

Field Evaluation Methodology for Quantifying Network-Wide Efficiency, Energy, Emission, and Safety Impacts of Operational-Level Transportation Projects

Heung Gweon Sin

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Hesham Rakha, Chair

John Collura

Antonio A. Trani

François Dion

Dusan Teodorovic

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(ABSTRACT)

This thesis presents a proposed methodology for the field evaluation of the efficiency, energy, environmental, and safety impacts of traffic-flow improvement projects. The methodology utilizes Global Positioning System (GPS) second-by-second speed measurements using fairly inexpensive GPS units to quantify the impacts of traffic-flow improvement projects on the efficiency, energy, and safety of a transportation network. It should be noted that the proposed methodology is incapable of isolating the effects of induced demand and is not suitable for estimating long-term impacts of such projects that involve changes in land-use. Instead, the proposed methodology can quantify changes in traffic behavior and changes in travel demand.

This thesis, also, investigates the ability of various data smoothing techniques to remove such erroneous data without significantly altering the underlying vehicle speed profile. Several smoothing techniques are then applied to the acceleration profile, including data trimming, Simple Exponential smoothing, Double Exponential smoothing, Epanechnikov Kernel smoothing, Robust Kernel smoothing, and Robust Simple Exponential Smoothing. The results of the analysis indicate that the application of Robust smoothing (Kernel of Exponential) to vehicle acceleration levels, combined with a technique to minimize the difference between the integral of the raw and smoothed acceleration profiles, removes invalid GPS data without significantly altering the underlying measured speed profile

The methodology has been successfully applied to two case studies provided insights as to the potential benefits of coordinating traffic signals across jurisdictional boundaries. More importantly two case studies demonstrate the feasibility of using GPS second-by-second speed measurements for the evaluation of operational-level traffic flow improvement projects. To identify any statistically significant differences in traffic demand along two case study corridors before and after traffic signal condition, tube counts and turning counts were collected and analyzed using ANOVA technique. The ANOVA results of turning volume counts indicated that there is no statistically significant difference in turning volumes between the before and after conditions. Furthermore, the ANOVA results of tube counts also confirmed that there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions.

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Chapter 1: INTRODUCTION

1.1 BACKGROUND

Traffic in the United States has increased by 30 percent over the past decade and is expected to increase by an additional 50 percent over the next decade (www.fhwa.dot.gov). In response to the extensive increase in traffic congestion, alternative congestion mitigation approaches have been implemented in the United States. These congestion mitigation approaches can be generally categorized as either supply enhancement or demand reduction approaches.

Initial supply enhancement projects included the construction of new roadways and the enhancement of existing roadways. However, these highway construction alternatives are extremely expensive and thus generally economically infeasible. Consequently, the transportation community has investigated alternative operational-level traffic improvement projects including, Intelligent Transportation System (ITS) applications. Advanced Traveler Information Systems (ATISs) and Advanced Traffic Management Systems (ATMSs) are two ITS alternatives that are commonly applied in the field.

In 1996 the Operation Time Saver became a major ITS deployment goal with the objective of reducing average travel time in urban areas by 15 percent. In order to achieve this goal, several ITS field operational tests were applied to evaluate the potential benefits of ITS. In addition, the Metropolitan Model Deployment Initiative (MMDI) was launched and four sites were selected for the field evaluation of ITS integration. Within this initiative, the City of Phoenix, San Antonio, Seattle, and New York City were selected for the deployment of ITS. The projects considered at each site were selected to serve as showcases for the newest wave of ITS deployments and as first steps toward a long-range goal of building a viable and efficient transportation infrastructure across the United States.

Less common ITS alternatives comprise demand reduction approaches, which include different forms of road pricing, toll roads, and car-pooling. These road-pricing alternatives are less common because in many cases they are politically challenging.

1.2 PROBLEM DEFINITION

The evaluation of the efficiency, energy, environmental, and safety impacts of operational-level projects is by no means trivial and the evaluation tools that are currently available are far from being mature. For example, transportation planners are currently attempting to include the evaluation of ITS applications within the traditional four-step planning process. Software including ITS Deployment Analysis System (IDAS) and Transportation Analysis Simulation System (TRANSIMS) are the first attempts at addressing this issue. IDAS is a sketch-planning analysis tool that estimates the impact and benefit/cost resulting from the deployment of ITS components. And TRANSIMS is a set of new transportation and air quality analysis and forecasting procedures. However, these approaches are typically very aggregate as in the case of IDAS or require extensive data collection and are not fully developed as in the case of TRANSIMS.

Furthermore, the current state-of-the-art energy, emission and safety models utilize average speed to compute the various Measures of Effectiveness (MOEs). These approaches ignore the fact that different instantaneous speed and acceleration profiles could produce the same average speed and result in various fuel consumption and emission levels (Rakha *et al.*, 1999).

Finally, the literature indicates that the field evaluation of the energy, environmental, and safety impacts of ITS is far from being developed. For example, environmentalists have made the claim that although traffic-improvement projects can result in immediate environmental benefits, these benefits are reduced over time as a result of temporal (changes in departure times) and spatial (diversion) shifts in traffic. This issue is referred to as induced demand in the literature. Most operational-level simulation models and field approaches are incapable of capturing these factors.

1.3 THESIS OBJECTIVE

The objective of this thesis is to develop a field evaluation methodology for quantifying network-wide efficiency, energy, emission, and safety impacts of operational-level transportation projects. Specifically, the approach considers traffic diversion, peak spreading/coiling, induced/foregone demand, and changes in instantaneous vehicle speed and acceleration levels.

The thesis demonstrates the feasibility of the approach to two field applications in Phoenix that were part of the MMDI. It should be noted that the application of the proposed approach is not restricted to the projects that are presented in the thesis. Instead, these applications demonstrate the feasibility of the proposed approach.

1.4 THESIS CONTRIBUTIONS

The thesis develops a cost-effective approach that can be utilized for the field evaluation of Intelligent Transportation System applications. The approach combines the use of tube counts, turning movement counts, and second-by-second floating car speed measurements utilizing fairly inexpensive Global Positioning System (GPS) technology (approximate cost of \$500). Furthermore, this approach is the first attempt to use GPS data for the evaluation of operational – level transportation projects.

Specifically, depending on the level of effort, the field evaluation of the efficiency, energy, environmental, and safety impacts of operational-level projects can be systematically quantified at a relatively low cost (as low as \$20k).

1.5 THESIS APPROACH AND LAYOUT

Given that the example applications in Chapters 5 and 6 involved traffic signal coordination, Chapter 2 first describes the different types of fixed-time traffic signal control and the state-of-the-art software. Subsequently, this chapter introduces the current state-of-the-art in assessing fixed-demand impacts and the associated changes in energy, emissions, and crash risk. Then, the concept of induced demand and the current-state-of-the-art tools for quantifying these impacts are described. Next, this chapter describes the current state-of-the-art modeling tools. Finally, the conclusions of this chapter are presented.

Chapter 3 presents a methodology for the field evaluation of efficiency, energy, emission and safety impacts of operational-level projects. This methodology considers induced travel demand & changes in vehicle speed & acceleration profiles. The methodology also addresses the accuracy issues that are related to GPS data.

As with any field data collection system, the accuracy of the parameters estimated greatly depends on the quality of collected GPS data. Therefore, prior to applications, Chapter 4 describes data smoothing techniques in detail. This chapter first presents how fuel consumption and vehicle emissions can be estimated from typical GPS data. A case study is then introduced in the following section. Subsequently, this chapter presents the impacts that erroneous GPS measurements can have on fuel consumption and vehicle emission estimates. Next, this chapter evaluates various data smoothing techniques that can be used to reduce the impacts of erroneous measurements. Finally, the summary and general conclusions of this chapter are presented.

Chapter 5 describes two example applications of the proposed methodology without considering the issue of induced travel demand. These example applications involve two signalized corridors in the Greater Phoenix Area.

Chapter 6 investigates the issue of quantifying change in traffic using ANOVA technique based on mid-link counts and turning volume counts. Finally, Chapter 7 presents the conclusions of the thesis and recommendations for further research.

Chapter 2: STATE-OF-PRACTICE IN OPERATIONAL-LEVEL PROJECT EVALUATIONS

The impact of operational-level projects on the efficiency, energy consumption, emissions, and crash risk of a transportation network can be viewed as a two-stage process, which is best described through an example illustration. For example, assume that the traffic signals along an arterial corridor are optimized resulting in reductions in delay along the corridor. The first stage of the two-stage process involves changes in the speed profiles of the vehicles traversing the corridor as a result of the signal timing changes. These changes in vehicle speed profiles in turn can result in changes in vehicle delay, stops, energy consumption, emissions, and crash risk. If the improvements in traffic conditions along the corridor are significant then spatial and temporal changes in traffic demand may occur. This is the second stage of the two-stage process and typically takes longer to materialize and requires significant improvements along the corridor for it to occur. Specifically, this stage might involve traffic diversion from other corridors to the corridor under consideration, or changes in driver departure times as a result of the improved traffic conditions along the corridor, or even the initiation of trips that did not exist prior to the signal optimization. The second stage is typically termed induced demand because of the additional demand that travels along the corridor under consideration. A more detailed description of the two-stage process is presented in Chapter 3. It should be noted that the quantification of the changes in travel behavior using such a two-stage process and its associated impact on the network-wide Measures of Effectiveness (MOEs) is by no means trivial and is far from attaining maturity, as will be demonstrated in this chapter.

In order to provide contexts for describing the current state-of-the-art in operational-level project evaluation, the example of signal coordination is utilized throughout the thesis. Consequently, this chapter first describes the different types of fixed-time traffic signal control and the state-of-the-art software that are commercially available for generating signal timing plans. Next, this chapter describes the current state-of-the-art in assessing fixed-demand impacts (first stage) and the associated changes in energy, emissions, and crash risk. Subsequently, the concept of induced demand is introduced and the current-state-of-the-art tools for quantifying these impacts are described. Next, this chapter describes the current state-of-the-art modeling tools that attempt

to quantify the efficiency, energy, environmental and safety impacts of operational-level projects, including Intelligent Transportation Systems (ITS). However, as will be demonstrated, the majority of the evaluation efforts involve traffic modeling as opposed to field evaluations because of the complexity of the problem. Finally, the conclusions of this chapter are presented prior to describing the proposed methodology in Chapter 3.

2.1 FIXED-TIME TRAFFIC SIGNAL CONTROL

2.1.1 BACKGROUND

Traffic congestion at signalized intersections in urban areas costs drivers millions of dollars in terms of lost time and in added fuel consumption and vehicle emissions due to traffic delay. In this section, the various types of traffic signal control strategies are reviewed briefly. Although there are several methods of controlling traffic at intersections, only traffic signal control methods are discussed because this type of intersection control constitutes the examples that were evaluated in the field.

