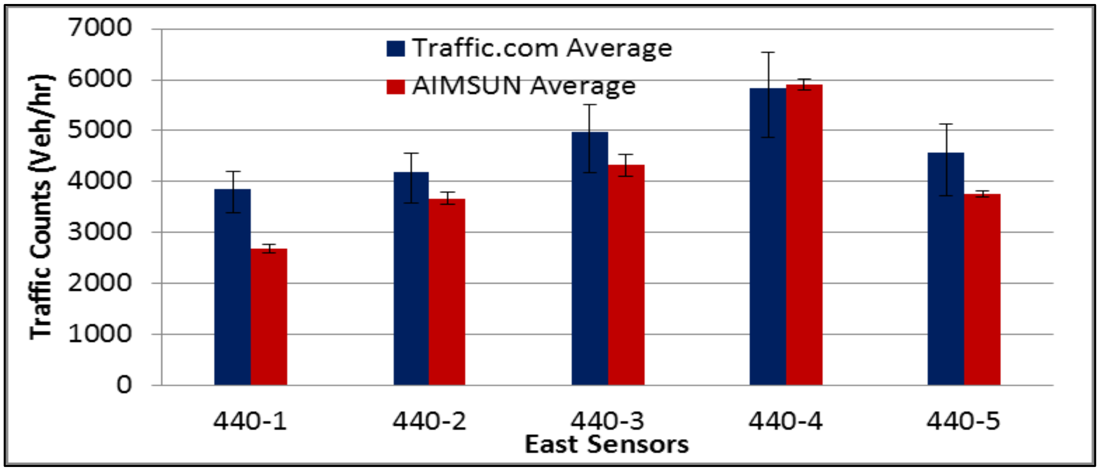


Figure 35 Vehicle Counts Comparison on I-440 East Direction Detectors

Table 13 Vehicle Counts Comparison on I-440 West Direction Detectors

West Sensors	Traffic.com	Max	Min	AIMSUN	St Dev	Percentage Difference	TRM Target Deviation	Number of lanes
440-1	3577	3861	3329	4432	62	-24	30	3
440-2	3507	3989	3046	3285	36	6	30	3
440-3	3957	4349	3570	3915	42	1	30	4
440-4	4940	5313	4336	6052	73	-23	30	4
440-5	4600	4973	4007	5373	89	-17	30	4

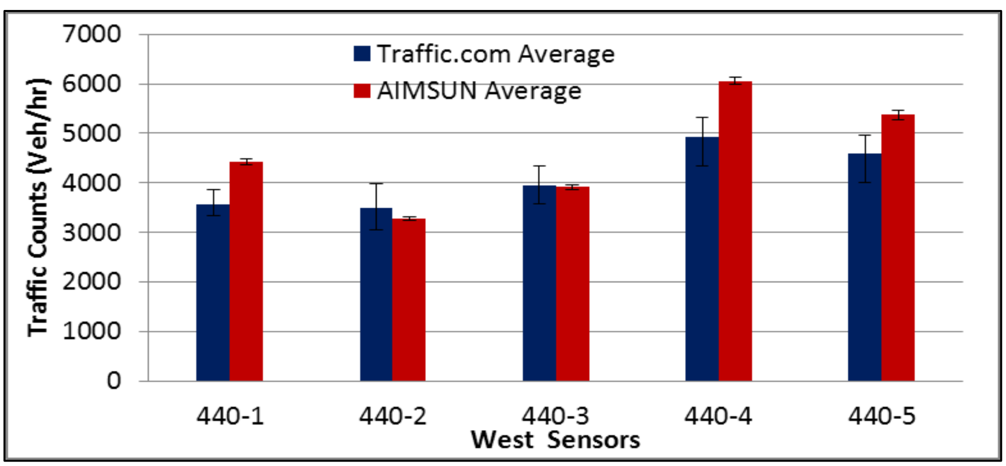


Figure 36 Vehicle Counts Comparison on I-440 West Direction Detectors

After doing the comparison on every detector according to TRM target deviation, goodness of fit test needs to be applied in order to check the relationship between AIMSUN estimates and Traffic.com real vehicle counts. The vehicle counts from Traffic.com and AIMSUN on every freeway on both directions were plotted against each other. The objective is to evaluate the R^2 and the slope of the line and tests statistically if the intercept is equal to zero and the slope to 1.0. Figures from Figure 37 to Figure 39 illustrate the vehicle counts on I-40, I-540 and I-440 respectively. Figure 40 shows all vehicle counts through the network.

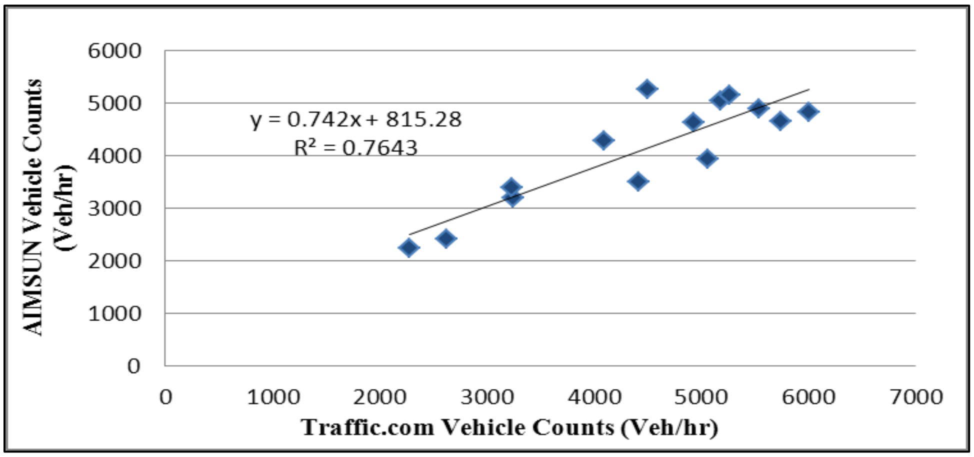


Figure 37 Bidirectional Vehicle Counts on I-40

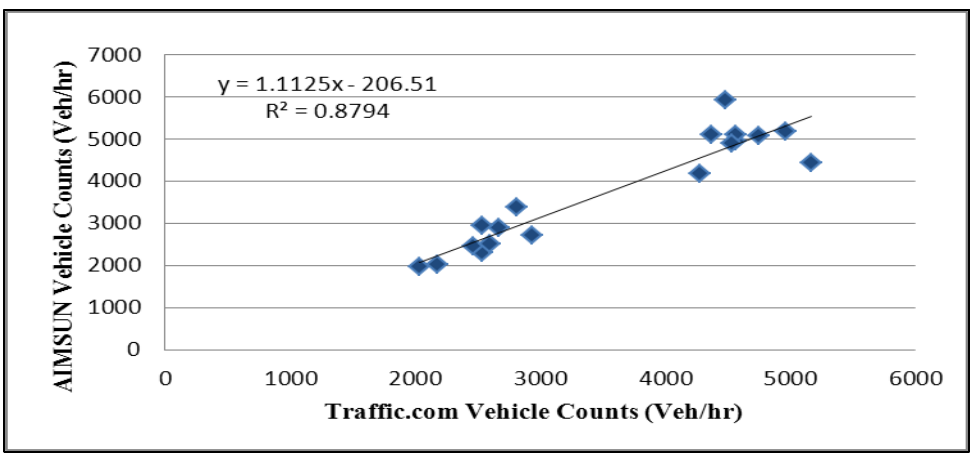


Figure 38 Bidirectional Vehicle Counts on I-540

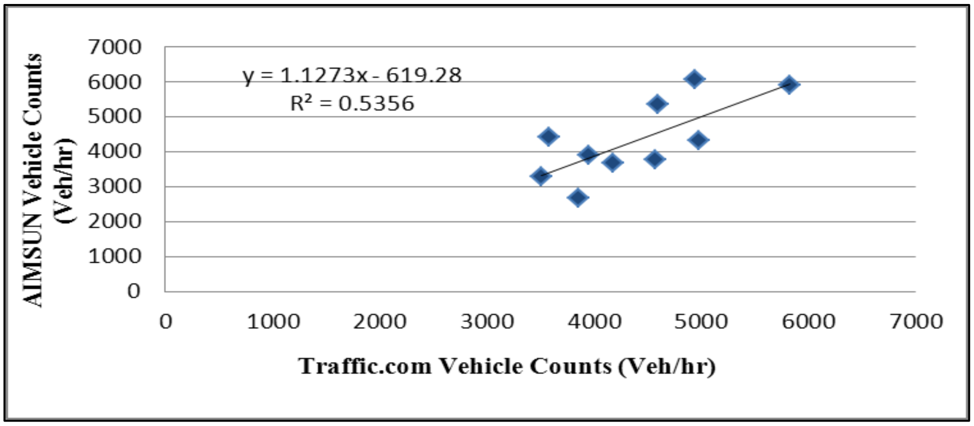


Figure 39 Bidirectional Vehicle Counts on I-440

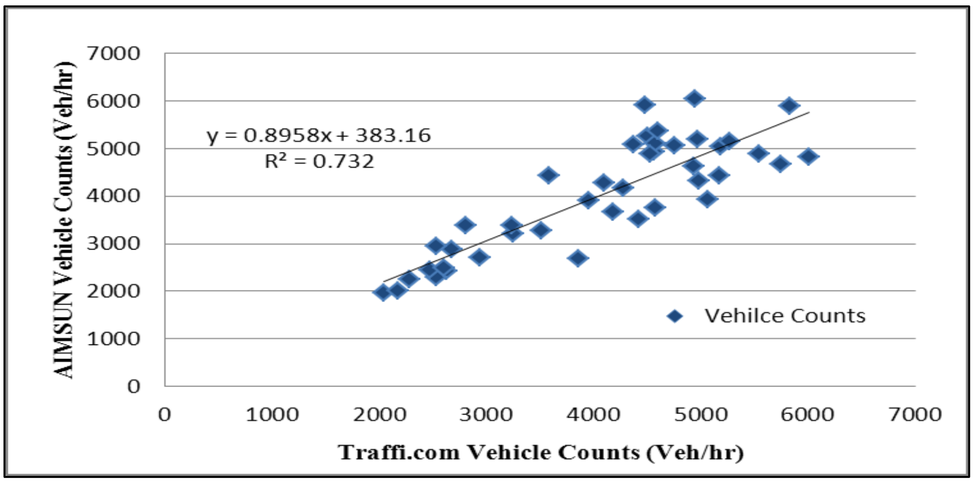


Figure 40 Vehicle Counts on I-40, I-540 and I-440 Combined (Entire Network)

The hypothesis test for the slope of regression line was done on significant level of 0.05

X values: vehicle counts from Traffic.com on all the detectors within the study area.

Y values: vehicle counts estimated from AIMSUN on all the detectors within the study area

H0: The slope of the regression line is not different from 1.
Ha: The slope of the regression line is different from 1.

In addition, there is a hypothesis test on the intercept since the intercept should be near zero. The following is the hypothesis about the intercept:

H0: The Intercept of the regression equation is equal to 0.
Ha: The Intercept of the regression equation is not equal to 0.

Table 14 summarizes test statistics for the traffic counts:

Table 14 ANOVA Results for the Regression Line of AIMSUN and Traffic.com Vehicle Counts

Sub-Network	R^2	Intercept	p- value intercept	Slope Coefficient			Figure #
				Slope Value	Upper 95%	Lower 95%	
I-40	0.76	815.28	0.16	0.74	1.00	0.48	Figure 37
I-440	0.54	-619.28	0.72	1.13	1.98	0.27	Figure 39
I-540	0.88	-206.51	0.60	1.11	1.33	0.89	Figure 38
Overall Network	0.73	383.16	0.29	0.90	1.07	0.72	Figure 40

Since the p-value of the intercept is higher than the significance level (0.05), we cannot reject the null hypothesis. This means that the intercept might be zero at this level of significance and sample size. On the other hand, since the 95th percentiles slope values include 1 for freeway and arterial segments, we fail to reject that the slope is not significantly different from one.

The overall network statistic results are acceptable; the slope of line is 0.80 with upper and lower 95 % equal to 1.07 and 0.72. Although, the sensor counts difference meet the TRM target deviation, there is evidence that some routes might either overestimate or underestimate the demand. This was checked in the validation process and check whether the TRM target deviation is enough for calibrating the network or not.

6.7.2 Macro Scale Validation (Route Based) Results

The validation process was done on two spatial scales: Macro scale and Micro scale. Macro scale validation was conducted at the route level, where AIMSUN travel times on routes were compared with INRIX travel time. Micro scale validation focused on comparing AIMSUN VSP, speed and acceleration for individual vehicles with PEMS vehicles activity data.

The first part of the validation process consists of a comparison between the average travel times on routes. Average travel time was calculated on every route in AIMSUN and was compared with PEMS route travel time and average travel time obtained from INRIX. The macro scale validation consists of two stages; the first stage is validation with PEMS travel time data. Second stage is the validation of AIMSUN routes travel times with INRIX.