Prior to discussing traffic signal control systems, a number of terms that are commonly used in traffic signal coordination are described. These terms include:

- **Cycle length:** the time period in seconds required for one complete sequence of signal indications. The cycle length is divided into a number of phases that are in turn divided into intervals such as red, green and amber intervals. The computation of interval duration is based on traffic demand and /or other parameters.
- **Phase split:** assigning green interval, the amber interval, and the red interval to minimize the potential hazards arising from the conflicts of vehicular and pedestrian movements, while maintaining the efficiency of flow through the intersection (Papacostas *et al.*, 1993).
- **Offset:** the time interval between the beginning of green phase at the intersection and the beginning of the corresponding same phase at the next intersection (Garber and Hoel, 1996).

2.1.2 ISOLATED SIGNAL OPERATIONS

According to their flexibility, isolated traffic signal control methods can be classified into three major groups: (1) pretimed; (2) semiactuated; (3) or fully actuated. Pretimed signal control is also known as fixed-time control. In pretimed control the cycle length and phase split are preset and remain unchanged during a given control period. Semiactuated signal control, however, utilizes a mix of pretimed and actuated signal control principles to control traffic at an intersection. In this type of control, detectors are typically installed on minor road approaches to adjust the green phase duration serving these approaches to the approach demand. Usually, green duration is allowed to vary between a minimum and maximum duration with the green extended by “n” seconds each time a new approaching vehicle is detected within a predefined interval. In the absence of demand, any unused green is then given to the main street. In the situation where two major roadways intersect, fully actuated signal control is preferable over semiactuated control as such a system has added capability to handle traffic fluctuations across all approaches. Such a control method is the most appropriate form of intersection control where the signal control system is not coordinated because it controls the timing and sequencing of the intersection according to observed traffic conditions and does not necessarily provide the same sequence every cycle (Orcutt, 1993).

2.1.3 COORDINATED SIGNAL OPERATIONS

An alternative approach to classifying traffic signal control involves classifying the control based on whether the control considers adjacent signals in computing the signal timings. If the control only considers the intersection in isolation it is termed isolated signal control, alternatively if it considers the adjacent signals in computing signal timings it is termed coordinated signal control.

The concept of traffic signal coordination attempts to ensure the progression of platoons of vehicles with minimum signal interruption using a common cycle length. However, it is not necessary to have the same duration of green, amber, and red within the common cycle length (Papacostas *et al.*, 1993).

The example application that is presented in Chapter 5 uses fixed-time traffic signal coordination as a basis for applying the proposed methodology.

2.1.4 STATE-OF-THE-ART TRAFFIC SIGNAL OPTIMIZATION SOFTWARE

Signal coordination software can be classified into two categories: on-line and off-line software. One of the most well known off-line software is TRANSYT-7F. This software is characterized as macroscopic software because it optimizes signal timings based on platoons of vehicles rather than on individual vehicles. It typically optimizes a Performance Index (PI) that is a linear combination of vehicle stops and delays, using a hill-climbing technique. The PI is defined as follows:

$$PI = \sum_{i=1}^n d_i + kS_i \quad (2.1)$$

Where:

d_i = total delay at intersection i

S_i = total number of stops at intersection i

n = number of intersections in the network

k = user-defined parameter specifying the importance of stops relative to delays

The inputs to the TRANSYT-7F model are traffic volumes, saturation flow rates, average link lengths and speeds, signal phasing, minimum intervals, and cycle lengths. With these inputs, TRANSYT-7F produces average delays, intersection and network-wide PIs, and fuel consumption and emission estimates at the end of each run. During each run, TRANSYT-7F computes the duration of greens and the progression offsets to minimize PIs (Papacostas *et al.*, 1993).

The Progression Analysis and Signal System Evaluation Routine (PASSER) program, another well-known off-line signal optimization software, is a diamond interchange signal optimization program developed for off-line processing and analysis purposes at the Texas Transportation Institute (TTI) in College Station, Texas. The latest version of the PASSER series, PASSER IV can be used for the evaluation of existing or proposed signalization strategies, the determination of signalization strategies which minimize the average delay, and the computation of signal

timing plans for individual interchanges or several interconnected interchanges. In addition, PASSER IV can be utilized for single arterials and multi-arterial (open or closed) network analysis. The model computes green splits using Webster's method and then simultaneously determines cycle length, offsets and phasing sequences that maximize progression bandwidth on all directions along each arterial in the defined network. The Measures-of-Effectiveness (MOE) of PASSER IV are phase intervals, offsets, splits, approach delays, volume-to-capacity ratios, level of service, stops, queue lengths, fuel consumption, and vehicular emissions (<http://ttisoftware.tamu.edu/passser4.htm>).

Recently, Synchro, a Window based software for signal optimization, has become widely used in traffic signal analysis and is generally similar in principle to PASSER II. The Synchro model optimizes phase split, cycle lengths, & offsets in addition to modeling actuated signals. The model also includes a simulation software (SimTraffic) for the evaluation of signal timings.

The example application that is presented in Chapter 5 involves the optimization of a signalized arterial using the Synchro software.

2.2 EVALUATION OF FIXED-DEMAND IMPACTS

2.2.1 STATE-OF-THE-ART ENERGY AND EMISSION MODELING

The majority of evaluation studies of fixed-demand impacts of operational-level projects have been achieved in terms of level of service (LOS). However, as urban population is growing, many research efforts are currently focusing on environmental impacts of transportation projects.

Most metropolitan cities in the United States are suffering from severe air pollution caused by vehicle emissions, creating concerns among transportation professionals, and the general public. Once a gasoline engine starts, it discharges carbon monoxide (CO), hydrocarbons (HC) and oxides of nitrogen (NO_x) which are three main types of emissions usually considered in vehicle emission modeling. Among these emissions, HC and NO_x, when they are combined with other chemicals, form ozone and other damaging oxidants in the presence of sunlight. In 1971, the Environmental Protection Agency (EPA) issued the national ambient standards for several air pollutants, which resulted in more attention being paid to the monitoring and modeling of air-

quality impacts of transportation systems, as well as in the integration of air-quality consideration into the transportation-planning process. These standards, however, did not successfully reduce air pollution problems, which brought the enactment of the 1990 Amendments to the Clean Air Act that imposed more stringent requirements for geographical areas that are under pollution standards (Papacostas *et al.*, 1993).

Recently, ITS has emerged as one promising solution for the air pollution problem. Deployment of ITS has notably contributed to the improvement of the transportation system in terms of vehicle fuel consumption and emissions. Consequently, many studies on the modeling of fuel consumption and vehicle emissions, as part of Intelligent Vehicle Highway Systems (IVHS)¹, were conducted to estimate the environmental impacts associated with these projects, as demonstrated in Table 2.1 that presents the results of several IVHS operational tests in the United States. The IVHS user services involve dynamic signal coordination, real-time information on traffic and travel time, and real-time remote transportation data collection via probe vehicles, call boxes, and emission sensors.

For IVHS operational tests, travel times, speeds, stops, and other traffic characteristics are obtained from various sources such as floating cars, instrumented vehicles, loop detectors, video surveillance systems, and automated data via traffic control centers. These traffic data are utilized to conduct statistical analyses of impacts and to calibrate traffic simulation models such as TRANSYT-7F, INTEGRATION, TRAF-NETSIM, and others (Little *et al.*, 1994).

In the case of emissions modeling, most of the projects reported in Table 2.1 used MOBILE, the vehicle emissions model developed by the EPA, but two of them, GENESIS and TravTek, utilized the emission models within the INTEGRATION 1.5 software. The INTEGRATION 2.20 traffic simulation software is a highly dynamic microscopic model that considers traffic as individual entities, and that combines traffic simulation and traffic assignment into a single simulation process. However, the INTEGRATION 1.5 software utilized for the TravTek evaluation was a mesoscopic model.

¹ IVHS is an old name for ITS.

TABLE 2.1 IVHS OPERATIONAL TESTS WITH ENVIRONMENTAL OBJECTIVES IN UNITED STATES

(Source: Little *et al.*, 1994)

Project Title (Location)	IVHS User Services	Major Goals	Data Collection and Analysis	
			Emissions	Fuel Consumption
ATSAC (Los Angeles, CA)	Dynamic signal coordination	<ul style="list-style-type: none"> • Reduce congestion • Improve travel times • Reduce air pollution 	Model HC, CO using MOBILE1	Model fuel consumption with TRANSYT-7F
GUIDESTAR or GENESIS (Minneapolis- St. Paul, MN)	Real-time information on travel times and transit through personal communication devices	<ul style="list-style-type: none"> • Reduce congestion • Increase mobility • Improve environmental quality, energy efficiency • Increase transit use 	Model HC, NOx, and CO using INTEGRATION	Model fuel consumption using INTEGRATION
SmarTraveler (Boston, MA)	Real-time information on traffic and transit via telephone service	<ul style="list-style-type: none"> • Increase mobility and transit ridership • Improve safety, air quality and energy efficiency 	Calculated impacts on emissions based on changes in VMT and average speed using MOBILE5a	Not calculated
TravTek (Orlando, FL)	Dynamic route guidance	<ul style="list-style-type: none"> • Assist drivers • Reduce delay, congestion, accident risk, fuel consumption and emissions • Evaluate display alternatives 	Model HC, CO, and NOx in terms of grams per liter of fuel consumption model using INTEGRATION	Empirical measurement of TravTek vehicle (1992 Olds Toronados) extrapolated to fleet with EPA data, and then fuel consumption rates are estimated by INTEGRATION
Planning and Modeling Data Environment (Riverside and San Bernardino, Co., CA)	Real-time remote transportation data collection via probe vehicles, call boxes, and emission sensors	<ul style="list-style-type: none"> • Demonstrate real-time data collection • Improve transportation and air quality planning 	Empirical measurements to ascertain number of high emitters.	Unknown

The model estimated various measures of performance such as travel time, travel distance, queue sizes and the expected number of stops per vehicle. Moreover, the individual vehicle's fuel

consumption and emissions of HC, CO and NO_x were estimated (Van Aerde *et al.*, 1996). For fuel consumption estimation of these three projects, TRANSYT-7F was utilized only in the ATSAC project, and the INTEGRATION software was utilized for the GENESIS and TravTek projects.

2.2.1.1 Emission Models

Vehicle emissions are dependent on numerous factors. Among the most important factors are temperature, altitude, fuel type, road geometry, vehicle load, speed, and acceleration. Consequently, the evaluation of the environmental impacts of vehicle emissions is a more challenging procedure when compared to other measures of effectiveness, including vehicle delay, stops, and LOS.

In general, the vehicle load appears to be one of the most important factors, but is not captured. In order to calculate total pollutants, emission models typically use three primary measures: average speed, vehicle miles traveled, and basic emission rates (U.S. DOT, 1995).

Two of the most popular emission models that are currently being used in the United States are the Environmental Protection Agency's (EPA's) MOBILE model and the California Air Resources Board's (CARB's) EMFAC model.

These models require several inputs such as vehicle type, age, vehicle average speed, ambient temperature and vehicle operating mode. These models yield specific emission rates that are multiplied by vehicle miles-traveled, number of trips and vehicle-hours traveled to estimate total emission levels. Basically, the MOBILE and the EMFAC models use average speed as a sole explanatory variable for estimating vehicle emissions, consequently ignoring the distribution of speeds and accelerations that occur during a trip. This variability is dependent on the type of facility and the level of congestion. In addition, both models do not represent current, real world driving conditions, as both are based on vehicle tests that considered only a limited number of driving cycles that are now outdated (Ahn, 1999). To overcome these limitations, Ahn *et al.* (1999) developed microscopic fuel consumption and emission models based on data collected at the Oak Ridge National Lab (ORNL). The regression models are 3rd order regression equations

that were fitted to data that were collected at the ORNL data. Equation 2.2 illustrates the specific form of the model that was developed.

$$F = a + bA + cA^2 + dA^3 + eS + fS^2 + gS^3 + hAS + iAS^2 + jAS^3 + kA^2S + lA^2S^2 + mA^2S^3 + nA^3S + oA^3S^2 + pA^3S^3 \quad (2.2)$$

Where:

F: Fuel consumption or emission rate (l/h or mg/s)

a: intercept

b, c, ..., p: coefficients

A: acceleration (m/s²)

S: speed (m/s)

This microscopic model utilizes second-by-second speed and acceleration data to estimate fuel consumption and vehicle emissions. The following are some of the conclusions drawn from the development of the model:

- The regression model's estimated values have correlation coefficients ranging from 0.85-0.95 when compared with actual CO, NO_x, and HC emissions.
- For the prediction of fuel consumption, the model shows very good match with actual fuel data. Specifically, the correlation coefficient between actual and estimated values is above 0.99.
- The model does not consider start-up emissions and the effect of ambient temperature on fuel and emission estimates. This limitation comes in part from limitation associated with the data set used to develop the model.

These microscopic models are incorporated within the proposed methodology, as described in Chapter 3.

2.2.1.2 Fuel Consumption Models

Fuel consumption models compute the amount of fuel consumed by vehicles based on a vehicle's engine design, emission control equipment, fuel type, and driving condition. The

current state-of-practice fuel consumption models use the average speed as a sole explanatory variable. However, since numerous research suggest that models based on VMT or average speed do not produce accurate fuel consumption rates, new models are now being developed to consider other important factors such as and road geometry, vehicle class and the operating characteristics of a vehicle (U.S. DOT, 1995).

Fuel consumption models can be categorized into two major types: Instantaneous Fuel Consumption models and Modal Fuel Consumption models. The former are usually applied to small size transportation analysis projects such as the analysis of isolated intersections or of parts of larger networks, and usually require second-by-second vehicle characteristics in order to compute accurate rates of instantaneous acceleration. The modal fuel consumption models, however, estimate emissions by considering three modes of driving conditions, namely: travel at constant speed (cruising), full or partial stop-and-gos from a constant speed, and stopped time or time spent idling. These models are easy to use and understand, however they do not consider any differences in driver's behavior (Ahn *et al.*, 1999).

2.2.2 GPS USE IN PROBE VEHICLE DATA COLLECTION TECHNIQUES

Recently, the concept of Global Positioning System (GPS) has received significant attention from transportation engineers and planners. In addition, GPS technology is currently being utilized in many other fields such as military, commercial, as well as personal use. The transportation research topics using GPS technology range from origin-destination travel analysis to highway inventory management.

In this thesis, GPS technology is utilized to measure second-by-second speed levels. These instantaneous speed measurements are used to compute vehicle delays, the number of vehicle stops, vehicle fuel consumption, vehicle emissions, and vehicle crash risk. A more detailed description of the methodology is described in Chapter 3.

Since this thesis utilizes GPS technology for the evaluation of operational-level traffic improvement projects, this section presents not only various probe vehicle techniques but also a

list of GPS products available at the time this thesis was written. Moreover, several GPS applications in the transportation field are introduced.

The probe vehicle technique is designed for collecting data in real-time and is utilized within intelligent transportation systems (ITS) for real-time traffic operations monitoring, incident detection, and route guidance applications (FHWA, 1998). In addition, many applications of this technique have recently been applied to the collection of travel time data. Table 2.2 shows the advantages and disadvantages of ITS probe vehicle systems for travel time data collection.

There are five ITS probe vehicle techniques:

- 1) Signpost-Based Automatic Vehicle Location (AVL),
- 2) Automatic Vehicle Identification (AVI),
- 3) Ground-Based Radio Navigation,
- 4) Cellular Geolocation, and
- 5) Global Positioning System (GPS).

TABLE 2.2 ADVANTAGES AND DISADVANTAGES OF ITS PROBE VEHICLE SYSTEMS FOR TRAVEL TIME DATA COLLECTION
(Source: FHWA, 1998)

Advantages	Disadvantages
Low cost per unit of data	High implementation cost
Continuous data collection	Fixed infrastructure constraints
Automated data collection	Requires skilled software designers
Data are in electronic format	Privacy issues
No disruption of traffic	Not good for small scale data collection

As shown in Table 2.3, among the five techniques, the GPS technology offers a low capital cost, a low installation cost, and a low data collection cost combined with high data accuracy. Based on comparison of ITS probe techniques in Table 2.2, GPS technology appears to provide the most economic approach for probe data collection. Consequently, this technology was incorporated within the proposed approach.

The GPS technology is described in further detail in the following sections, as it is central to the proposed approach.

TABLE 2.3 COMPARISON OF ITS PROBE VEHICLE TECHNIQUES
(Source: FHWA, 1998)

Technique	Costs				Data Accuracy
	Capital	Installation	Data Collection	Data Reduction	
Signpost-Based Automatic Vehicle Location (AVL)	High	High	Low	High	Low
Automatic Vehicle Identification (AVI)	High	High	Low	Low	High
Ground-Based Radio Navigation	Low	Low	Low	Low	Moderate
Cellular Geo-location	High	High	Low	Moderate	Low
Global Positioning System (GPS)	Low	Low	Low	Moderate	High

2.2.2.1 GPS Technology

The GPS is a satellite positional system managed by the U.S. military. This system is widely used for both military and civilian purposes requiring geographical positional information. Specifically, with specially coded satellite signals transmitted from the GPS, a GPS unit receives the signal and processes it to compute its position, speed and time. In general, various GPS products provide speed information based on changes in the receivers' position over time, satellite Doppler frequencies, or both (Dana, 2000).

As is the case with any data collection technology, GPS data include several sources of error. These sources of errors include Selective Availability (SA), Geometric Dilution Of Precision (GDOP), and a range of other errors including satellite's internal and external errors, receiver errors, atmospheric errors, and multipath errors as detailed in Table 2.4.

SA is a man-made error controlled by the U.S. Department of Defense. As shown in Table 2.4, this error downgrades GPS accuracy from 1 to 100 meters for real-time measurement. SA was known to be the biggest cause of GPS data errors until it was turned off in November 2000.

TABLE 2.4 SOURCES OF INACCURACY AND PROBLEMS
(Source: Javad Positioning Systems, 1998)

Sources		Problems	Comments	
Range Errors	Satellite Clock	<ul style="list-style-type: none"> One billionth of a second (one nanosecond) of inaccuracy in a satellite clock results in about 30 centimeters of error in measuring the distance to that satellite. For this reason, the satellites are equipped with very accurate (Cesium) atomic clocks. Even with the best efforts of the control centers in monitoring the behavior of each satellite clock, their errors cannot be precisely determined. 	With all efforts, a distance error of about one meter is inevitable.	
	Receiver Clock	Same problem as satellite clock.	Without any atomic clock, it is possible to minimize inaccuracy in distance measurements using at least four satellites.	
	Satellite Orbit Error	<ul style="list-style-type: none"> The accuracy of our computed position depends on the location of the satellites (the points of references). The predicted orbital information of satellites from several ground monitoring stations, includes a few meters of error that will create about another error in computing our position. 		
	Atmospheric Errors	Ionosphere (Upper layer of the atmosphere)	<ul style="list-style-type: none"> The speed of light, used in measuring distance, varies due to atmospheric conditions The ionosphere contains charged particles that slow down the code and speed up the carrier. The effects of the ionosphere can introduce measurement errors greater than 10 meters. 	<ul style="list-style-type: none"> Using a mathematical model for the effects of the ionosphere, error can be reduced by 50%. The dual frequency system practically remove the ionosphere effects.
		Troposphere (The lower level of the atmosphere)	<ul style="list-style-type: none"> Troposphere contains water vapors and has the effects of slowing down both code and carrier. Dual frequency receivers can not remove the effects of the troposphere. 	<ul style="list-style-type: none"> The effects of the troposphere can be removed by measuring its water vapor content, temperature and pressure, and applying a mathematical model that can compute the delay of the troposphere.
	Multipath	The direct satellite signal to the antenna of the receiver can be interfered by reflected signals from the ground and the objects near the antenna.	If the indirect path is longer than 10 meters than direct path, then the multipath effect can be reduced by signal processing techniques.	
	Receiver Errors	Receivers may cause some errors by themselves in measuring code or carrier.	High quality receivers provide better quality and only cause negligible errors.	
Geometric Dilution Of Precision (GDOP)	<ul style="list-style-type: none"> Unlike range errors, the error in computed position depends on the number and the geometry of the satellites used. The effect of the geometry of the satellites on the position error is called Geometric Dilution Of Precision, which can be interpreted as the ratio of the position error to the range error. 	<ul style="list-style-type: none"> If four satellites are used for locating our position, they take tetrahedron form by lines connecting the ground receiver to each satellite used. The larger the volume of the tetrahedron, the smaller the GDOP. The larger the number of satellites the smaller the GDOP. 		
Selective Availability (SA)	The US Department of Defense has introduced man-made errors to degrade the position accuracy of GPS to about 100 meters and this is called SA.	Military receivers are SA free and SA can be turned on and off by the GPS system administrators.		

However, SA errors can be reduced by using GPS receivers supporting differential correction. In this case, the accuracy of the measurement can be increased to 1 meter (Wolf *et al.*, 1999). Differential correction is achieved using a base station receiver and an antenna placed at a known position. Depending on the temporal lag associated with the differential correction, GPS data is either real-time differential GPS (rtDGPS) or post-processed differential GPS (ppGPS) data. Table 2.5 shows a list of sample GPS receivers together with their accuracy and price. The most expensive GPS equipment is the Ashtech Z 12, which has less than 1 m real-time differential accuracy, while the cheapest is the Garmin products with 3 to 10 m real-time differential accuracy.

Above all, the range in price and accuracy shown in Table 2.5 reinforces the need to determine the desired level of accuracy of data collected using GPS systems prior to starting the data collection effort.