The PEMS data base contained about 35 vehicles. Vehicles were extracted from PEMS data base based on route travel time for the test day 20 October 2010 which is the base day for the demand model. The calibration process of demand model focused on October 20 day as the base test day along with the day before and the day after. PEMS vehicles were extracted from the data base based on this test travel time and space mean speed within a specified range. The range was + or – 2.5 mph difference in space mean speed, based on previous work that showed that the VSP distributions were fairly stable within an average speed range of 10 kph (50). Comparisons were made for two routes, Route 1 inbound and Route 1 outbound. The numbers of PEMS vehicles meeting this criterion were e as follows:

17 vehicles on Route 1 Inbound I-540, 9 vehicles on Route 1 Inbound Six Forks, 13 vehicles on Route 1 Outbound I-540 and 12 vehicles on Route 1 Outbound Six Forks.

Validation of AIMSUN Speeds/ Travel Times

Table 15 shows the comparisons between travel times in AIMUSN, PEMS and INRIX, in addition to the statistics obtained from an average of 20 AIMSUN replications. It is clear from Table 15 comparison that both PEMS and INRXI travel times are quite different from AIMSUN values. Therefore, it is inferred that there is a problem in AIMSUN model and it need to be recalibrated. The next step is focusing on recalibrate AIMSUN model and modifies it so AIMSUN can replicate results that are comparable to INRIX.

Table 15 Route Travel Times Comparison between AIMNSUN, PEMS and INRIX

	Route 1 IN		Route 1 OUT	
Parameter	I-540	Six Forks	I-540	Six Forks
Mean AIMSUN Travel Time	14.52	4.05	13.09	4.34
AIMSUN Standard Deviation of the Mean	0.28	0.17	0.33	0.08
Max Travel Time	15.11	4.47	13.69	4.57
Min Travel Time	14.14	3.88	12.55	4.17
PEMS Route Travel Time	9.65	5.12	10.77	7.72
INRIX Route Travel Time	12.13	N	9.52	N

* Travel time is in minutes

The AIMSUN model was recalibrated in order to produce comparable results to INRIX and PEMS travel times. The recalibration process focused on changing some network geometric configurations such as on and off ramps deceleration lanes and acceleration lanes. After AIMSUN model recalibration, an additional 20 runs were simulated in AIMSUN. Table 16 contains the final validation results at the macro level.

Table 16 Route Travel Times Comparison after Recalibration

	Route 1 IN		Route 1 OUT	
	I-540	SIX FORKS	I-540	SIX FORKS
Mean AIMSUN Travel Time	10.02	4.04	10.82	3.96
AIMSUN Travel Time Standard Deviation of the Mean	0.31	0.21	0.43	0.21
PEMS Route Travel Time	9.65	5.12	9.52	4.40
INRIX Route Travel Time	12.13	5.12	10.77	4.40

* PEMS and INRIX travel time are the same as in Table 15

Table 16 shows that AIMSUN new values for travel time are much closer to both INRIX and PEMS. For Route 1 in, the I-540 AIMSUN travel time is 10 min, and at INRIX is 12 min and 9.6 min with PEMS. For Route 1 OUT, the I-540 AIMSUN travel time is 10.82 min, and INRIX's is 10.77 min and 9.52 min in PEMS.

6.7.3 Micro Scale AIMSUN Model Validation Results

The main objective here is to check if vehicles in AIMSUN with similar travel time as PEMS vehicles would generate the same overall activity pattern, namely speed and VSP distribution. The research question here is: for vehicles in AIMSUN and those in PEMS having similar travel times on the same route as AIMSUN, would these two groups generate similar speed and VSP distribution?

6.7.3.1 Extracting Vehicle Trajectories from AIMSUN

An Application Program Interface (API) was written in Python language in order to interact with AIMSUN micro simulator. This API collects speed, acceleration, current vehicle position, current occupied lane, and the current distance of every vehicle from the start of every section. The API collects these data at the end of every simulation step, so the results are vehicle trajectories on a second by second basis. Every vehicle was tracked by the API from the start till the end of its destination. The output files contain the following: Time Step, Vehicle ID, Section ID, Current Position, Current Speed and Current Lane. The current position is defined as the distance of vehicle from the start of its current section. In addition, vehicle current position can be defined in terms of X, Y in the API. Appendix B contains more details about the API code.

6.7.3.2 Comparing AIMSUN Vehicle Trajectories with PEMS Activity Data:

A separate output was generated for every route since the API was run separately for every route. The output of the API file was a large text file (1.5 GB) since the API is extracting all vehicles in the population.

Section IDs were extracted from AIMSUN for every route. These section IDs for every route were used in extracting the data from API output. Every sub route (I-540 or Six Forks) has its unique section IDs, these IDs were extracted from API output by using SAS code. SAS code was written in order to extract specific sections from the output and all moving vehicles on those sections. Afterwards, vehicles which are moving only of route sections were selected from the output and the other vehicles were removed. The objective of this process is to reduce the data as efficiently as possible since the output is very large due to extracting all vehicles from the simulator.

6.7.3.3 Selecting Vehicles from AIMSUN and PEMS Data Sets

The next step is to extract the appropriate sample of vehicles from AIMSUN output and from PEMS data base. For AIMSUN vehicles, the travel time was calculated for every vehicle on every route. Then, vehicles were sorted by travel time. The total travel time on every route for every vehicle was the filter which was used in extracting vehicles. Vehicles with a specified travel time range from those tested by PEMS were extracted. The range of travel time which was used in extracting vehicles from AIMSUN was defined based on space mean speed range. Frey et al. (2006) showed that VSP distributions are not statistically different within range of space mean speed. For example, if the space mean speed is 50 mph, so within a range of speeds from 48.5 to 52.5, the VSP distributions are not statistically different. Therefore, the selection criteria were depending on the range of + or – 2.5 mph difference in space mean speed. Vehicles were selected from AIMSUN with travel time in this range of space mean speed.

The same selection criterion was applied in extracting PEMS vehicles. PEMS database contains 35 vehicles traveling at different times and days under different weather conditions. The calibration process focused on 10/20/2010 when the Toyota Camry was tested, which constituted the base travel time.

Table 17 shows the sample size (total number of seconds) and number of vehicles extracted from AIMSUN and PEMS database that matched the selection criteria.

Table 17 Extracted AIMSUN and PEMS Vehicles

	Route 1 IN		Route 1 OUT	
	I-540	Six Forks	I-540	Six Forks
N1 (PEMS Vehicles)	16	9	12	12
N2 (AIMSUN Vehicles)	321	21	158	37
Number of PEMS Seconds	9520	2900	7900	3871
Number of AIMSUN Seconds	177028	6136	86558	8843

The extracted vehicles from AIMSUN and PEMS were used to calculate VSP and develop VSP distributions, cumulative speed distributions and cumulative acceleration distributions. All these distributions depend on the extracted sample size from AIMSUN and PEMS presented in Table 17. VSP was calculated for the extracted vehicles on second by second bases for AIMSUN vehicles and PEMS vehicle. Road grade was assumed to be zero on VSP equation, both on AIMSUN and PEMS VSP since road grade values are not significant in this network. Therefore, VSP values obtained from PEMS data base were modified based on zero road grade assumption since it was calculated originally by the actual road grade.

6.7.4 Speed Profiles

This section shows sample comparisons between individual vehicles speed profiles. Each figure shows three vehicles at different travel times: one at the lowest travel time (Veh 1), one at the mean (Veh 2) and one at the highest (Veh 3), all within the ± 2.5 mph range from the mean.

6.7.4.1 Freeway Speed Profile Comparisons

The following figures illustrate the speed traces for extracted vehicles from AIMSUN vehicles (API output) and PEMS vehicles database. Figure 41 and Figure 43 show AIMSUN traces for the two freeway sections, while Figure 42 and Figure 44 show the selected PEMS traces for those same freeway sections.