TABLE 2.5 LIST OF GPS PRODUCTS
(Source: Wolf *et al.*, 1999)

Group	Product	Price	Accuracy			
			Autonomous		Differential	
			w/o SA	W SA	RtDGPS	PpDGPS
Low	Garmin 35 LP TrackPack	\$250	15 m	100 m	3-10 m	N/A
	Garmin GPS II Plus	\$250	15 m	100 m	1-5 m	N/A
Mid	GeoResearch Workhorse	\$1,795	25 m	100 m	1-5 m	< 1 m
	Garmin Survey II	\$3,060	15 m	100 m	3-10 m	1-5 m
High	Ashtech GG24 (G/GPS)	\$9,340	10 m	16 m	* 1 m	* 0.5 cm
	3S GNSS-300 (G/GPS)	\$8,900	10 m	10 m	*3-10 m	*1-5m
	Ashtech Z12 (GPS only)	\$22,000	15 m	100 m	< 1 m	0.5 cm

rtDGPS = real-time differentially corrected GPS

ppDGPS = postprocessed differentially corrected GPS

GLONASS, the Russian satellite system, data do not need correction since it provide positional data information without selective availability; these values are for the GPS differential correction.

2.2.2.2 GPS Applications within the Transportation Profession

As briefly mentioned in the beginning of this section, many transportation researchers have applied GPS technology to their research fields. This subsection provides more detailed examples of GPS applications within the transportation field.

For example, Draijer *et al.* (2000) performed a pilot study to analyze travel behavior utilizing GPS technology in combination with an electronic travel diary in the Netherlands. The study monitored all modes of travel rather than just motorized travel, and concluded that, although it is possible to analyze travel behaviors of all travel modes using GPS technology, the data quality differs between them.

In 1993, Guo *et al.* (1995) studied the application of GPS technology for estimating network travel times in Phoenix, Arizona. The authors combined GPS technology with Geographical Information Systems (GIS) and collected travel time information by running test vehicles on 800 miles of arterial roadways, as well as about 100 miles of freeway and high occupancy vehicle (HOV) lanes.

Hatipkarasulu *et al.* (2000) utilized GPS technology for the analysis of car-following behavior and developed a GPS methodology for the collection of car-following data under actual highway driving conditions that was not possible with traditional data collection techniques. In their work, the authors used two test vehicles to collect vehicle speed and location information, and then linearly referenced the information using GIS techniques. After that, the authors utilized the data to investigate the relationships between the relative position, speed and acceleration of the two test vehicles.

Quiroga and Bullock (1998), also, developed a methodology for travel time studies utilizing GPS and GIS technologies. It includes a data collection, a data reduction, and a data reporting procedures that have been implemented in Baton Rouge, Shreveport, and New Orleans in Louisiana.

The data collection procedure utilizes GPS technology to collect time, location, and speed for every one seconds with a GPS positional accuracy of about 2-3m. In the data reduction procedure, a data reduction application with a user-friendly interface within the GIS was developed to transform GPS travel time data into segment travel times and average speeds because a GPS receiver produces large records of data and the processing of GPS data requires significant time. Such huge numbers of GPS data was processed efficiently using the data reduction application.

As the last procedure, the data reporting procedure generates thematic maps and strip map tabular reports using GIS and database querying and reporting tools instead of drawing speed-distance or speed-time profiles along the corridor of interest. To generate tabular reports that include average speeds and average cumulative travel time for both directions of travel during AM peak, off peak, and PM peak, Microsoft Access report macros were used.

Furthermore, the authors included three analyses: segment lengths, sampling rates, and central tendency. The segment lengths analysis is to estimate required segment analysis using concepts from sampling theory that is originated from Nyquist's theorem. From the analysis, 0.2 mile long segment was recommended to characterize the effect of most physical discontinuities like signalized intersections, ramps, and interchanges.

The sampling rate analysis suggests 1-2s to minimize errors in obtaining segment speeds based on examination of the effect of using different time intervals between consecutive GPS data points on segment GPS data coverage and segment speed variability.

To find a good estimator of central tendency of segment speed, the central tendency analysis evaluated harmonic mean speeds and median speeds. According to the analysis, median speeds are very similar to harmonic speeds in most cases. Based on the analysis, the authors suggest the use of median speeds.

For traffic congestion studies, Taylor *et al.* (2000) developed an integrated GPS-GIS system that collects on-road traffic data from a probe vehicle that provides time, distance, location, speed,

fuel consumed, air pollutant emissions, engine performance, operating state variables, and delay and queuing data for every one seconds as shown in Table 2.6. The key element of the integrated system is the use of differential GPS data to determine vehicle locations over time. The positional accuracy the GPS receiver is about ± 5 m and its instantaneous speed accuracy is ± 2 km/h.

TABLE 2.6 VEHICLE PARAMETERS LOGGED IN REAL TIME BY THE PROBE VEHICLE
(Source: Taylor *et al.*, 2000)

Variable	Measurement units	Variable	Measurement units
Time	s	Air conditioning	on/off
Distance	m	Power/economy mode	on/off
Speed	km/h	Engine gear	gear (1-4)
Fuel Consumption	l	HC	ppm
Engine revolutions	rpm	NO _x	ppm
Manifold pressure	Pa	CO	ppm
Throttle position	ratio	CO ₂	ppm
Engine temperature	°C	O ₂	ppm
GPS position	Latitude and Longitude		

The approach was applied to a major road corridor in the southern part of the Adelaide metropolitan region in South Australia, which involved comparisons of travel conditions along two parallel routes in the corridor based on travel time, stopped time, mean journey speed, proportion stopped time, acceleration noise, mean velocity gradient, and congestion index of each data collection run.

2.2.3 STATE-OF-THE-ART SAFETY MODELING

In many traditional safety models, safety is presented as the number of accidents per million miles traveled. These models predict safety based on accident databases using factors such as VMT and speed (U.S. DOT, 1995).

Even though many safety models are based on speed and VMT, a safety model developed by Avgoustis *et al.* (2000) is particularly reviewed in this chapter as this model can be utilized to estimate the crash risk using second-by-second speed data.

There are three national accident databases including, the General Estimates System (GES), the Fatality Analysis Reporting System (FARS) and the Crashworthiness Data System (CDS). In

order to assist traffic safety professionals in identifying traffic safety problems and evaluating motor vehicle safety standards and highway safety initiatives, in 1975, the National Center for Statistics and Analysis (NCSA) developed an accident database called FARS which includes data on all fatal traffic crashes within the United States. In 1979, CDS was developed by the National Automotive Sampling System (NASS) and is used for the identification of potential preexisting traffic safety problems as well as for the evaluation of vehicle safety systems and designs. Finally, the General Estimates System (GES) database was developed in 1988 by the NCSA and is the largest and most complete accident database which includes three main files, including an Accident file, a Vehicle/Driver file, and a Person file.

The safety model developed by Avgoustis *et al.* (2000) is a regression model that was calibrated using the GES accident database. This model was developed and demonstrated how it could be utilized to evaluate the impacts of alternative transportation system implementations and in this case, traffic signal coordination. The model includes a main program and three subroutines: accident rate subroutine, accident damage subroutine, and accident injury subroutine.

The accident rate subroutine computes the accident risk for a specific facility. As indicated by Equation 2.3, this risk is defined by the free-speed of the facility in kilometers per hour, and two regression coefficients (c_1 and c_2).

$$p_1 = \exp(c_1 * spd + c_2) \tag{2.3}$$

Where:

p_1 = accident risk in crashes per million vehicle seconds,

spd = free-speed in kilometers per hour (20-70 mph),

c_1 and c_2 = regression coefficients.

Using Equations 2.4 to 2.7, the accident damage subroutine calculates four major damage levels (minor, moderate, major and no damage) based on the speed of a facility and a series of regression coefficient.

$$\text{Dam (1)} = c_1 + c_2 * S + c_3 * S^2 + c_4 * S^3 \quad (2.4)$$

$$\text{Dam (2)} = c_5 + c_6 * S + c_7 * S^2 + c_8 * S^3 \quad (2.5)$$

$$\text{Dam (3)} = c_9 + c_{10} * S + c_{11} * S^2 + c_{12} * S^3 \quad (2.6)$$

$$\text{Dam (4)} = c_{13} + c_{14} * S + c_{15} * S^2 + c_{16} * S^3 \quad (2.7)$$

Where:

Dam (1) = no damage crashes

Dam (2) = minor damage crashes

Dam (3) = moderate damage crashes

Dam (4) = major crashes

S = speed in kilometers per hour

Finally, the accident injury subroutine calculates five different levels of injury severity incurred on the passengers of a vehicle for all crashes on a specific facility as defined by its free-speed. Equations 2.8 to 2.12 implement these calculations.

$$\text{Inj (1)} = c_1 + c_2 * S + c_3 * S^2 + c_4 * S^3 \quad (2.8)$$

$$\text{Inj (2)} = c_5 + c_6 * S + c_7 * S^2 + c_8 * S^3 \quad (2.9)$$

$$\text{Inj (3)} = c_9 + c_{10} * S + c_{11} * S^2 + c_{12} * S^3 \quad (2.10)$$

$$\text{Inj (4)} = c_{13} + c_{14} * S + c_{15} * S^2 + c_{16} * S^3 \quad (2.11)$$

$$\text{Inj (5)} = c_{17} + c_{18} * S + c_{19} * S^2 + c_{20} * S^3 \quad (2.12)$$

Where:

Inj (1) = no injury crashes

Inj (2) = possible injury crashes

Inj (3) = non incapacitating injury crashes

Inj (4) = incapacitating injury crashes

Inj (5) = fatal injury crashes

S = speed in kilometers per hour

2.3 EVALUATION OF INDUCED DEMAND IMPACTS

The concept of induced demand was originated from microeconomics and was later introduced to transportation system capacity improvement project evaluations. In microeconomics, it is a demand response to a reduction in the price of a commodity, while in transportation it is a response to a reduction in the cost of vehicle travel. As discussed in Chapter 1, most operational-level simulation models and field approaches are incapable of capturing induced demand effects. Thus, in this section, the definitions of induced travel demand and the concept of elasticity are introduced, and related researches are reviewed. This description provides a background prior to discussing the proposed approach in Chapter 3.

2.3.1 DEFINITIONS OF INDUCED TRAVEL DEMAND

The definition of “Induced Travel Demand” differs from study to study, but these differences are minor. For example, Noland *et al.* (2000) defined induced travel simply as “an increase in travel that occurs as a result of any increase in the capacity of the transportation system.” Barr (2000), however, defines “Induced Travel” as any increase in highway system usage caused by a highway capacity addition or other transportation system change which results in reduced travel times and /or costs.

In the TRB Special Report 245 (1995), “Induced Traffic” is further defined as the increase in highway system usage caused by an addition to highway capacity. Furthermore, the report explains that induced traffic includes new and longer motor vehicle trips that are made because the highway capacity addition has reduced travel cost, and that induced traffic does not include shifts in the route used to make a trip or shifts in the time of day a trip is made, because such changes generally do not result in a net increase in highway system use. In the report, it is also claimed that induced traffic does not include any increase in traffic that occurs for other reasons such as population and income growth.

2.3.2. POTENTIAL EFFECTS OF HIGHWAY CAPACITY IMPROVEMENTS

The capacity increase of transportation systems can be achieved in two ways. First, it can be accomplished by expanding the transportation infrastructure, such as building new highways and/or adding more lanes to existing highways. Second, it can also be attained by considering

transportation system management options, such as traffic signal coordination. Many studies have focused on analyzing the relationship between a transportation infrastructure capacity increase and induced travel demand in response to this capacity change. Transportation system capacity improvement projects result in several potential effects, as summarized in Table 2.7. In particular, short-term effects include changes in vehicle speed profiles, which occur directly after the capacity improvement projects are initiated. As time passes drivers may change their route of travel, their time of departure, or even their mode of travel. These changes in travel behavior result in what is termed medium-term effects in this thesis, and typically occur between one and six months after the capacity improvement project is initiated. The long-term effects relate to changes in land-use or changes in the origin or destination of a trip.

TABLE 2.7 THE POTENTIAL EFFECTS OF ARTERIAL OR HIGHWAY CAPACITY IMPROVEMENTS
(Source: TRB, 1995)

Short Term Effect	Medium Term Effects	Long Term Effects
<ul style="list-style-type: none"> • Changes in vehicle speed profiles • Changes in route of travel 	<ul style="list-style-type: none"> • Changes in departure times (no VMT increase) in order to avoid the periods of congestion • Changes in travel mode • Changes in destinations (net additional VMT) • Increase in number of trips 	<ul style="list-style-type: none"> • changes in household auto ownership • choices regarding employment location • choices regarding residential location

Figure 2.1 shows the relationship between travel cost and vehicle miles. In the figure, curve D is an original demand curve and curve D' describes a demand after a certain time period. The demand curves indicate that as cost per vehicle-mile decreases, vehicle miles increase. In addition, curves S and S' represent the before and after supply curves that are attributable to the highway capacity improvement project. These curves show that as vehicle miles increase, the cost per vehicle-mile increases. Point **a** shows the short-term equilibrium between the original demand and the original supply, while the point **c** represents the short-term equilibrium between the original demand and the new supply formed by increased highway capacity.

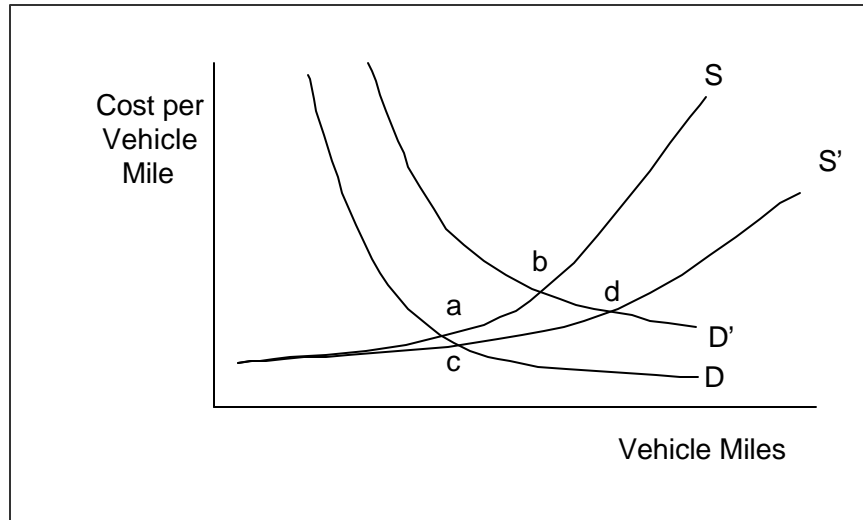


FIGURE 2.1 COMBINED EFFECTS OF HIGHWAY CAPACITY ADDITIONS AND TRAVEL GROWTH FROM OTHER FACTORS ON HIGHWAY USE

(Source: Transportation Research Board National Research Council, 1995)

Specifically, without any increase in demand due to socioeconomic variables such as population and individual disposable income growth, the point **c** would be a new equilibrium point due to increased supply, i.e., the additional supply with lower travel cost induced the increased travel. Population and income, however, increase over time and result in travel demand increase. Thus, a new demand curve must be considered **D'** and if there is no highway capacity increase, then the point **b** is a new equilibrium point. In response to this increased demand, if highway capacity is increased, then another new equilibrium point would be the point **d** (Transportation Research Board, 1995).

2.3.3 DEMAND ELASTICITY

In order to show the effects that are attributable to highway capacity improvements, most of the research related to induced travel demand analysis utilize elasticity, which is a well known economics measure to explain the relationship between demand for a good and changes in its price. This concept is shown in Figure 2.2. In transportation analysis, elasticity is used to estimate the percentage change in transportation system use originating from a percentage change in the travel cost. Figure 2.2 explains the law of demand under which a consumer's demand quantity Q of goods or services shrinks as their price P rises, and, conversely, increases when the price drops, under the assumption that everything else is being constant.

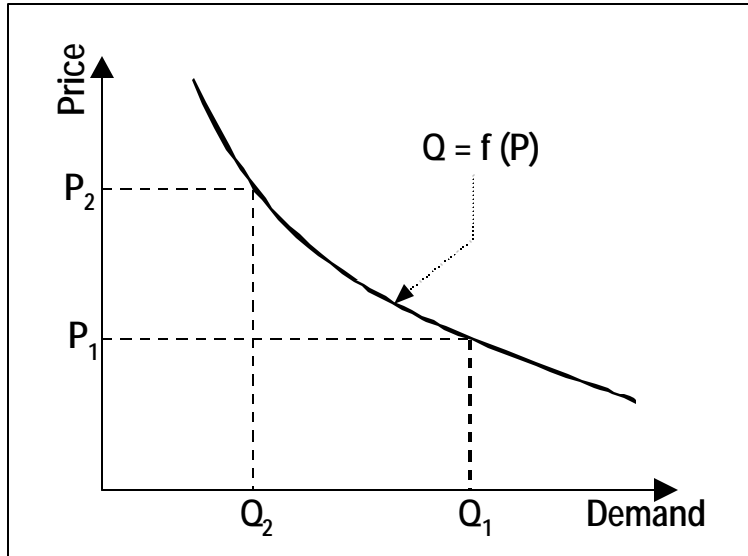


FIGURE 2.2 A HYPOTHETICAL DEMAND CURVE

(Source: Papacostas *et al.*, 1993)

Following the concepts of Figure 2.2, the price elasticity of demand, E , is defined by Equation 2.13 (Papacostas *et al.*, 1993).

$$E = \frac{dQ/Q}{dP/P} = \frac{dQ}{dP} \frac{P}{Q}$$

$$\text{Where: } dQ = Q_2 - Q_1$$

$$dP = P_2 - P_1 \tag{2.13}$$

$$Q = \frac{Q_1 + Q_2}{2}$$

$$P = \frac{P_1 + P_2}{2}$$

Equation 2.13 is a basic elasticity equation. If $E < -1$, the demand is elastic, and if $E > -1$, the demand is inelastic. In addition, if $E = -1$, the demand is unitarily elastic.

2.3.4. STATE-OF-THE-ART INDUCED DEMAND STUDIES

Typically, literature on induced demand use log-linear regression models to analyze the relationship between VMT and several independent variables such as lane mileage, area, and demographic parameters. For example, Noland *et al.* (2000) analyzed a data set from the Texas Transportation Institute (TTI) using a cross-sectional time series modeling approach and developed the regression model of Equation 2.14.

$$\log(VMT/PC_{it})=c+\mathbf{a}_i+\mathbf{t}_t+\sum_k \mathbf{b}^k \log(X_{it}^k)+\lambda \log(LM/PC_{itl})+\mathbf{e}_{it} \quad (2.14)$$

Where:

VMT/PC_{it} = VMT per capita in metropolitan area i , for year t

C = constant term

α_i = fixed effect for metropolitan area i , to be estimated

τ_t = fixed effect for year t , to be estimated

β^k = coefficients to be estimated (for demographic and other parameters)

λ = coefficient to be estimated for lane mile (LM) parameter

X_{it}^k = value of demographic and other variables for metropolitan area, i , and time, t

LM/PC_{itl} = proxy for cost of travel time (lane miles per capita) by metropolitan area, i , for year, t

ϵ_{it} = random error term

An instrumental variable is specified as:

$$\log(LM/PC_{itl})=c+\mathbf{a}_i+\mathbf{t}_t+kIV_{it}\sum_k \mathbf{b}^k \log(X_{it}^k)+\mathbf{e}_{it} \quad (2.15)$$

Where:

IV_{it} is the instrument, specified both across urbanized areas and time.

Using the equation, the authors estimated elasticities of a lane mile, per capita income, fuel cost, and population density. The authors found elasticities of 0.655, 0.354, -0.017, and -0.174 for each independent variable (lane miles per capita, per capita income, fuel cost and population density). For example, fuel cost elasticity of -0.017 can be interpreted as showing that VMT will decrease by -0.017% for every 1% increase in fuel cost.

In order to investigate induced travel effects in the U.S. Mid-Atlantic region, Fulton *et al.* (2000) developed a fixed effects model as follows:

$$\log(VMT_{it}) = \alpha_i + \beta_t + \sum_k \lambda^k \log(X_{it}^k) + \epsilon_{it} \quad (2.16)$$

Where:

- VMT_{it} = daily VMT for county i in year t.
- α_i = fixed effect for county i, estimated in the analysis
- β_t = fixed effect for year t, estimated in the analysis
- λ^k = coefficients to be estimated
- X_{it}^k = the value of explanatory variable k for county i and year t.
- ϵ_{it} = the outcome of a random variable for county i in year t, assumed to be normally distributed with mean 0.

Equation 2.16 is similar to equation 2.15, but includes fewer independent variables. As shown in Table 2.8, the authors applied their regression model to the five geographic areas in the Mid-Atlantic region: Maryland, North Carolina, Virginia, the Washington DC/Baltimore extended metropolitan area, and all three states surrounding the D.C. area. For these regions, the estimated coefficients of lane miles range from 0.3 to 0.6 and the coefficients of population vary between 0.5 and 0.655. In addition, the coefficients of income per capita ranged from 0.026 to 0.195. Counter-intuitively, the coefficient for the DC metropolitan area was the lowest value among the four states for each independent variable. This result is explained by the fact that this area has the largest use of transit and, under this situation, transportation infrastructure capacity increases could result in larger elasticity effect by attracting travelers from other modes (Fulton *et al.*, 2000).