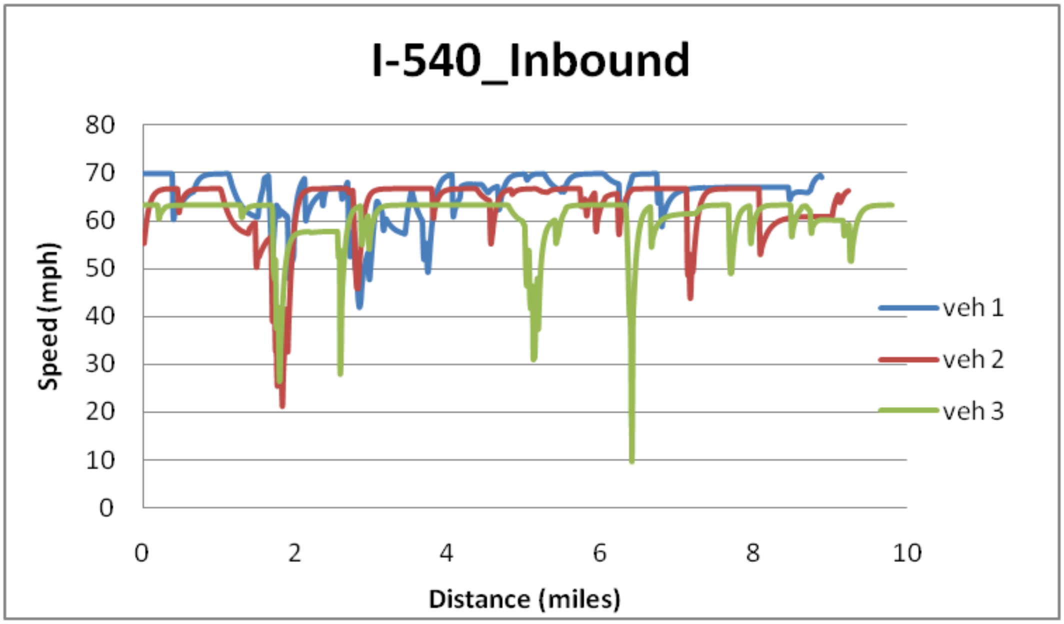


Figure 41 AIMSUN Speed Profiles Comparisons for Route 1 Inbound

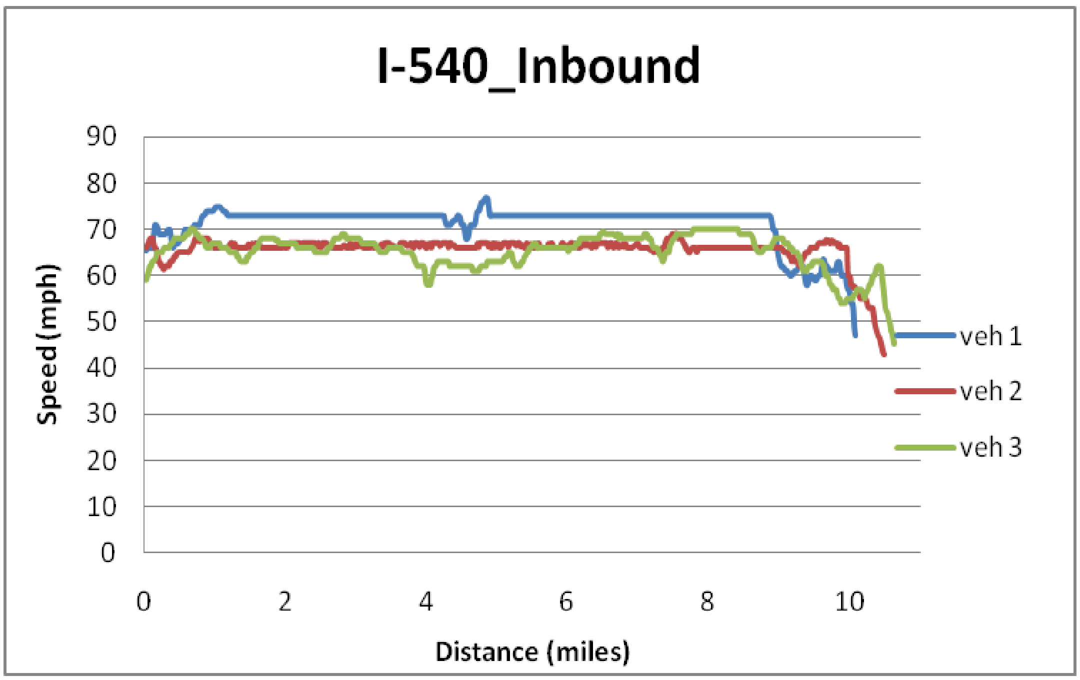


Figure 42 PEMS Speed Profiles Comparisons for Route 1 Inbound

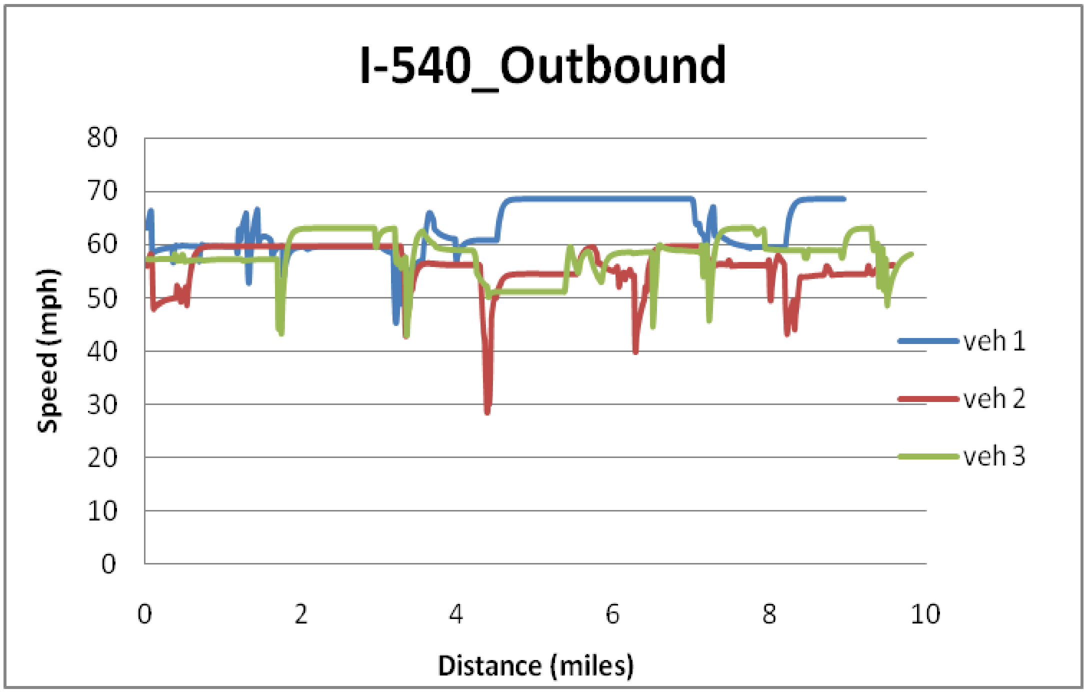


Figure 43 AIMSUN Speed Profiles Comparisons for Route 1 Outbound

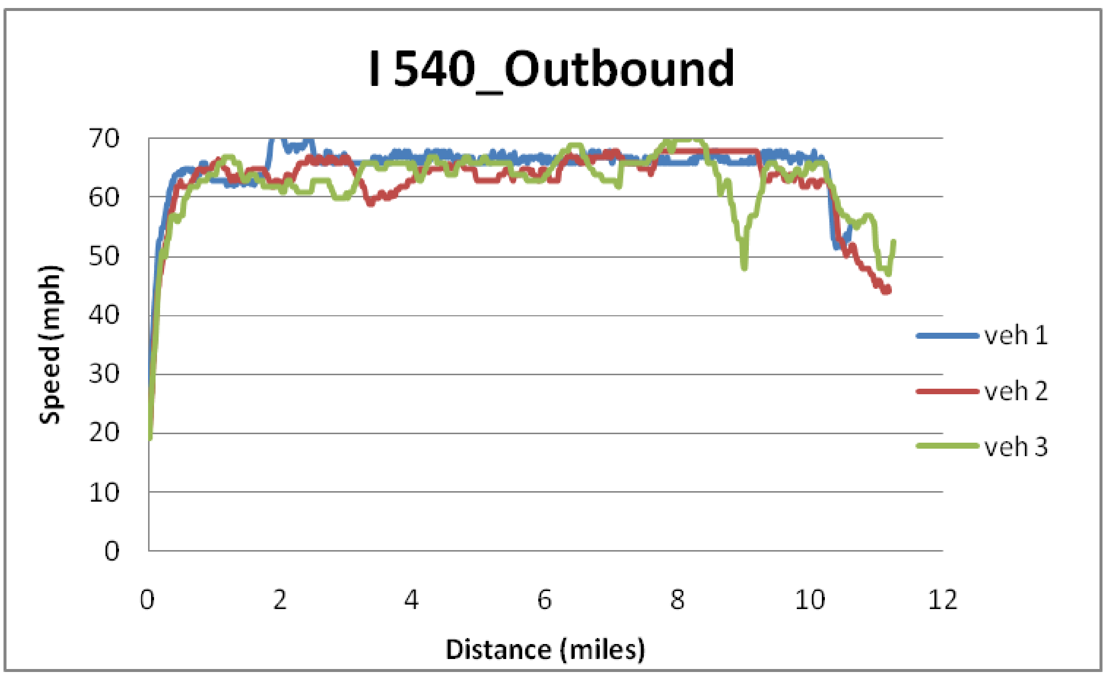


Figure 44 PEMS Speed Profiles Comparisons for Route 1 Outbound

Figures 41-44 illustrate the speed traces of AIMSIN and PEMS vehicles in order to study the difference between AIMSUN speed estimates and PEMS actual field speed for freeway segments. PEMS speed traces on freeways are smoother compared with AIMSUN speed traces. PEMS vehicles reduce their speed slightly at on and off ramps in order to change lanes and continue on their path. On the other hand, AIMSUN vehicles reduce speed more sharply at on and off ramps in order to wait for gaps to change lanes. AIMSUN vehicles behavior explains the reason of significant decreases in AIMSUN vehicles speed traces. Furthermore, AIMSUN tends to maintain constant speed trace at the freeways segments and reduce the speed sharply at on and off ramps in order to change lanes. Afterwards, AIMSUN vehicle increase their speed then maintain a constant (desired) speed.

6.7.4.2 Arterial Speed Profile Comparisons

The following figures 45-48 illustrate the speed traces on an arterial Six Forks Road for the three vehicles with travel times within the specified range Route 1 outbound and inbound.

Figures 45-48 show the speed traces for PEMS and AIMSUN vehicles on arterial segments in order to contrast AIMSUN individual vehicle behaviors against PEMS. AIMSUN maintains constant speed at the midblock segment of arterials and decrease the speed sharply prior to every signalized intersection. Afterwards, the speed increases to maintain the constant speed. AIMSUN individual vehicles behavior is not matching PEMS vehicles behavior which represents the real world driving. PEMS vehicles increase and decrease speed gradually at every signalized intersection. In addition, PEMS vehicles speed changes according to different traffic conditions and doesn't maintain constant speed as AIMSUN.

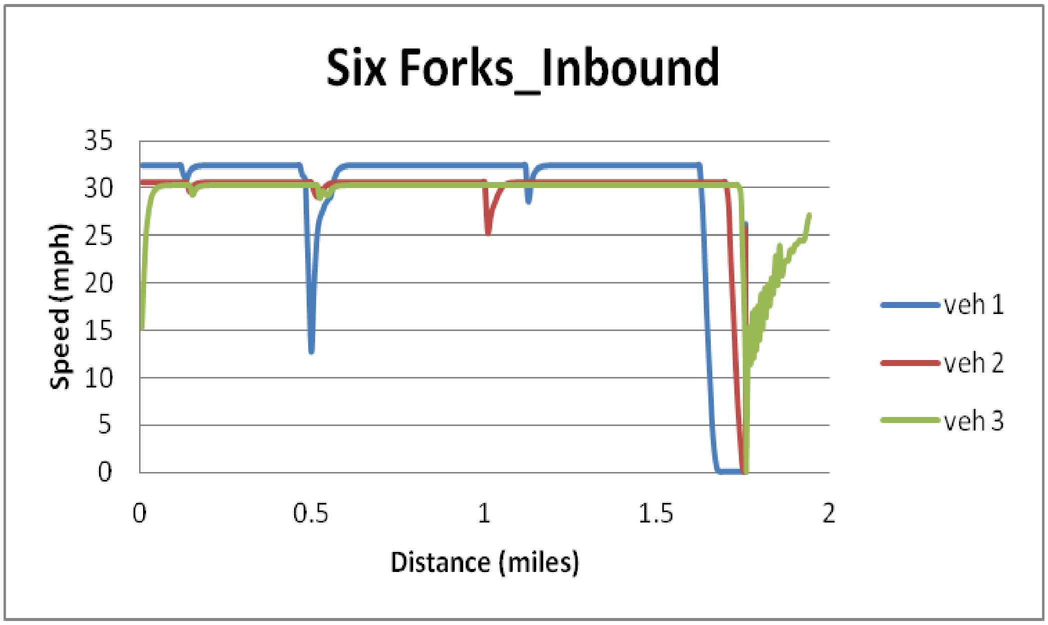


Figure 45 AIMSUN Speed Profiles Comparisons for Route 1 Inbound

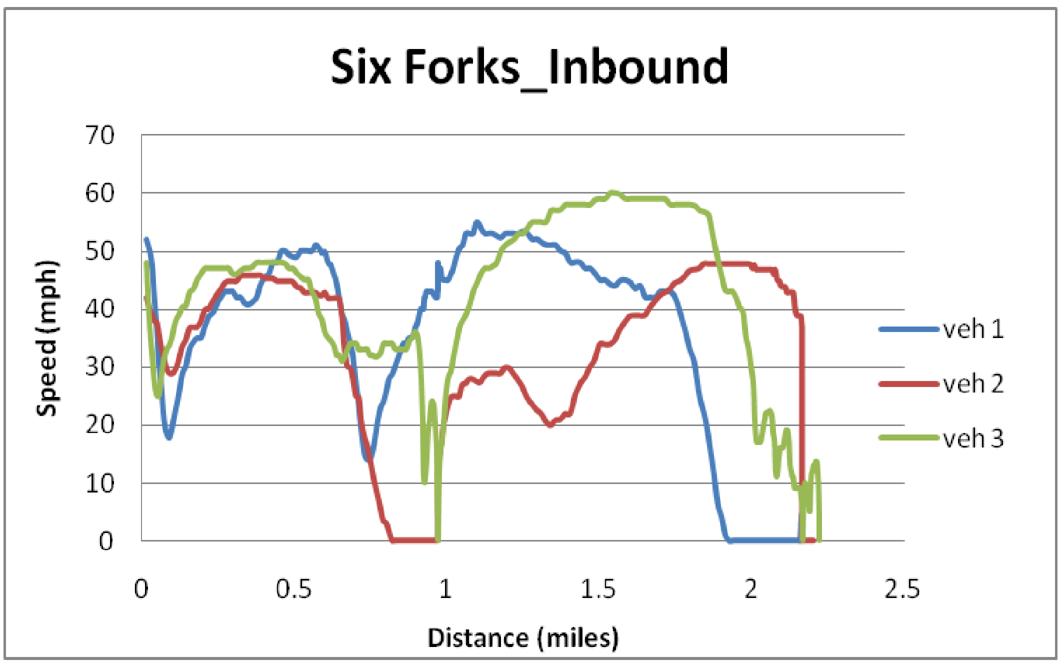


Figure 46 PEMS Speed Profiles Comparisons for Route 1 Inbound

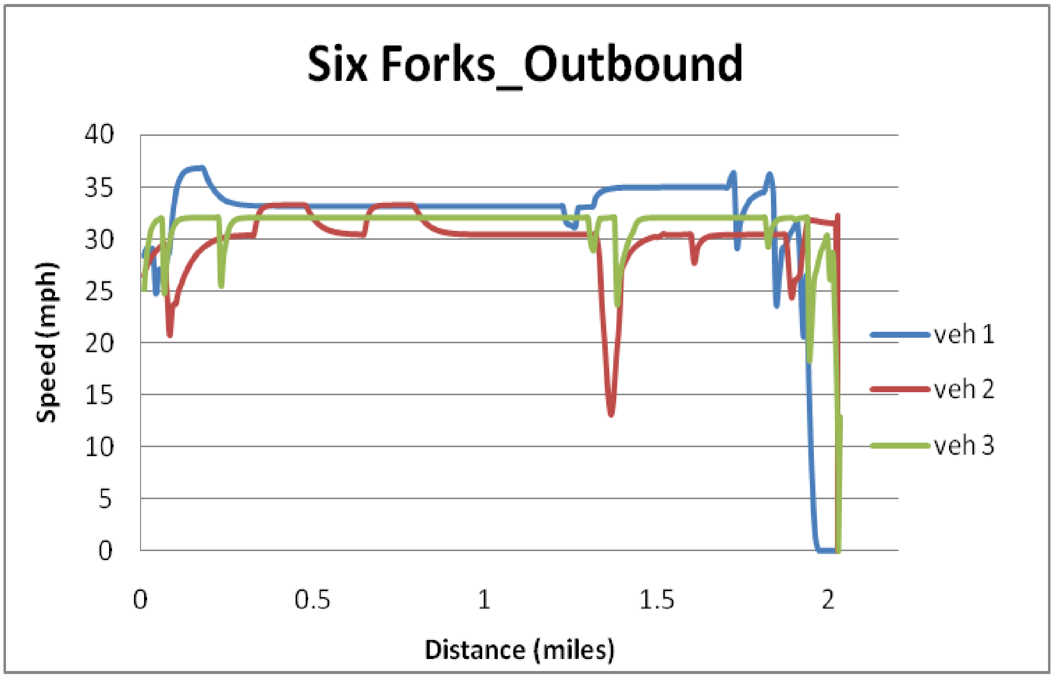


Figure 47 AIMSUN Speed Profiles Comparisons for Route 1 Outbound

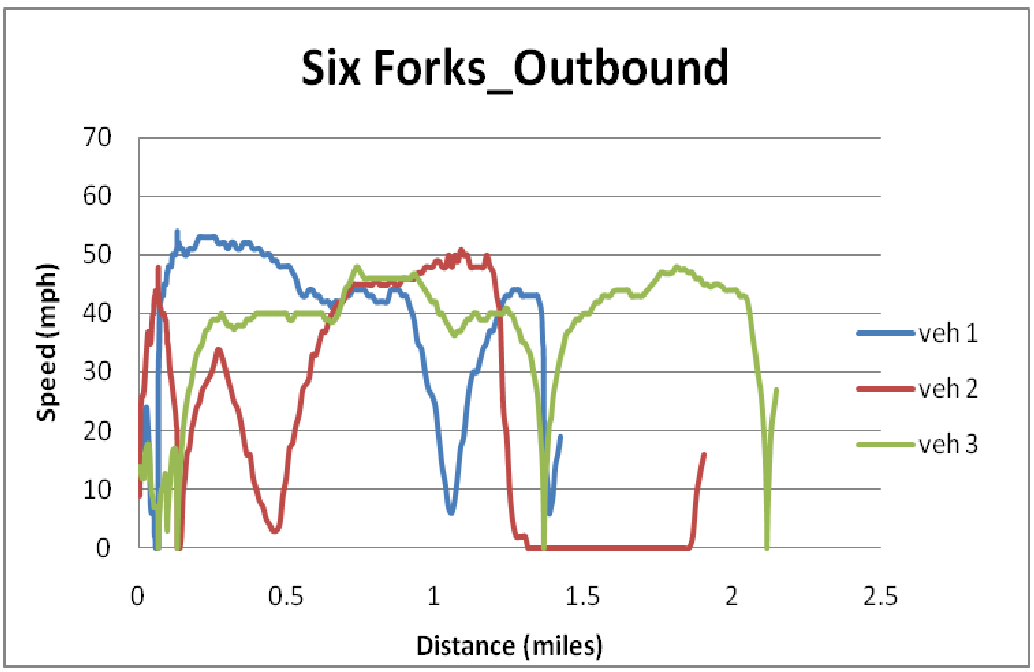


Figure 48 PEMS Speed Profiles Comparisons for Route 1 Outbound

6.7.5 VSP Distribution Comparisons

VSP distributions were calculated based on the VSP binning approach (14 VSP modes). The VSP distributions were estimated based on the percentage of route or sub-route travel time spent in every VSP mode. The VSP bins ranges are defined in Table 18.

Table 18 VSP Bins Definitions

VSP Mode	VSP Range (kW/ton)
1	Below -2
2	-2 – 0
3	0 – 1
4	1 – 4
5	4 – 7
6	7 – 10
7	10 – 13
8	13 – 16
9	16 – 19
10	19 – 23
11	23 – 28
12	28 – 33
13	33 – 39
14	Over 39

6.7.5.1 Route 1 (Inbound) VSP Distribution Comparisons

Figure 49 and Figure 50 show the VSP distributions comparisons for Route 1 inbound on two sub routes: I-540 and Six Forks. At I-540, VSP mode 6 and 7 from AIMSUN are higher than PEMS VSP. VSP mode 6 and 7 represent mostly cruise mode. It is inferred that at the freeways AIMSUN takes more time at cruise mode compared with PEMS. On the other hand, for modes 8, 9 and other acceleration modes, AIMSUN experiences less time than PEMS in the acceleration mode. For other deceleration modes such as 1 and 2, AIMSUN spends less time decelerating comparing with PEMS. Figure 50 shows the VSP distribution comparisons for Six Forks. Most of AIMSUN VSP modes are under VSP mode 4, which means that AIMSUN maximized cruise mode at Six Forks route (mode 4 is a cruise mode). For acceleration and deceleration modes, AIMSUN took less time compared with PEMS.

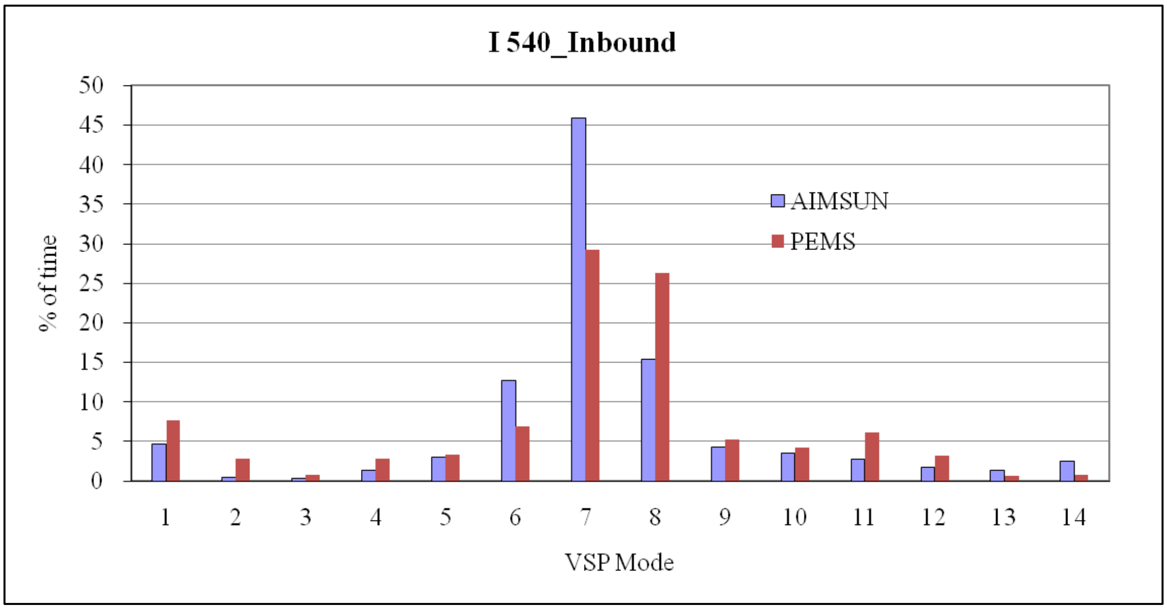


Figure 49 PEMS and AIMSUN VSP Distributions: I-540 Inbound

6.7.5.2 Route 1 (Outbound) VSP Distributions Comparisons

Figure 51 illustrates the VSP distributions for I-540 on Route 1 outbound. PEMS VSP took more time compared with PEMS for acceleration and deceleration modes. For cruise mode 6, AIMSUN took longer time compared with PEMS. Figure 52 shows VSP distributions for Six Forks on Route 1 outbound. It is clear from the figure that most

AIMSUN VSP is under VSP mode 4 which is cruise mode. This means that AIMSUN over estimate cruising mode at arterial roads such as Six Forks Road. The next step is to compare AIMSUN VSP distributions and PEMS VSP distributions statistically in order to test the significance of the difference.

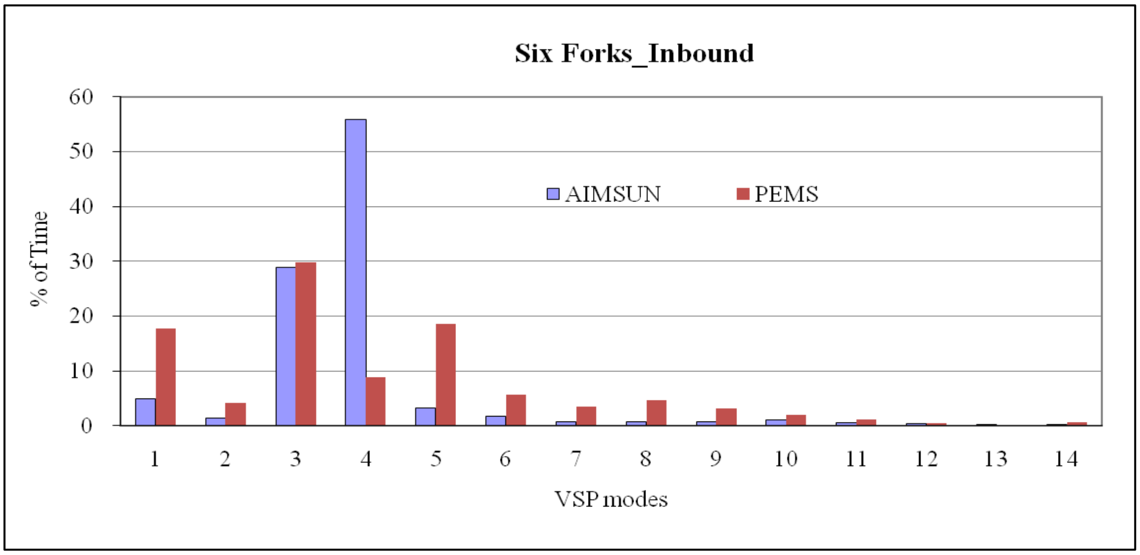


Figure 50 PEMS and AIMSUN VSP Distributions: Six Forks Inbound

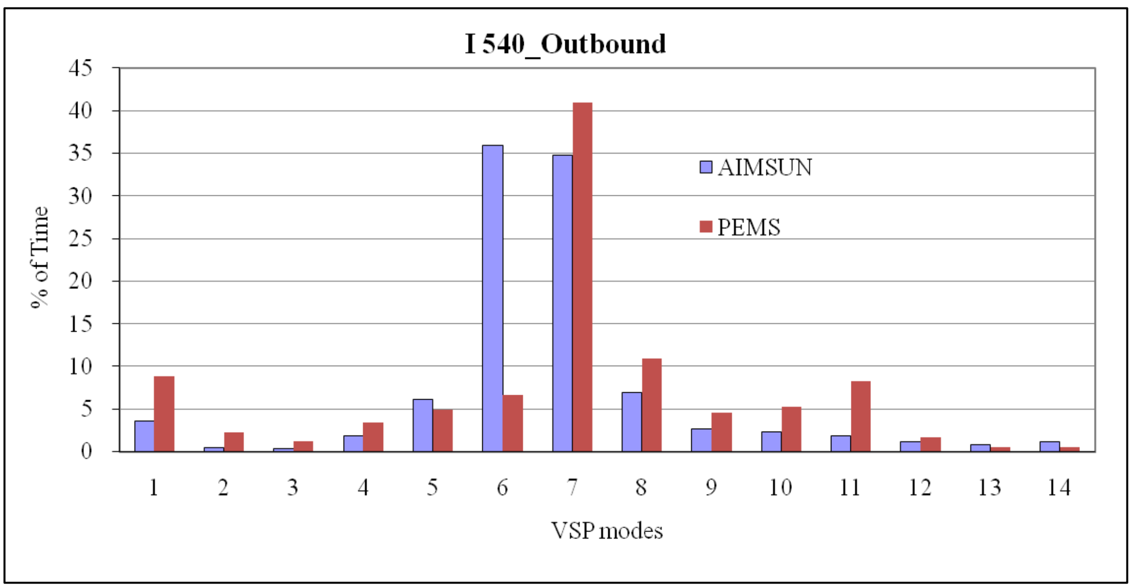


Figure 51 PEMS and AIMSUN VSP Distributions: I-540 Outbound

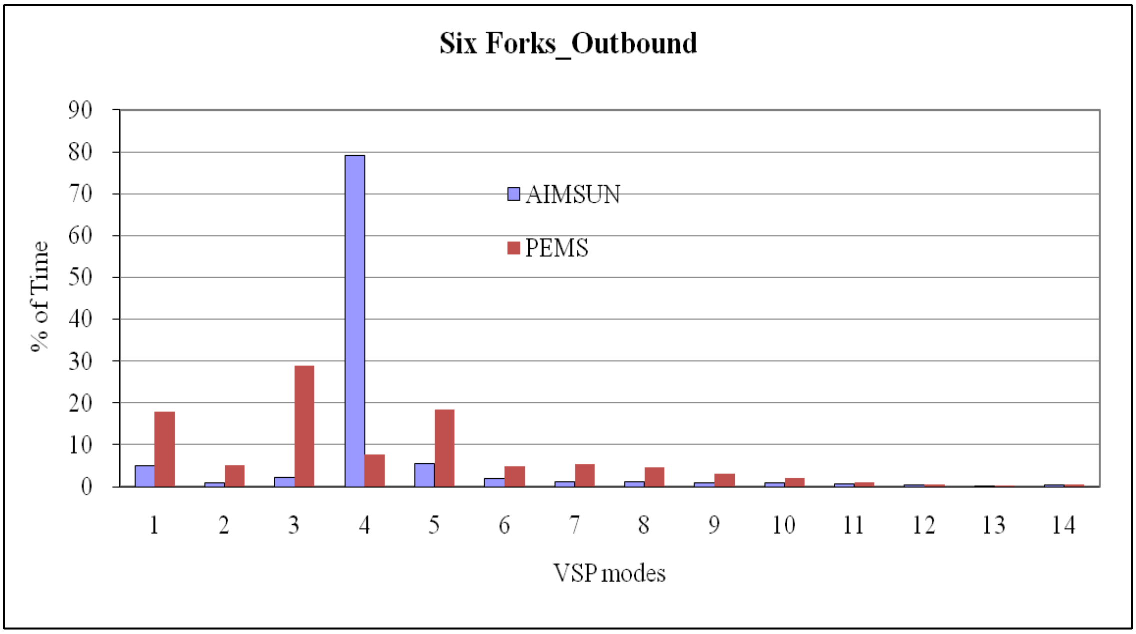


Figure 52 PEMS and AIMSUN VSP Distributions: Six Forks Outbound

6.7.5.3 Statistical Tests of VSP Distributions

There are two groups of distributions, those obtained from PEMS vehicles and those generated from AIMSUN. The non-parametric statistical test (Kolmogorov-Smirnov) KS was selected to be applied to these comparisons. KS test is the most appropriate test for evaluating the overall differences between two cumulative distributions. The KS test is based on the maximum distance between two curves, KS test focus on the relative distribution of the data. In addition, the advantage of KS test is that there is no need of making assumption about the distribution of data. The test hypothesis (at p=0.05) was as follows:

Ho: two populations have the same VSP distribution
Ha: two population's VSP distributions differ significantly;

Table 19 show the different KS test results which were conducted to compare AIMSUN and PEMS VSP distributions. In addition, Table 19 illustrates the number of vehicles which were extracted from AIMSUN and PEMS databases. N1 and N2 are the total number of seconds extracted from AIMSUN and PEMS vehicles (vehicles trajectories sample size).