TABLE 2.8 RESULTS OF INDUCED DEMAND EFFECTS ANALYSIS FOR MID-ATLANTIC REGION
(Source: Fulton *et al.*, 2000)

Dependent Variable	LOG (VMT)				
	All States	Maryland	North Carolina	Virginia	Washington, DC-Baltimore metropolitan area
Log (Lane Miles)	0.564*	0.451	0.435	0.508	0.327
Log (Population)	0.569	0.655	0.585	0.504	0.502
Log (Income Per Capita)	0.195	0.026	0.057	0.110	0.167

* Elasticity between dependent variable VMT and independent variable lane mile.

As discussed in the Section 2.3.2, most state-of-the-art induced demand studies have focused on analyzing the relationship between a transportation infrastructure capacity increase and induced travel demand in response to this capacity change.

2.4 STATE-OF-THE-ART EVALUATION OF INTELLIGENT TRANSPORTATION SYSTEM (ITS) PROJECTS

Many metropolitan cities in the United States have shown an interest in ITS to improve their transportation systems, but such ITS projects are often costly. Therefore, before or after any investment in ITS projects, it is necessary to estimate or evaluate the potential benefits and related costs associated with these projects.

In this section, existing ITS project evaluation methods are reviewed, and various measures-of-effectiveness are introduced. In addition, the benefits derived from these project evaluations are summarized and compared.

2.4.1 ITS PROJECT EVALUATION METHODS

Prior to discussing the evaluation methods of operational projects, it is necessary to review why evaluations of ITS projects are required in the first place. The main reasons for evaluating ITS projects are as follows:

- to understand the impacts of ITS,

- to quantify the benefits of ITS,
- to make future ITS investment decisions, and
- to improve the performance of existing system operations or design (U.S. DOT, 1998).

Before and after the implementation of ITS projects, it is necessary to evaluate each project using an appropriate evaluation technique. To date, many evaluation techniques have been developed and applied. These techniques can be classified into four classifications: 1) Technical Evaluation, 2) Empirical Evaluation, 3) Model-Based Evaluation and 4) Subjective Evaluation. Among these four evaluation techniques, model-based evaluation and empirical evaluation techniques are the most widely used. The empirical evaluation approach provides field data that can be used to calibrate and validate traffic simulation models for any ITS operational test, while the model-based approach furnishes flexibility in evaluating any ITS project (Bang, 1998).

2.4.2 ITS PROJECT EVALUATION MODELS

For ITS project evaluation, various models are developed and tested. Such ITS project evaluation models can be classified into two types, microscopic models and macroscopic models.

2.4.2.1 Microscopic Models

The evaluation of the Fixed-Demand impacts of ITS projects typically involves the usage of microscopic simulation tools in order to capture the changes in vehicle speed profiles & the impact of these changes on the various MOEs. Numerous microscopic simulation software are currently available. These software include the CORSIM, VISSIM, Paramics, INTEGRATION, and AIMSUN models. Apart from the INTEGRATION model, these models cannot capture traffic diversion. Furthermore, all models do not capture induced-demand impacts.

2.4.2.2 Macroscopic Models

Although TRANSYT-7F is a well-known macroscopic model, following two models are much bigger in model scale. Recently, new ITS evaluation tools such as “Screening for ITS (SCRITS)” and “The ITS Deployment Analysis System (IDAS)” have been introduced. The former is a screening-level spreadsheet analysis tool for estimating the user benefits of ITS strategies at the corridor/subarea or system level. Its primary measures of effectiveness are vehicle hours of travel

(VHT), vehicle miles of travel (VMT), emissions (CO, NO_x, HC), vehicle operating costs, fuel consumption, safety, and economic benefits. Like SCRITS, IDAS estimates the relative costs and benefits of potential ITS investments at the corridor/subarea or system level. However, IDAS performs more detailed analysis of costs and benefits compared to SCRITS. Furthermore, IDAS utilizes a travel demand model to explain effects of ITS, as illustrated in Figure 2.3 (DeCorla-Souza, 2000).

For any evaluation of ITS projects, the goal and measure of effectiveness of the evaluation should be defined in advance. In general, many ITS evaluation methods are closely related with the evaluation approach suggested by the U.S. DOT (1998). Typically, the goals of an ITS Program are as follows:

- Increase Transportation System Efficiency and Capacity,
- Enhance Mobility,
- Improve Safety,
- Reduce Energy Consumption and Environmental Costs,
- Increase Economic Productivity, and
- Create an Environment for an ITS Market.

The related measures of performance associated with each goal are further described in Table 2.8. These measures of performance represent factors that can be measured in the field.

2.4.3 ITS OPERATIONAL FIELD TESTS

Extensive modeling studies have been conducted for the evaluation of ITS alternatives. A full description of all these studies & their respective benefits is beyond the scope of this thesis. However, for illustrative purposes, several ITS evaluations that were conducted in the U.S. are described in order to demonstrate the potential benefits of ITS, as summarized in Table 2.9.

Furthermore, given that the focus of these evaluations was on ATMS, these evaluations are relevant to the case studies that are presented in Chapters 5 and 6. The operational-level projects include such elements as traffic signal control, en-route driver information, and incident management.

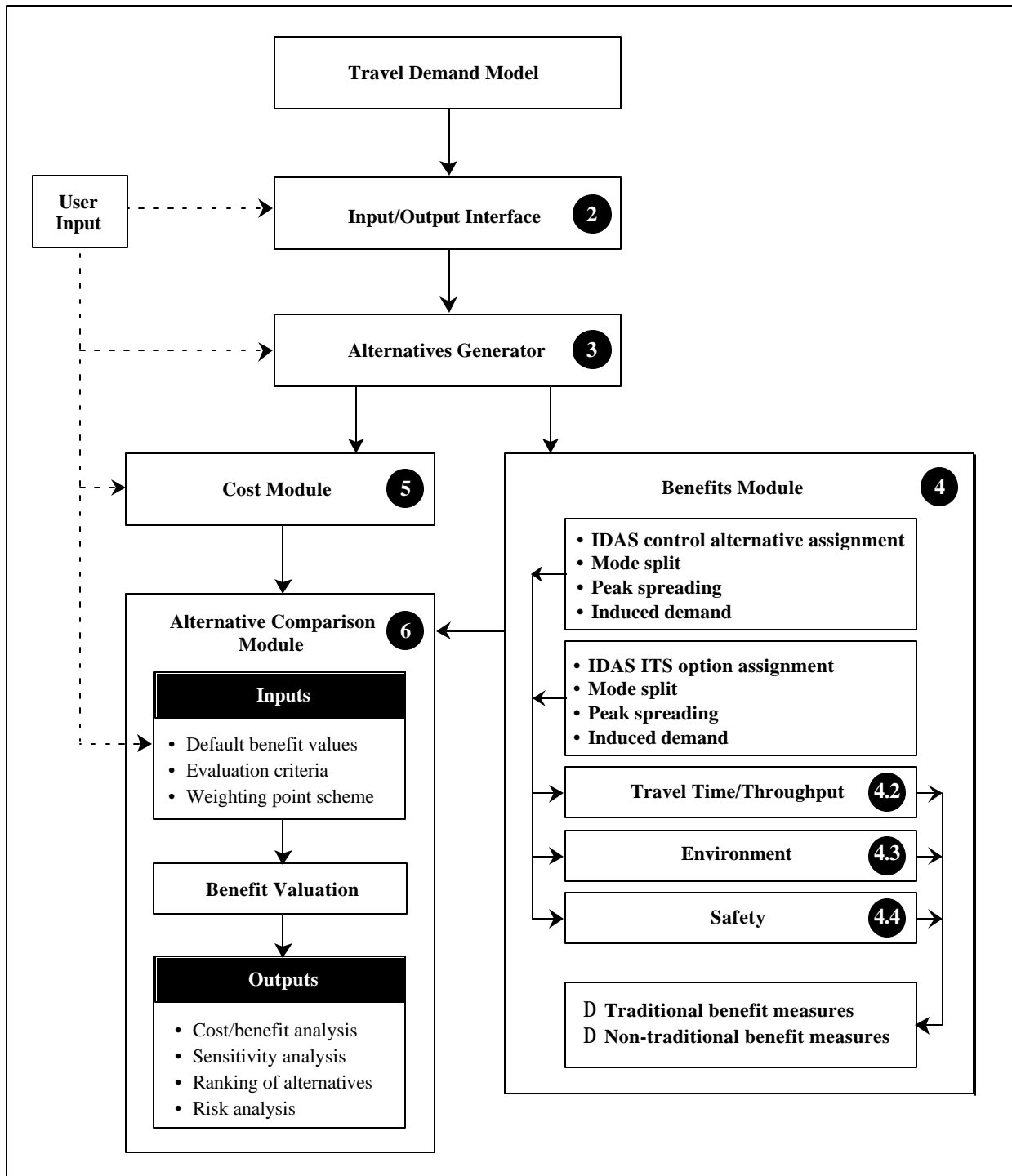


FIGURE 2.3 IDAS MODEL STRUCTURE
(Source: FHWA, 1998)

TABLE 2.9 ITS BENEFITS MEASURES BASED UPON U.S. DOT'S ITS GOALS
(Source: U.S. DOT, 1998)

ITS Goal	Related Measures of Performance
Increase Transportation System Efficiency and Capacity	Traffic flows / volumes / number of vehicles Lane carrying capacity Volume to capacity ratio Vehicle hours of delay Queue lengths Number of stops Incident-related capacity restrictions Average vehicle occupancy Use of transit and High Occupancy Vehicle (HOV) modes Intermodal transfer time Infrastructure operating costs Vehicle operating costs
Enhance Mobility	Number of trips taken Individual travel time Individual travel time variability Congestion and incident-related delay Travel cost Vehicle miles traveled (VMT) Number of trip end opportunities Number of accidents Number of security incidents Exposure to accidents and incidents
Improve Safety	Number of incidents Number of accidents Number of injuries Number of fatalities Time between incident and notification Time between notification and response Time between response and arrival at scene Time between arrival and clearance Medical costs Property damage Insurance costs
Reduce Energy Consumption and Environmental Costs	NOx emissions SOx emissions CO emissions VOC emissions Liters of fuel consumed Vehicle fuel efficiency
Increase Economic Productivity	Travel time savings Operating cost savings Administrative and regulatory cost savings Manpower savings Vehicle maintenance and depreciation Information-gathering costs Integration of transportation systems
Create an Environment for an ITS Market	ITS sector jobs ITS sector output ITS sector exports

Most of the operational-level projects are related with traffic control systems such as roadway surveillance, traffic condition monitoring or probe vehicles, freeway ramp metering and freeway lane control signals, arterial street signal control systems, signal preemption for priority vehicles, and high occupancy vehicle (HOV) lanes.

The benefits of traffic control systems are usually calculated in terms of system efficiency, travel mobility, and safety. As an example, typical benefits obtained in actual projects are shown in Table 2.10. For each project, the benefits are based on U.S. DOT's evaluation guidelines described in Table 2.9. Most of the reported benefits in Table 2.10 have been generated by ramp metering on freeways or traffic-adaptive signal control systems on arterial streets. However, the table only presents the general magnitude of benefits and provides little information regarding the actual evaluation parameters or scenarios.