Table 19 KS Test Results: AIMSUN vs. PEMS VSP Distributions

	Route 1 IN		Route 1 OUT	
	I-540	Six Forks	I-540	Six Forks
*N1 (PEMS Vehicles)	9520 (16)	2900 (9)	7900 (12)	3871 (12)
*N2 (AIMSUN Vehicles)	177028 (321)	6136 (21)	86558 (158)	8843 (37)
KS	0.23	0.38	0.28	0.39
Critical Value	0.02	0.04	0.02	0.03
Hypothesis	Reject	Reject	Reject	Reject

** N1 and N2 are total number of seconds extracted from vehicles trajectories*

It is inferred from the table that the computed KS value is above the critical value for Route 1 outbound and Route 1 Inbound Six Forks and I-540 on Route 1 Inbound. Therefore, there is no evidence to suggest that the two population distributions are the same for Route 1 outbound and Route 1 Inbound Six Forks. While the vehicles in AIMSUN and PEMS have the same average travel time, AIMSUN didn't produce the same distribution of speed or VSP as PEMS did. This means that AIMSUN distribution for the speed and its acceleration values didn't match the field speed distribution (PEMS speed distribution) for this specified sample size.

Thus, for the I-540 segments on Route 1 inbound and Route 1 outbound, the validation was accepted on the Macro level but it is not accepted on the micro level. In order to understand the difference between AIMSUN and PEMS VSP distributions, the speed and acceleration cumulative distributions were generated.

6.7.6 Speed and Acceleration Cumulative Distributions Comparisons

Cumulative acceleration and speed distributions comparisons between AIMSUN and PEMS were conducted on different routes in order to gain insights into how AIMSUN estimates VSP. Figure 55-60 show the cumulative distribution of the speed and acceleration in AIMSUN and PEMS for various sub-routes.

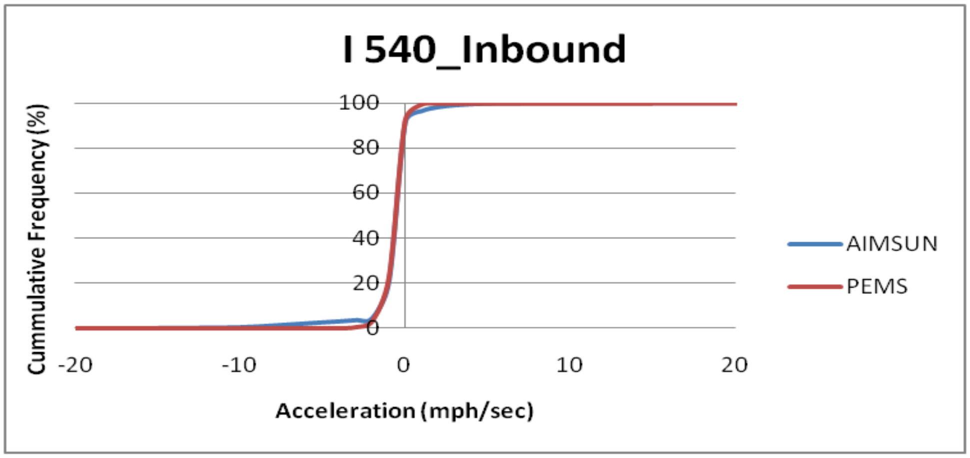


Figure 53 Acceleration Cumulative Distribution: Route 1 Inbound (I-540)

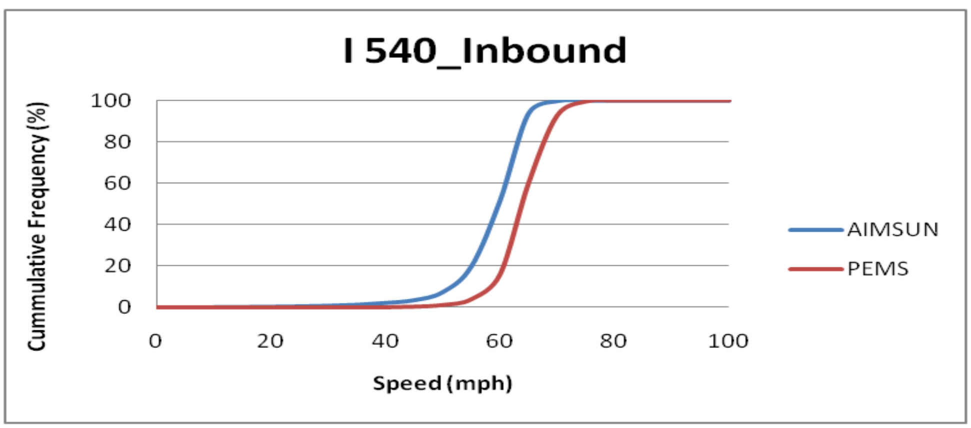


Figure 54 Speed Cumulative Distribution: Route 1 Inbound (I-540)

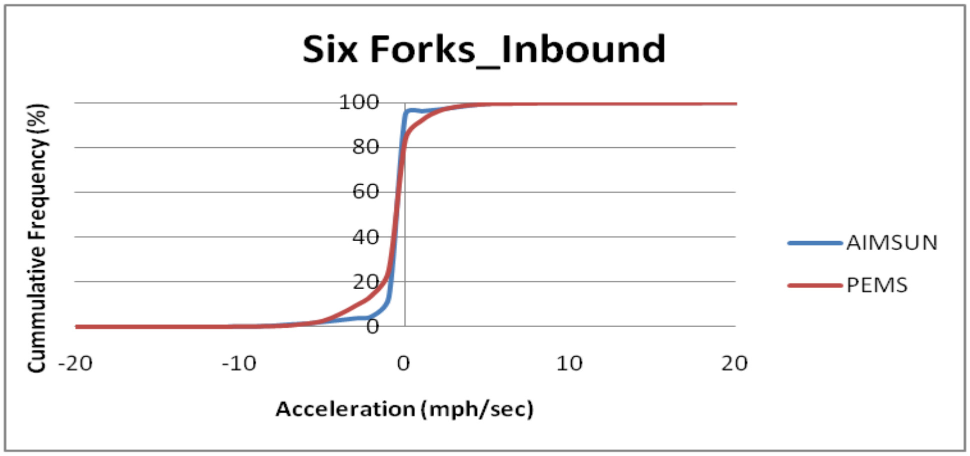


Figure 55 Acceleration Cumulative Distribution: Route 1 Inbound (Six Forks)

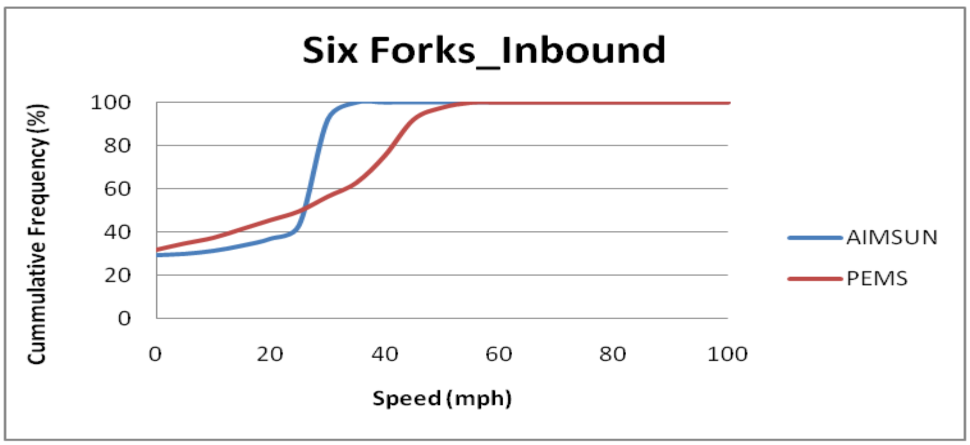


Figure 56 Speed Cumulative Distribution: Route 1 Inbound (Six Forks)

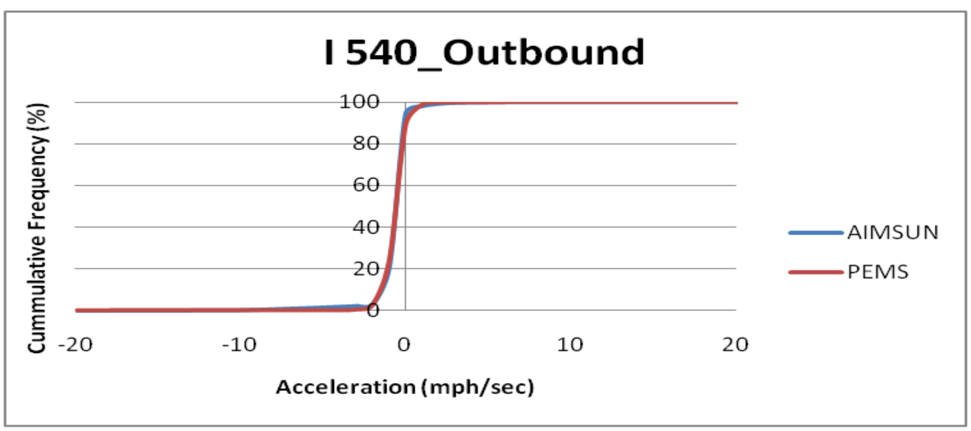


Figure 57 Acceleration Cumulative Distribution: Route 1 Outbound (I-540)

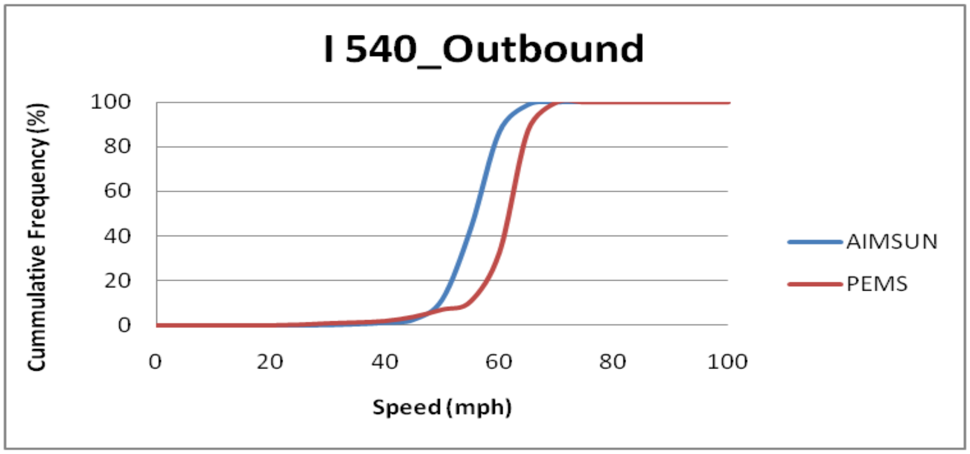


Figure 58 Speed Cumulative Distribution: Route 1 Outbound (I-540)

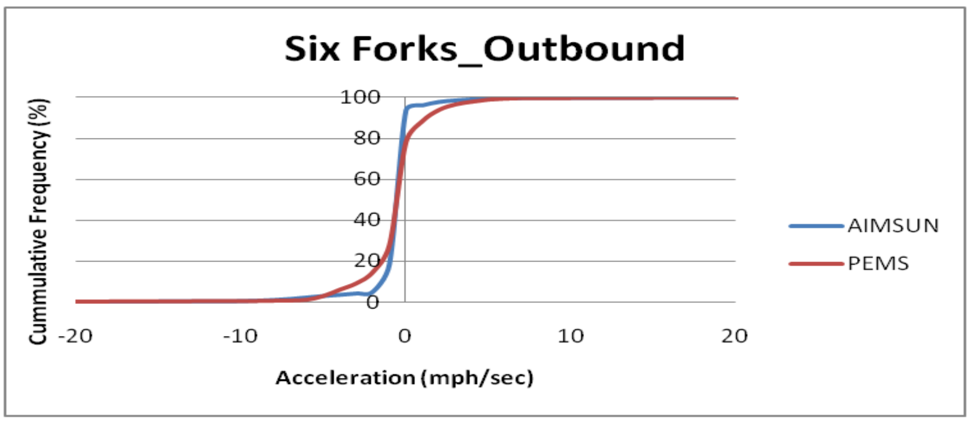


Figure 59 Acceleration Cumulative Distribution: Route 1 Outbound (Six Forks)

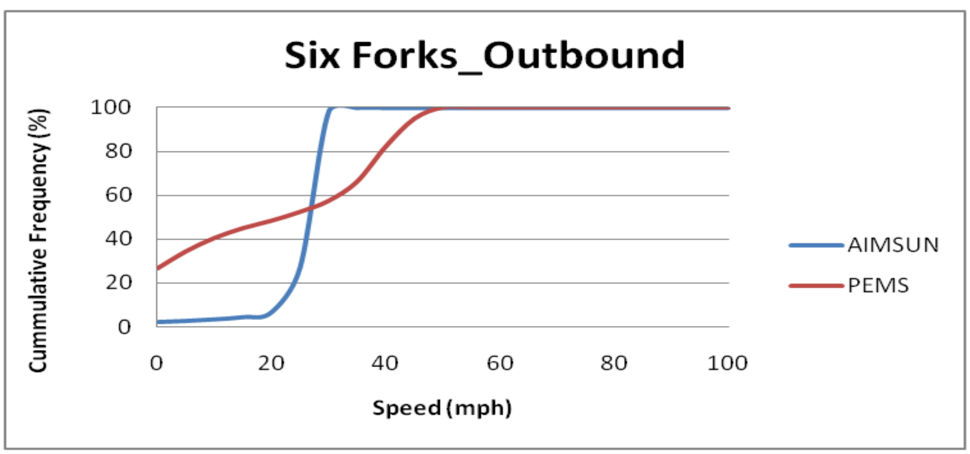


Figure 60 Speed Cumulative Distribution: Route 1 Outbound (Six Forks)

For the Six Forks arterial road, AIMSUN underestimates the deceleration rates compared with PEMS decelerations. However, AIMSUN overestimates the acceleration rates compared with PEMS acceleration rates. In addition, the speed distributions for Six Forks show that AIMSUN speed was lower than PEMS at lower speeds, but it was higher than PEMS at higher speeds. On the other hand, for I -540 Inbound, AIMSUN deceleration was higher compared with PEMS and AIMSUN acceleration was lower than PEMS. For I-540 outbound, AIMSUN was higher than PEMS for both acceleration and deceleration rates. AIMSUN estimated speed was higher than PEMS speed in the case of inbound and outbound I-540.

The objective of the comparison between AIMSUN and PEMS vehicles is to contrast AIMSUN estimates of activity data against PEMS real world activity data. AIMSUN individual vehicles behavior differs from PEMS vehicles which were tested in field. For Freeways, AIMSUN simulates individual vehicles by producing constant speed and maintains this speed for the entire simulation period. When vehicle approaches an on or off ramp, it decreases its speed sharply. After the end of weaving section, the vehicle increases its speed to reach the constant speed which AIMSUN sustains. AIMSUN doesn't provide vehicles the appropriate distance to search for accepted gap and to change between lanes. This is a problem in individual vehicles behavior, in particular, gap acceptance and lane changing algorithms. The gap acceptance and lane changing models in AIMSUN need to be recalibrated against PEMS in order to produce results matching real world driving behaviors.

On the other hand, AIMSUN also tends to maintain constant speed on arterial segments. When a vehicle comes close to intersection, it decreases its speed suddenly. Once beyond the intersection, the vehicle increases its speed to reach its constant speed which AIMSUN sustains. The same phenomenon as freeway segments case, vehicles are decelerating to very low speed in order to search for accepted gap and change lanes. The gap acceptance and lane changing algorithms in AIMSUN need to be calibrated against to ensure that AIMSUN estimates vehicles activity data comparable to PEMS real world activity data. Furthermore, AIMSUN overestimates acceleration and deceleration rates for arterial segments on this case study. AIMSUN increases and decreases the speed with very high rate of change on arterial segments compared with PEMS vehicles. The acceleration and decoration rates in AIMSUN are high compared with PEMS vehicles which change its acceleration and deceleration gradually. AIMSUN values for max and min acceleration and deceleration values need to be revised according to PEMS real world rates.

6.7.7 Relative Comparisons between Average Fuel Consumption and Emissions Rates

The objective of this section is to investigate the impact of the differences in AIMSUN and PEMS VSP distributions on projected vehicle emissions and fuel consumption. Emissions were estimated from both AIMSUN and PEMS activity results. The objective was to ascertain whether the difference in AIMSUN estimation for activity data compared with PEMS will also yield significant variations in fuel and emissions estimates. Emissions were estimated using VSP modal emissions rates obtained from a PEMS vehicle tested on the studied routes. The 2006 Toyota Camry tested on 20 October 2010 was selected as the representative vehicle for which VSP-based emission rates as well as total route emissions were computed (that vehicle fuel and VSP-modal fuel and emission rates are listed in Table 3).

The VSP distribution was calculated for each route illustrating yielding the probability of every VSP mode. Emissions rates (in mg per second) for every VSP mode were multiplied by VSP mode probability (fraction of all possible seconds under every VSP mode). The average emissions rate per route was calculated by taking the summation of all emissions rates under all VSP modes. Table 20 presents the average emissions rate per second for each route as well as the percentage of difference between AIMSUN and PEMS average emissions rates. The total emissions per vehicle were calculated by multiplying the fuel and emissions rate by route (gm/sec/route) with the corresponding (AIMSUN or PEMS) estimate of vehicle average travel time on each route. Table 21 shows total emissions per vehicle on every route in addition to the percentage of difference between AIMSN and PEMS emissions rates.

Table 20 Comparison of Route-Based Average Fuel and Emission Rates per Unit Time

		Route 1 Inbound		Route 1 Outbound	
		I-540	Six Forks	I-540	Six Forks
Nox (mg/sec)	AIMSUN	3.99	1.42	3.57	1.70
	PEMS	3.97	1.83	3.73	1.84
	% Difference	**0.61%**	**-22.63%**	**-4.22%**	**-7.29%**
HC (mg/sec)	AIMSUN	1.89	0.81	1.78	0.89
	PEMS	1.86	0.99	1.79	1.00
	% Difference	**1.60%**	**-18.32%**	**-0.39%**	**-11.13%**
CO (mg/sec)	AIMSUN	18.68	5.31	15.65	6.12
	PEMS	17.99	7.98	17.13	7.95
	% Difference	**3.83%**	**-33.39%**	**-8.64%**	**-22.96%**
CO2 (g/sec)	AIMSUN	4.16	1.56	3.81	1.75
	PEMS	4.12	2.04	3.94	2.05
	% Difference	**1.09%**	**-23.48%**	**-3.31%**	**-14.72%**
FuelUse (g/sec)	AIMSUN	1.33	0.50	1.21	0.56
	PEMS	1.31	0.65	1.25	0.65
	% Difference	**1.11%**	**-23.53%**	**-3.35%**	**-14.74%**

*Percentage difference is calculated as (AIMSUN-PEMS)/PEMS x 100%

Table 21 Comparison of Total Route Fuel and Emissions per Vehicle

		Route 1 Inbound		Route 1 Outbound	
		I-540	Six Forks	I-540	Six Forks
Nox (mg/veh)*	AIMSUN	2400.52	344.00	2317.31	404.90
	PEMS	2297.88	563.45	2128.81	485.28
	% Difference	**4.47%**	**-38.95%**	**8.86%**	**-16.56%**
HC (mg/veh)*	AIMSUN	1135.13	196.78	1154.92	211.00
	PEMS	1075.98	305.33	1020.10	263.79
	% Difference	**5.50%**	**-35.55%**	**13.22%**	**-20.01%**
CO (mg/veh)*	AIMSUN	11228.19	1288.04	10163.06	1454.68
	PEMS	10414.32	2450.64	9787.49	2098.12
	% Difference	**7.81%**	**-47.44%**	**3.84%**	**-30.67%**
CO2 (g/veh)*	AIMSUN	2502.19	377.55	2472.23	415.62
	PEMS	2383.86	625.30	2249.77	541.50
	% Difference	**4.96%**	**-39.62%**	**9.89%**	**-23.25%**
FuelUse (g/veh)*	AIMSUN	796.87	120.07	786.90	132.19
	PEMS	759.04	198.99	716.33	172.26
	% Difference	**4.98%**	**-39.66%**	**9.85%**	**-23.27%**

*Percentage difference is calculated as (AIMSUN-PEMS)/PEMS x 100%

Observations from Table 20 indicate that for the freeway facilities, the range of differences between the two methods is fairly narrow, ranging from -8.6% to +3.8% for the average rate, and from +3.84% to + 13.22% for the total route fuel and emissions. The fact that all except one set of observations yielded differences that were under 10% is a positive indication that AIMSUN's estimates are a reasonable representation of PEMS. At the route level, one must realize that variations in projections may be attributed to changes both in emissions rates, as well as to the travel time estimates between PEMS and AIMSUN (see Table 16). In fact, Table 21 shows that all of AIMSUN freeway route estimates are higher than PEMS, since the AIMSUN predicted travel times exceed those in PEMS by a significant 8.6% on average.

The situation is much less promising when comparing rates and totals for the arterial facilities. Here the range in fuel and emission rates differences varies from -7.3% to -33.4%, a wide and significant margin. The differences are even larger when comparing total fuel and emissions at the route level, in this case ranging from -16.6% to -47.04%. The latter difference is of course compound by the fact that AIMSUN predicted travel times were also lower than PEMS by a significant 16% on average.

In summary, these findings point out to the need to further study how AIMSUN models arterial vehicle activities at the micro-scale level. The differences in both activity and emission rates are beyond the normal range of uncertainties one would expect in such experiments. One thing that is evident in the AIMUN speed traces on arterials is both the preponderance of free flow speeds and of major speed drops at intersections. The PEMS profiles on the other hand show a much smoother transition in speeds over time and space. How to reconcile the two profiles is left for future research, which must look at the model car-following and lane changing parameters as a means to address the evident discrepancies in the driving schedule.

On the other hand, it appears that for uninterrupted flow facilities, the simulation model yielded reasonable results across the board, within 10% of the real world activity estimates. Additional freeway routes should be evaluated in a similar manner to confirm this important finding.

Chapter 7 Conclusions

This thesis investigated two potential approaches for integrating micro simulation models with field-based emissions data. The first approach was to use a micro simulation internal fuel and emissions model calibrated with field PEMS emissions data. PEMS instantaneous emissions and fuel consumption information were used to calibrate the fuel and emission models in a traffic micro simulation model AIMSUN. Thus, the internal emissions model in AIMSUN calibrated with PEMS emissions factors could be used to evaluate the environmental impacts of different traffic strategies.

The second approach was to contrast the simulated vehicle activity results of AIMSUN with PEMS field activity data. PEMS activity data were considered to be a valuable source for evaluating AIMSUN activity outputs at both the macro and micro scales. AIMSUN micro-scale activity includes speed and acceleration on a second by second basis. These resulting speed and acceleration profiles were validated against real traffic data on macro and micro levels. This validation is important because AIMSUN internal emissions model uses the speed and acceleration in estimating emissions. Furthermore, these activity results of AIMSUN can be extracted from AIMSUN and be used in develop external emissions model to estimate emissions using external models.

7.1 Conclusions

Several conclusions were drawn from the research efforts described in this thesis:

- The internal emissions model in AIMSUN can be readily used in the micro simulation process for estimating emissions and fuel consumption; however it needs to be used with caution. AIMSUN internal fuel consumption and emissions models depend mainly on individual vehicles speed and acceleration distributions. These speed and acceleration distributions have not been validated against real traffic data and need to be compared with extensive filed measurements. Therefore, when AIMSUN speed and acceleration distributions are not reliable, the emissions will not be estimated correctly.

- AIMSUN internal fuel consumption and emissions model are working based on specific model forms. These algorithms are calibrated with fuel consumption and emissions field data. The fuel consumption and emissions model forms in AIMSUN cannot be changed and restrict the user to use AIMSUN emissions and fuel consumption equations. It was found that the PEMS emissions data didn't fit well the AIMSUN emission equations. This lack of flexibility restricts the calibration of the AIMSUN fuel consumption and emissions model with PEMS field emission data. This conclusion is also tied to the fact that this work was done by only one vehicle, perhaps not generating enough of a variability to generate appropriate trends.
- Strictly using field sensors for calibrating demand models in micro simulation models can sometime be ineffective. When sensors don't have good spatial coverage over the network, calibrating demand based on sparse sensors locations will not be enough for demand estimation purposes over all the network sections. Simply using demand percentages from sensors data in establishing time dependent matrixes may not represent the real demand for these matrixes time intervals. The estimated demand by time demand matrixes at its time periods cannot be compared with the actual traffic

counts at these specific periods. Therefore using sensors in calibrating micro simulation models cannot be representative for the actual demand, if it doesn't have full spatial coverage over the simulated network, especially for large networks.