2.5 SUMMARY AND CONCLUSIONS

This chapter demonstrated the issues that are involved in the evaluation of the efficiency, energy, emissions, and safety impacts of operational-level projects. These issues include changes in vehicle speed profiles, with their associated impacts on the various MOEs, and potential changes in demand as the result of these capacity enhancements. The chapter demonstrated that while such an evaluation might appear simple at first glance it is indeed extremely challenging because the evaluation requires not only very reasonable approach, but also reliable data.

Furthermore, the chapter has demonstrated that the current state-of-the-art approaches to evaluating the impacts of operational projects are still in their infancy.

In addition, it can be noted that a review of the literature does indicate that the current state-of-the-art tools are based on traffic modeling and simulation with little effort devoted to field evaluation. Consequently, there is a need for a systematic field evaluation approach that can quantify the impacts of operational-level projects on the efficiency of traffic flow, the energy consumption, the environment, and the safety of the transportation network. Furthermore, while the chapter does demonstrate that there are some individual tools that can capture individual

TABLE 2.10 REPORTED BENEFITS OF TRAFFIC CONTROL SYSTEMS IN THE U.S.
(Source: U.S. DOT, 1998)

ITS Component, Bundle, User Service, or System	Benefits Attributed to Traffic Control Functions	Comments
<p align="center">TransGuide Phase One, San Antonio, 1996</p> <p>[traffic control functions include roadway surveillance, traffic condition monitoring, changeable message signs, and lane control signals]</p>	<ul style="list-style-type: none"> • 16% reduction in crashes • 15% reduction in crash rate • \$4.3 million benefit from crash reduction (\$32,200 per non-fatal crash) • Improved confidence and satisfaction in traffic information • Excellent comprehension of traffic control signs 	
<p align="center">Flow Signals, Houston TranStar, 1996-97 Analysis</p> <p>[ramp metering]</p>	<ul style="list-style-type: none"> • 0% to 24% reduction in travel time • 0% to 33% increase in speed • Annual travel time savings of 431,250 vehicle-hours • \$5.555 million benefit from travel time savings (\$12.88 per vehicle-hour) 	Benefits based upon ramp Metering in a single corridor (IH-10).
<p align="center">Ramp Metering, Houston TranStar, 1998 Analysis</p>	<ul style="list-style-type: none"> • Annual travel time savings of 393,00 vehicle-hours • \$5.733 million benefit from travel time savings (\$14.97 per vehicle-hour) 	Benefits based upon ramp Metering in four corridors (IH-45, US 290, IH-10, US 59), all of 1997.
<p align="center">Ramp Metering, Denver, CO</p>	<ul style="list-style-type: none"> • 5% to 50% reduction in crash rate • 27% to 37% reduction in travel time • 13% reduction in vehicle-hours of delay 	
<p align="center">Ramp Metering, Portland, OR</p>	<ul style="list-style-type: none"> • 43% reduction in total crashes • 7% reduction in transit travel time 	
<p align="center">Ramp Metering, Minneapolis-St. Paul, MN</p>	<ul style="list-style-type: none"> • 24% to 27% reduction in total crashes • 27% reduction in crash rate • 14% to 27% reduction in travel time 	Ramp metering along a single Corridor (I-35).
<p align="center">Ramp Metering, Seattle, WA</p>	<ul style="list-style-type: none"> • 38% reduction in crash rate • 48% reduction in travel time • 10% to 100% growth in traffic • 48% increase in average speed 	Ramp metering along a single Corridor (I-5). Benefits Documented in a six-year study of the ramp metering and freeway management system.
<p align="center">Ramp Metering, Detroit, MI</p>	<ul style="list-style-type: none"> • 50% reduction in total crashes • 71% reduction in injuries • 7% reduction in travel time • 40% reduction in incident delay* • 42% reduction in fuel consumption* 	* Estimates based on no changes in the vehicle miles traveled.
<p align="center">Ramp Metering, Long Island, NY</p>	<ul style="list-style-type: none"> • 20% reduction in travel time 	
<p align="center">Automated Traffic Signal Control (ATSAC), Los Angeles, CA</p>	<ul style="list-style-type: none"> • 41% reduction in vehicle stops • 13% reduction in travel time • 14% increase in average speed • 13% reduction in fuel consumption • 20% reduction in intersection delay 	
<p align="center">Automated Traffic Signal Control, Abilene, TX</p>	<ul style="list-style-type: none"> • 13% reduction in travel time • 22% increase in average speed • 37% reduction in delay • 6% reduction in fuel consumption 	
<p align="center">Adaptive Traffic Signal Control, Detroit, MI [SCATS]</p>	<ul style="list-style-type: none"> • 6% reduction in injury accidents • 27% reduction in injuries • 100% reduction in serious injuries • 89% reduction in left-turn accidents • 19% increase in peak hour speeds • 30% reduction in intersection delay 	In addition to SCATS, FAST - TRAC also included Improvements in intersection Geometry and signal phasing.
<p align="center">Adaptive Traffic Signal Control, Toronto, Ontario [SCOOT]</p>	<ul style="list-style-type: none"> • 8% reduction in travel time • 17% reduction in vehicle delay • 22% reduction in vehicle stops • 6% reduction in fuel consumption 	Benefits from a two-month Study of the SCOOT system on two corridors and the Central Business District (CBD), totaling 75 signals.

components of the identified problem, there is a need for a systematic approach to enhance and combine these individual building blocks. The following chapter describes a methodology that attempts to address this ever-challenging task.

Chapter 3: PROPOSED EVALUATION METHODOLOGY

This chapter describes a proposed methodology for the field evaluation of the efficiency, energy, environmental, and safety impacts of traffic-flow improvement projects. The importance of developing such tools is demonstrated by the release of a National Cooperative Highway Research Program (NCHRP) Request for Proposals (RFP) in 1999 entitled "Predicting Short-term and Long-term Air Quality Effects of Traffic-Flow Improvement Projects."

The methodology that is developed as part of this research effort attempts to address the objectives of the NCHRP RFP, however, it differs in a number of aspects. First, the proposed methodology uses field data as opposed to traffic modeling to quantify the impacts of traffic-flow improvement projects. Second, the proposed methodology goes beyond the objectives of the NCHRP proposal by quantifying the efficiency, energy, and safety impacts of such projects in addition to the NCHRP proposed air quality impacts. It should be noted, however, that the proposed methodology is incapable of isolating the effects of induced demand. Instead, the proposed methodology quantifies any changes in demand.

Prior to describing the proposed methodology, the problem scope is described in order to demonstrate the need for such a methodology. Subsequently, the methodology is described in terms of its building blocks and how these building blocks interact. It should be noted that while this research effort does not necessarily develop all of the building blocks that constitute the methodology, it does ensure consistency between the building blocks and, furthermore, it develops a comprehensive evaluation approach.

3.1 PROBLEM OVERVIEW AND SCOPE

Estimating the effects of traffic-flow improvement projects in metropolitan areas on air quality and energy involves a lengthy chain of factors. These factors were described in an earlier study (TRB, 1995) as follows:

In general, the need or demand for travel arises from the distribution of residences and businesses in a region and their activity requirements. Residential and business locations in a region are, in turn, determined by historical development patterns, availability of land, and

zoning and land use policies. The amount and frequency of travel are affected by regional economic conditions, area demographic and income characteristics, and the cost and availability of local transportation services.

Regional travel is distributed as vehicle and passenger flows on the supply of transportation facilities $\frac{3}{4}$ the transportation network $\frac{3}{4}$ which may include more than one mode (e.g. transit and highways) and more than one form of transport (e.g. automobiles, trucks, bicycles, and walking). Motor vehicles operating on specific links of the network emit pollutants and use energy in varying amounts depending on the type of vehicle, its speed and operating condition (i.e. whether it is warmed up), and the length of the trip. In addition, other factors, such as topography, meteorological conditions, and other sources of emissions, interact with vehicle emissions to affect regional air quality.

The TRB study also discussed how increases in the highway supply can cause changes in traffic flows on the affected links (e.g., changes in speed distribution and variation, and/or shifts in traffic volumes) that might result in changes in the energy consumption and emissions of vehicles traveling on those links. These changes can evolve over time in response to changes in the amount of travel or in land use patterns, with corresponding effects on emissions and energy use. The study concludes that the incremental effects of all these changes on emissions, air quality, and energy use must be estimated to determine the full effects of capacity changes.

The TRB study also discussed the spatial and temporal impacts of traffic-flow improvement projects as follows:

There is both a spatial and a temporal dimension to these analyses. A change in supply may involve adding capacity and improving traffic flow at only one location on the highway system. However, the network character of the system is likely to affect travel patterns at other locations. Traffic may be diverted from alternative routes, or travelers may shift their time of travel to preferred travel times to take advantage of the new capacity or change their mode of travel if they are encouraged to reduce auto trips by using transit or bicycle or by walking. If the addition of the new capacity is sufficiently large, it can induce new or longer trips, influence auto purchasing decisions, and cause residents or businesses to change their location to take advantage of the improved access. Similarly, emissions from these changes are not confined to the location of the project, but depending on local atmospheric conditions (e.g. heat and wind patterns), may have broader effects on the air quality of the region and beyond. Individual

highway projects may not have measurable effects on regional air quality, but the cumulative impacts of many projects could. Thus, whereas a highway capacity enhancement project may be localized, its effects are unlikely to be.

In conclusion, the evaluation of the environmental impacts associated with transportation improvement projects requires comprehensive evaluation tools that are not only sensitive to vehicle dynamics, but are also capable of capturing other longer-term issues that might occur as a result of these traffic improvement projects.

3.2 PROPOSED METHODOLOGY OVERVIEW

The problem scope that was presented earlier demonstrates that the evaluation of operational-level projects is extremely challenging because of the dynamic nature of the problem. Specifically, travel behavior may change both spatially and temporally. These spatial changes include changes in routes of travel and/or changes in land-use or trip composition, while the temporal changes include changes in trip departure times. In addition, to these spatial and temporal effects other changes in the transportation network may occur simultaneously. These changes include the natural growth in travel demand, the interaction of different operational projects, and the typical randomness in travel behavior.

The focus of the proposed methodology is to quantify the short-term (less than 1 month) and potentially medium-term (less than 2 years) impacts of traffic-flow improvement projects. In quantifying these impacts the methodology conducts two levels of analyses. For each level of analysis a minimum of two data collection efforts are conducted, including a prior and an after data collection effort. If medium-term impacts are to be evaluated a third data collection effort could be conducted within two years of the project initiation.

The first of the analysis levels quantifies changes in vehicle speed profiles by measuring instantaneous speed levels in the field. Using these second-by-second speed measurements the efficiency of travel can be quantified based on microscopic procedures that are developed as part of this research effort. These efficiency measures include changes in delay and number of vehicle stops as a result of the traffic-flow improvement project. In addition, the methodology

combines the use of statistical models, that were developed earlier, for the estimation of vehicle fuel consumption and emission impacts (Ahn *et al.*, 1999 and Rakha *et al.*, 2000) and statistical crash risk models that were described in Chapter 2.