- Micro simulation models are very sensitive to the geometric details of the road links such as the lengths of acceleration and deceleration lanes. These geometric details may not affect the outputs at the macro scale but have an apparent strong effect at the micro scale since it will affect individual vehicle behavior. The speed, accelerations and Vehicle Specific Power (VSP) distributions for individual vehicles are sensitive to geometric details. For example, if the acceleration length is inadequate or is not matching the actual field length, vehicle speed and acceleration distribution on the micro level would be affected. In the second case study, the modeled acceleration lane in AIMSUN didn't match the actual length. Therefore, vehicle micro speed and acceleration distribution at the acceleration lane didn't match PEMS distributions. In the recalibration process, this length was modified.
- The distribution of speeds and accelerations need to be validated against real world traffic data and field measurements at the micro scale. AIMSUN overestimated deceleration rates compared with PEMS for freeway segments. For acceleration rates, AIMSUN overestimated acceleration rates on arterial segments compared with PEMS. On the other hand, AIMSUN overestimated freeways speeds compared to PEMS. For arterials, AIMSUN underestimated the deceleration rates and overestimated the acceleration rates compared with PEMS field measurements. In addition, the speed distributions for the arterial on Six Forks Rd. showed that

AIMSUN speeds were lower than PEMS at lower speed but higher than PEMS at higher speeds. AIMSUN activity model is estimating vehicle activity based on default values for speed and acceleration. Those values didn't turn speed and acceleration distributions matching real world distributions.

- Matching the average travel time on links and routes level from simulation and the field is not sufficient for calibrating and validating micro simulation models for fuel use and emissions purposes. Although, some vehicles might have the same travel time on the same route, their speed and VSP distribution might be completely different. In the case study proposed in the thesis, extracted simulated vehicles from AIMSUN have the same route travel time as the PEMS vehicles travel time; however, it was found that the speed and VSP distributions for those two sets of vehicles were statistically different.
- Although, some vehicles might have the same travel time on the same route, their speed and VSP distribution might be statistically different. The difference between AIMSUN and PEMS VSP distributions varied from one individual vehicle mode to another mode. On freeways, AIMSUN VSP distribution tended to be higher (i.e. more skewed to the right) than PEMS VSP distribution for the cruise mode. On the other hand, AIMSUN VSP tended to be lower than PEMS for the acceleration and deceleration modes.
- In the case of surface streets most of AIMSUN VSP values were under the cruise mode, therefore AIMSUN was higher than PEMS for cruise modes. The difference between AIMSUN and PEMS VSP for cruise mode was high and statistically

significant. Overall AIMSUN VSP distributions for freeways and arterials were statistically different from PEMS VSP distributions.

- The difference between AIMSUN and PEMS emission estimates were generally acceptable for freeway facilities. At the route level, the difference in total route emissions and fuel consumption ranged from +3.84% to + 13.22%. The difference in average emissions rate varies from -8.6% to +3.8%. On the macro level, AIMSUN travel time was higher than PEMS travel time. This travel time variation caused the difference on route emission rates. Therefore, macro scale validation for micro simulation model is vital for accurate route based emissions. For micro level, the flow on the freeways was uninterrupted flow with speed drops at interchanges. Thus, AIMSUN yielded acceptable fuel consumption and average emission rates per vehicle compared with PEMS.
- Conversely, the margin of difference between the two models was significantly high for arterial segments. The range in fuel and emission rates differences varied from -7.3% to -33.4%. The differences are even larger when comparing total fuel and emissions at the route level, ranging from -16.6% to -47.04%. PEMS travel time was higher than AIMSUN travel time by 15 % on average. Therefore, this difference yielded high variation in emissions and fuel consumption estimates on the route level. In addition, AIMSUN on the micro level yielded larger difference in average emissions rate per vehicle. The percentage of difference between AIMSUN and PEMS estimates on arterials were beyond the expected percentages. AIMSUN maintains free flow speed on arterials with major speed drops at intersections.

AIMSUN individual vehicles behavior is different compared with PEMS vehicles. The speed traces for PEMS vehicles maintained smoother speed change at intersections. These different vehicle behaviors yielded large emissions differences.

7.2 Recommendations for Future Research

There are several recommendations along the line of this work that are worth pursuing.

- Individual vehicle motion is affected by gap acceptance behavior in micro simulation models. AIMSUN micro simulator has default values for min accepted gap and minimum distance for choosing acceptable gap. These default values need to be recalibrated and redefined based on micro validation with PEMS activity data. The min distance for choosing gaps and min accepted gap should be redefined. Afterwards, comparisons between individual AIMSUN vehicles VPS, speed and acceleration distributions should be conducted with PEMS distributions. The objective is to match individual vehicles behavior in AIMSUN with PEMS real world vehicle behavior after modifying gap acceptance values.
- Furthermore, car following models affect individual vehicles behavior and may cause a mismatch with PEMS real driving behavior. Therefore, the car following model parameters may need to be refined according to comparisons with PEMS on micro scale. AIMSUN has different car following models; different trials with these models need to be done.
- The first application in this thesis focused on calibrating AIMSUN internal fuel consumption and emissions model with PEMS emissions data. The first application

was tied to the fact that this work was done by only one vehicle, perhaps not generating enough of a variability to generate appropriate trends. A potential future extension of this work is to calibrate AIMSUN emission model with PEMS fleet average emissions factors. PEMS data base contains about 35 vehicles that were tested in field. PEMS data sets contain fuel consumption and emissions for individual vehicles based on second by second basis. The fleet of emissions factors was used in calibrating AIMSUN internal emissions model. PEMS fleet average might generate appropriate trends that could be matched and fitted with AIMSUN emissions algorithms and equations.

- The API enables user to interact with AIMSUN micro simulator and to integrate any kind of models with AIMSUN platform. One of the future research recommendations is to integrate MOVES or a simplified version of it with AIMSUN through the API. MOVES emissions modal rates can be defined in the API and became a part of AIMSUN micro simulation process. The API will extract the activity data from the micro simulator and then integrates these activity results with MOVES to calculate emissions. The extracted activity data from AIMSUN and MOVES emissions rates was used to develop external model to estimate emissions. The external model will calculate emissions of AIMSUN vehicles activity out of AIMSUN model. Afterwards, when AIMSUN runs, the output will contain emissions results based on MOVES emissions rates. MOVES emissions model was developed by EPA and represents US fleet average emissions rates. Unlike, AIMSUN internal emissions model was developed by TSS and it is more consistent with Europe vehicle emissions standard. Therefore, it is recommended to integrate MOVES emission model with AIMSUN in order to evaluate emissions for US networks.

- The developed external emissions model would be a valuable source for validating AIMSUN internal emissions model. After calibrating AIMSUN emissions model with PEMS fleet, emissions output of this model was compared with MOVES external model output. The objective to check whether AIMSUN emissions algorithms are estimating emissions which are comparable with MOVES estimates.
- AIMSUN yielded acceptable fuel consumption and emissions estimates for freeways compared with PEMS. The difference between AIMSUN and PEMS emissions estimates for uninterrupted lows were in the expected range. Therefore, it is recommended to simulate more freeways in AIMSUN on the same approach in order to ensure the repetition of these important results. On the other hand, the difference between AIMSUN and PEMS emissions were beyond the accepted range for arterials. It is recommended for future research to focus on car-following model and lane changing parameters in order to reconcile the two profiles and get acceptable emissions estimates from the micro simulator.

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Appendices

Appendix A: Traffic.com Data

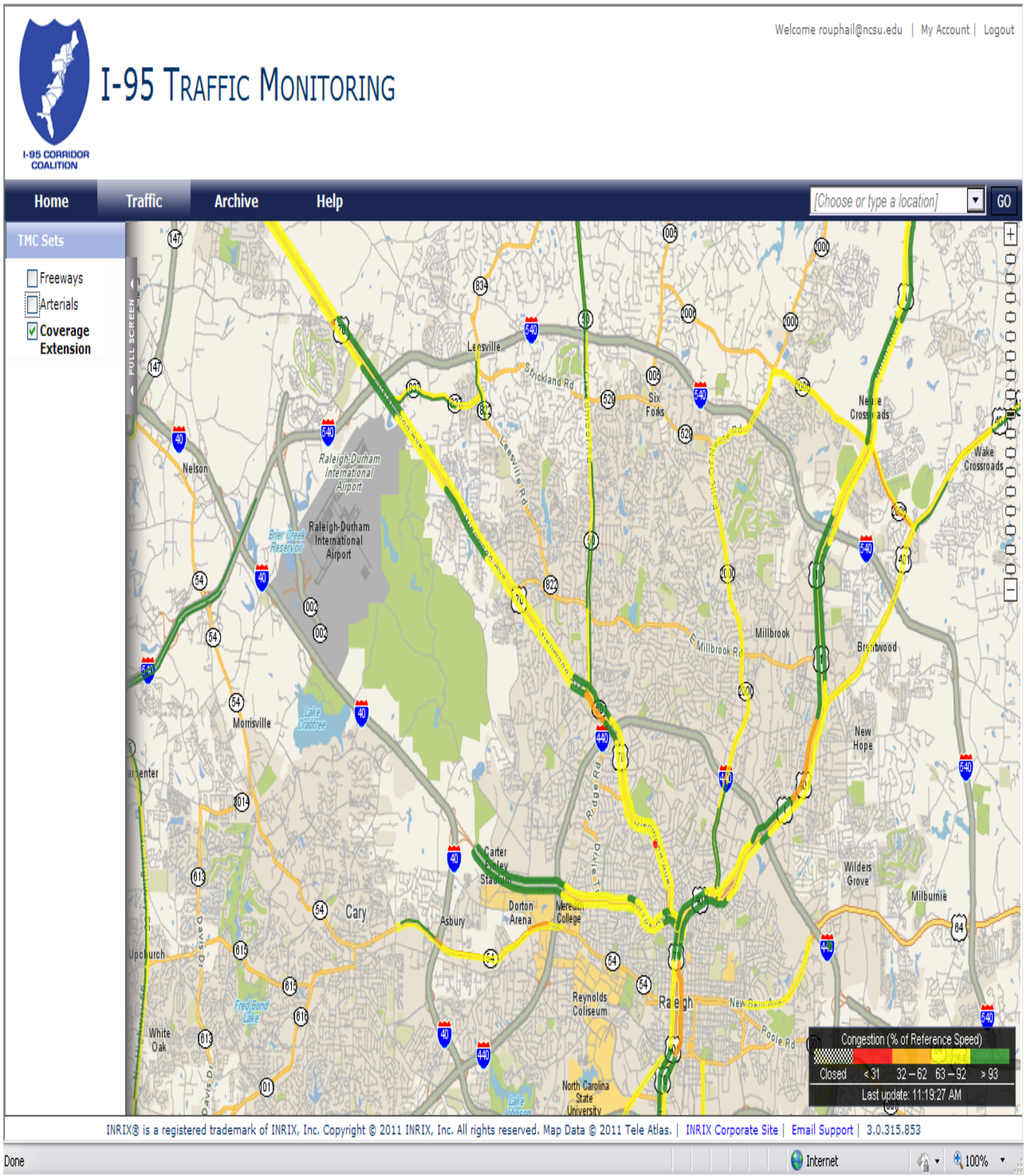

Figure A1 Traffic.com Coverage for the Research Triangle Area

Table A1 Traffic.com Sensor information – I540

	Direction	Sensor ID	Location	# of lanes
540-1	both	72720	1.0 Mile East of Slater Rd	4
540-2-east	east	72719	0.17 Mile West of Globe Rd	5
540-2-west	west	72718	0.17 Mile West of Globe Rd	5
540-3-east	East	72716	0.79 Mile West of Glenwood Ave	3
540-3-west	west	72717	0.79 Mile West of Glenwood Ave	5
540-4-east	east	72714	1.87 Mile West of Leesville Rd	5
540-4-west	west	72715	1.87 Mile West of Leesville Rd	3
540-5	both	72713	0.68 Mile West of Leesville Rd	3
540-6	both	72712	0.54 Mile West of Ray Rd	3
540-7	both	72711	0.79 Mile West of SR-50	3
540-8	both	72710	0.05 Mile West of Chander Dr	3
540-9-east	east	72709	0.28 Mile East of Six Forks Rd	4
540-9-west	west	72708	0.28 Mile East of Six Forks Rd	4

Table A2 Traffic.com Sensor information – I40 & Wade ave

	Direction	Sensor ID	Location	# of lanes
40-1-east	east	72678	0.18 Mile West of Davis Dr	4
40-1-west	west	76267	0.18 Mile West of Davis Dr	4
40-2	both	76997	0.64 Mile West of Page Rd	4
40-3-east	east	72676	1.79 Mile West of Airport Blvd	5
40-3-west	west	72677	1.79 Mile West of Airport Blvd	5
40-4	both	72675	0.39 Mile North of Airport Blvd	4

Table A2 Continued

40-5-east	east	72673	0.22 Mile North of Aviation Pkwy	5
40-5-west	west	72674	0.22 Mile North of Aviation Pkwy	5
40-6	both	72672	0.08 Mile North of Old Reedy Creek Rd	4
40-7	both	72671	1.37 Mile West of Trenton Rd	4
40-8	both	72670	0.08 Mile West of Trenton Rd	4
WAD-1-east	east	72723	0.22 Mile West of Edwards Mill Rd	3
WAD-1-west	west	72724	0.22 Mile West of Edwards Mill Rd	3

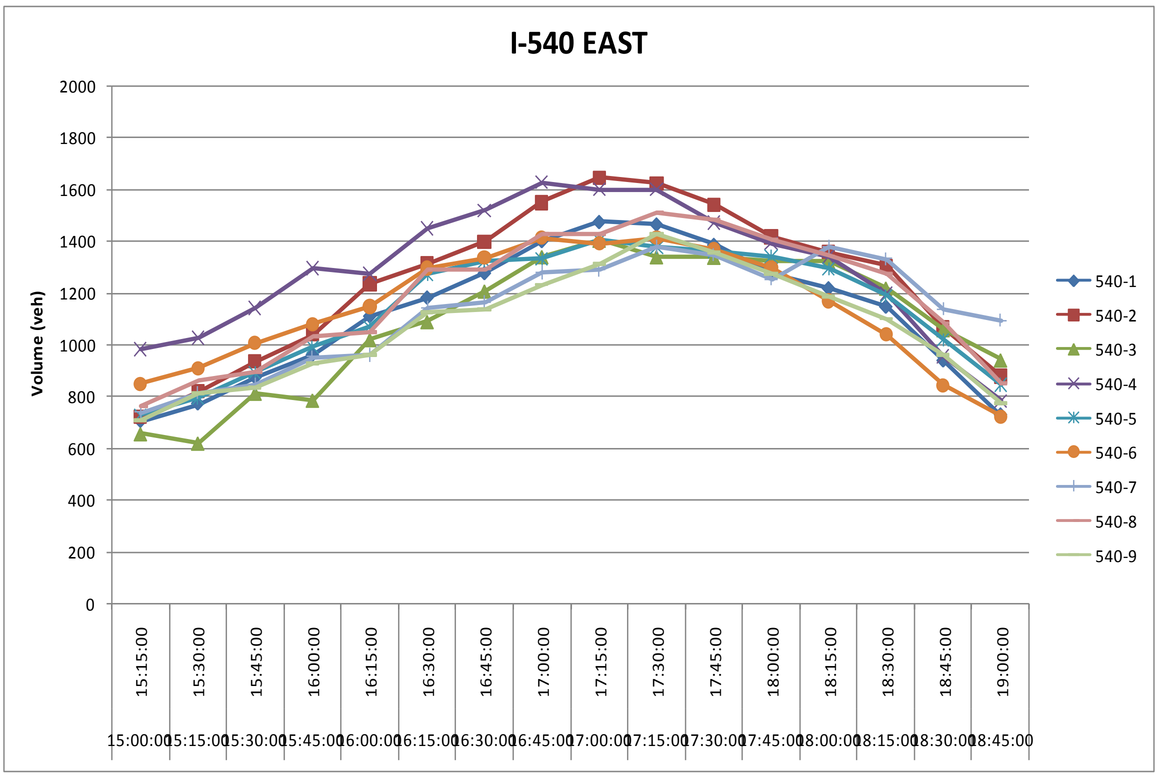

Figure A2 Traffic Volume for I-540 East for Time period from 15:15 to 19:00

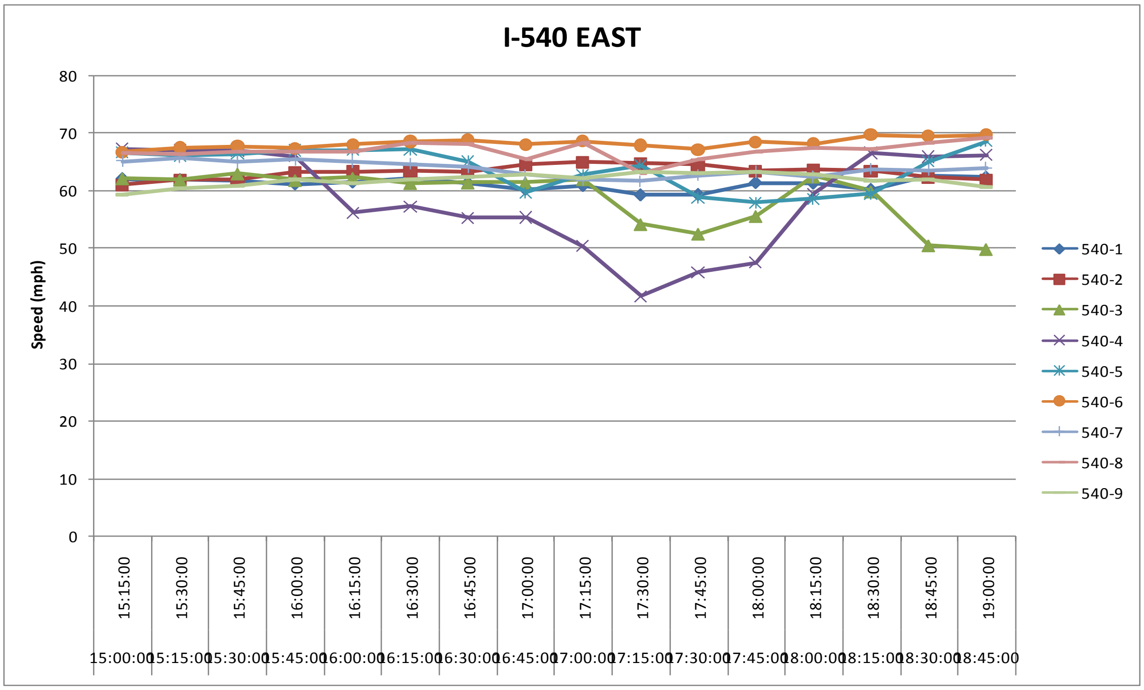

Figure A3 Traffic Speed for I-540 East for Time period from 15:15 to 19:00

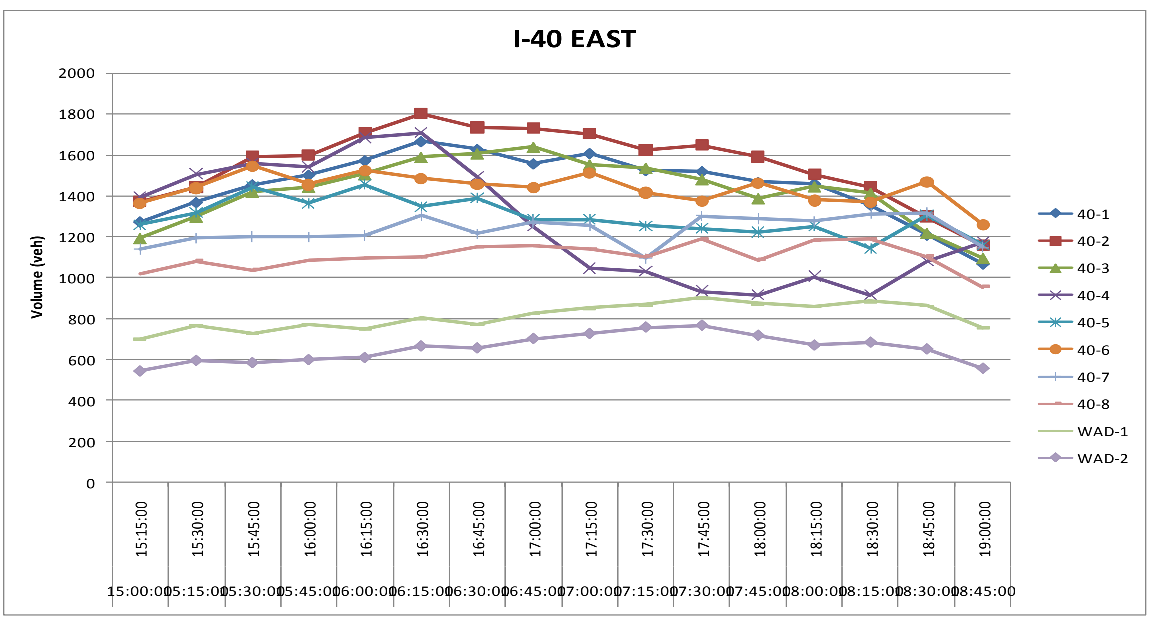

Figure A4 Traffic Volume for I-40 East for Time period from 15:15 to 19:00

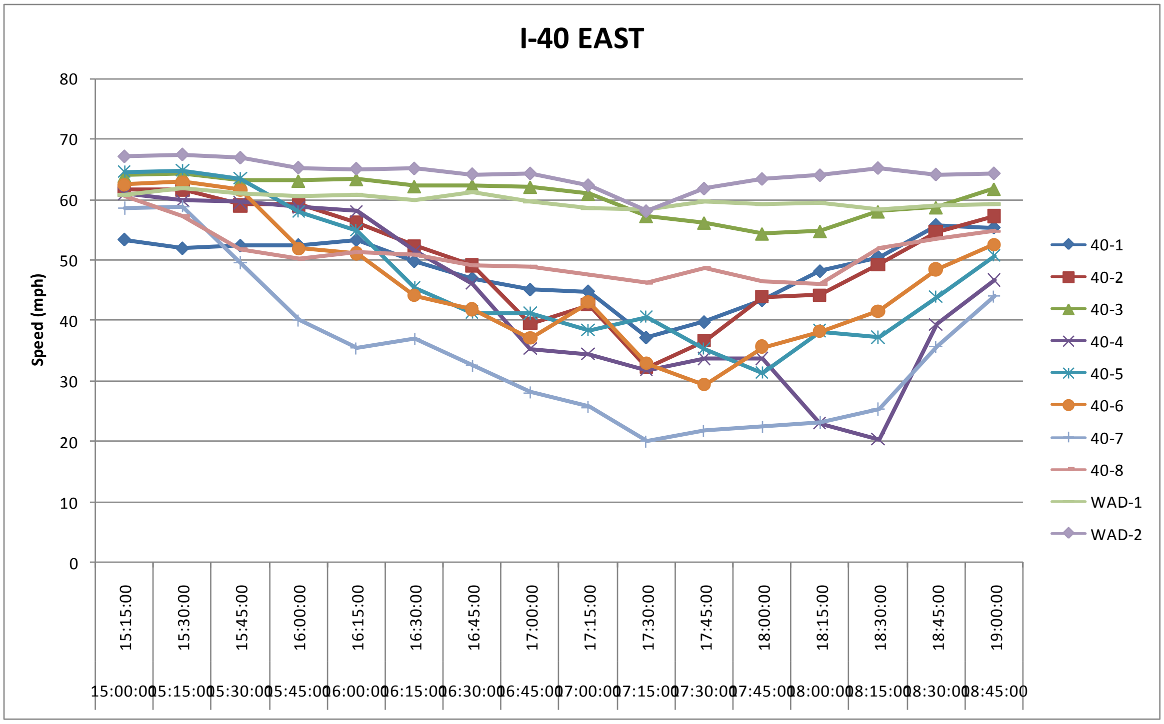

Figure A5 Traffic Volume for I-40 East for Time period from 15:15 to 19:00

Appendix B: API Code

```
from AAPI import *

filePath="c:/ HassanScript/"

def AAPILoad():

	AKIPrintString( "AAPILoad" )

	return 0

def AAPIInit():

	global f

	AKIPrintString( "hola" )

	f=open(filePath+'Output.txt','w')

	return 0

def AAPIManage(time, timeSta, timTrans, SimStep):

	global fs

	nba = AKIInfNetNbSectionsANG()

	for i in range(nba):

		id = AKIInfNetGetSectionANGId(i)
```

```
        nb = AKIVehStateGetNbVehiclesSection(id,True)
        for j in range(nb):
                infVeh = AKIVehStateGetVehicleInfSection(id,j)
                string = str(time)+"\tVehicle\t" + str(infVeh.idVeh)
                string=string + "\tSection\t" + str(infVeh.idSection)
                string=string + "\tLane\t" + str(infVeh.numberLane)
                string= string + "\tCurrentPos\t" + str(infVeh.CurrentPos)
                string=string + "\tCurrentSpeed\t" + str(infVeh.CurrentSpeed)
                string = string + "\n"
                f.write(string)
                f.flush()
nbj = AKIInfNetNbJunctions()
for i in range(nbj):
        id = AKIInfNetGetJunctionId(i)
        nb = AKIVehStateGetNbVehiclesJunction(id)
        for j in range(nb):
```

```
                    infVeh = AKIVehStateGetVehicleInfJunction(id,j)
                    string = str(time)+"\tVehicle\t" + str(infVeh.idVeh)
                    string =string + "\tNode\t"+ str(infVeh.idJunction)
                    string= string + "\tFrom\t" + str(infVeh.idSectionFrom)
                    string= string + "\tTo\t" + str(infVeh.idSectionTo)
                    string= string + "\tCurrentPos\t" + str(infVeh.CurrentPos)
                    string= string + "\tCurrentSpeed\t" + str(infVeh.CurrentSpeed)
                    string=string+"\n"
                    f.write(string)
                    f.flush()
        return 0
def AAPIPostManage(time, timeSta, timeTrans, acycle):
        return 0
def AAPIFinish():
        global f
```

```python
    AKIPrintString( "AAPIFinish" )

    f.close()

    return 0

def AAPIUnLoad():

    AKIPrintString( "AAPIUnLoad" )

    return 0

def AAPIPreRouteChoiceCalculation(time, timeSta):

    AKIPrintString( "AAPIPreRouteChoiceCalculation" )

    return 0
```