The objective of second level of analysis is to determine potential short-term changes in corridor demand as a result of the traffic-flow improvement project under consideration. Medium-term changes in traffic demands can be quantified if a third data collection effort were collected within two years of the project initiation. It should be noted, however, that as the temporal lag between the before and after data collection effort increases, the higher the level of uncertainty that observed changes in demand are attributed to the project under consideration.

3.2.1 LIMITATIONS OF THE CURRENT STATE-OF-PRACTICE

Although the literature describes attempts at developing modeling tools for the evaluation of traffic-flow improvement projects, the literature does not indicate any systematic field evaluation approach for the evaluation of traffic-flow improvement projects.

Furthermore, while there might appear to be a considerable number of commercially available traffic models that are capable of modeling individual key components of the proposed methodology, the majority of these models were not developed to provide the type of analysis that is required to predict short-term and long-term impacts of network-level traffic-flow improvement projects. Specifically, the literature (TRB, 1995) indicates that "*travel demand models were originally developed to help size and locate highway and transit facilities in a region. Travel volume forecasts could be approximate for estimating capacity requirements, but such forecasts are inadequate for providing facility- and time-specific travel volume and speed data necessary to estimate the emission impacts of specific projects (Harvey and Deakin, 1993; DeCorla-Souza, 1993). Similarly, MOBILE5 emission models were designed to predict macro-level emissions for input into emissions inventories, not to provide precise estimates of emission rates for vehicles traveling on individual highway links (Guensler, 1993).*"

The key limitations of the majority of current models can be summarized in three broad categories, as follows: appropriateness of the models, validity of the models, and the links

between the models (TRB, 1995). Unfortunately, models are being used to solve problems for which they were not originally designed, as indicated earlier. Furthermore, there are many uncertainties in the models themselves, which are manifested, in wide variances around some model estimates. These reflect the limited state-of-knowledge of the underlying phenomena that the models are attempting to capture. Finally, there is a mismatch of detail between the outputs generated and the inputs required by the different models in the modeling chain. For example, there is a lack of adequately detailed data from travel demand models for input into emission and atmospheric dispersion models.

3.2.2 PROPOSED METHODOLOGY

The proposed methodology attempts to address an apparent void in the current state-of-the-art evaluation techniques. Specifically, the proposed methodology attempts to quantify the impact of traffic-flow improvement projects on different MOEs using field data. This approach can be utilized to quantify short-term project impacts, and, with caution, could be utilized to evaluate medium-term impacts. However, as was mentioned earlier, the level of confidence in the conclusions that are derived from the methodology decrease as a function of the time lag between the after data collection effort and the project initiation. This reduction in confidence is attributable to the higher probability for changes in flows as a result of other confounding factors that are not necessarily related to the project under consideration.

The methodology requires a minimum of two data collection efforts, namely a "before" and an "after" data collection effort. The before data collection effort serves as a base case for the project evaluation. Each data collection effort involves two sources of data. The first of these data sources includes instantaneous vehicle speed measurements. These speed measurements can be collected using fairly inexpensive GPS technology, as was demonstrated in Chapter 2. The second data source includes link and turning movement counts that can be gathered using fairly inexpensive traffic and turning movement counters (approximately \$1000).

Using the instantaneous vehicle speed measurements instantaneous acceleration levels can be computed, as illustrated in Figure 3.1. The accuracy of the instantaneous speed and acceleration levels is extremely critical in estimating vehicle fuel consumption and emission rates, as will be

demonstrated in Chapter 4. Consequently, it is paramount that feasible vehicle dynamics (speed/acceleration combinations) together with robust data smoothing techniques be applied to the data. The use of robust smoothing ensures that the measured speed and estimated acceleration levels are feasible. The details of the data smoothing techniques will be described in Chapter 4.

Using the instantaneous speed measurements the proposed methodology estimates a number of measures of effectiveness (MOEs). These MOEs include vehicle stops, delay, fuel consumption, emissions (HC, CO, and NO_x), and a vehicle's crash risk. The computation of each of these MOEs will be discussed in further detail in the following sections. However, it should be mentioned at this point that the current emission models only estimate vehicle exhaust emissions for hot stabilized conditions. Consequently, the evaporative emissions of HC are shown in darker shade in Figure 3.1. Further research is underway to develop emission models that capture the additional emissions associated with vehicle starts and the additional emissions that are associated with catalytic converter malfunctions.

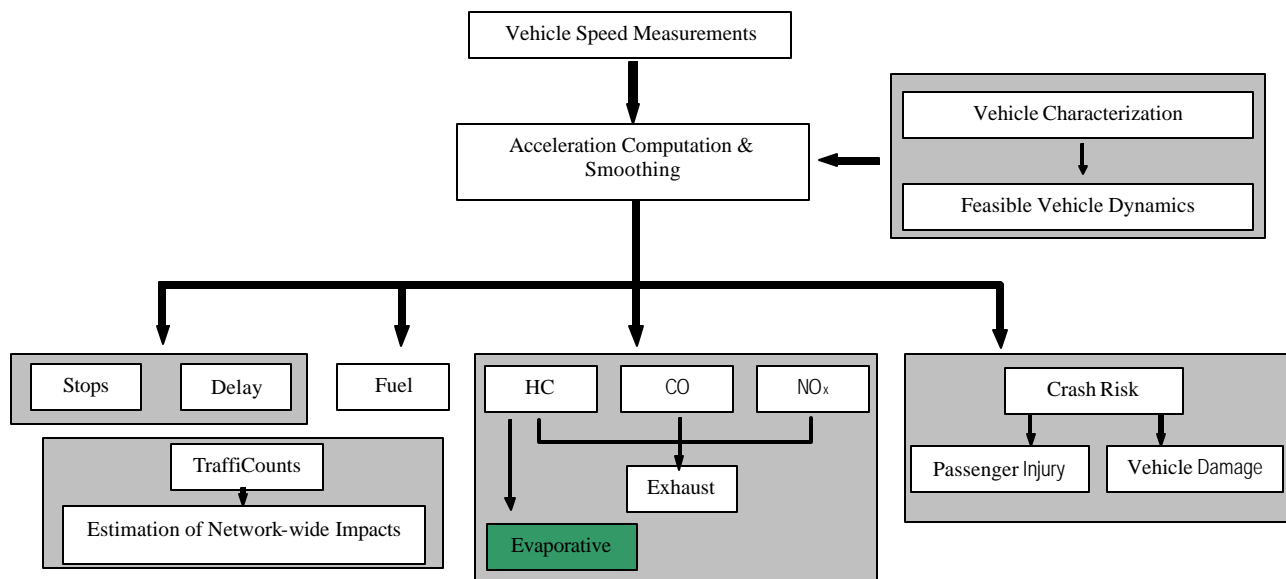


FIGURE 3.1 PROPOSED METHODOLOGY FOR ESTIMATING TRAFFIC-FLOW IMPROVEMENT PROJECT MOE IMPACTS

3.2.3 GPS DATA COLLECTION ISSUES

As mentioned earlier, a minimum of two GPS data collection efforts are required for evaluation purposes. In order to isolate the impact of the traffic-flow improvement project, consistency between the before and after data collection efforts should be ensured. In achieving consistency, data should be collected on similar days of the week (typically Tuesday through Thursday) and over identical periods within a day (typically during a peak and off-peak period). In addition, to the temporal consistency in data collection, spatial consistency should be ensured. Specifically, the data should cover identical spatial extents of the corridor under consideration. In doing so the GPS data may be combined with a GIS database in order to ensure spatial consistency. A more detailed description of the proposed data collection efforts are provided in the example applications that are presented in Chapter 5.

As is the case with any data collection technology, GPS data include erroneous GPS measurements. Therefore, Chapter 4 illustrates some problems caused by the erroneous GPS measurements when estimating vehicle fuel consumption and emissions and to propose solutions to address these problems.

3.2.4 STATISTICAL ISSUES

The methodology involves multiple data collection runs for each of the before and after scenarios in order to establish typical variability within a scenario. Subsequently, statistical tests are conducted in order to test the significance of any observed differences between the before and after scenarios. If differences are observed in the estimated MOEs further statistical tests of link and turning movement counts are conducted in an attempt to identify any potential short-term changes in demand.

The first step in a statistical decision process is to set up a statistical hypothesis that is to be tested. Specifically, in conducting the statistical test a null hypothesis is established (denoted by H_0), which typically involves the assumption that the traffic-flow improvement project does not result in changes in various MOEs. Four potential outcomes of the test are possible, as summarized in Table 3.1. Outcomes I and IV are favorable because the statistical conclusions are consistent with the actual conditions, while outcomes II and III are unfavorable because the

statistical conclusions are inconsistent with the actual conditions. The analyst typically specifies a level of allowable error for the unfavorable outcome II, which is termed the level of significance. The level of significance typically ranges from 1 to 10 percent, with a 10 percent level of significance indicating a 1 in 10 probability of outcome II. Outcome III is typically not addressed in most statistical tests.

TABLE 3.1 POSSIBLE OUTCOMES OF A HYPOTHESIS TEST

	No Evidence of Difference	Evidence of Difference
Before/After Identical	I	III
Before/After Different	II	IV

As indicated earlier, the proposed methodology involves establishing a null hypothesis that the traffic-flow improvement project does not result in changes in various MOEs. Statistical tests using Analysis of Variance (ANOVA) techniques are utilized to compare and contrast the impact of different explanatory variables on the various MOEs. These explanatory variables include the time-of-day, direction of travel, and before/after variable, as will be demonstrated in Chapters 5 and 6.

ANOVA tests enable the break down of the variance of the measured variables into the portions caused by the factors under consideration, both singly or in combination, and a portion caused by experimental error. Specifically, an analysis of variance consists of two components. First, the partitioning of the total sum of squares of deviations from the mean into two or more component sums of squares, each of which is associated with a particular factor or with experimental error. Second, a parallel partitioning of the total degrees of freedom. Using the sum of squared error and the corresponding degrees of freedom the mean sum of squared error is computed within and between groups of variables. Within group variance represents variability within a group, and between group variance quantifies the variance around the overall mean or grand mean. Utilizing the within group and between group variances, the ANOVA test evaluates the significance of a treatment effect. Specifically, if between group variance is larger than within group variance, there may be a treatment effect. An *F*-test is used to verify the statistical difference between the between and within variances. The *F* value is computed as the ratio of variance between factors to the variance within factors. If the calculated *F* value is greater than the tabulated theoretical *F* value for the specified degrees of freedom and level of significance it can be concluded that there

is evidence of a statistical difference between treatments within the pre-specified degree of significance.

It should be noted that in conducting these statistical tests the evaluator should be cognizant of the assumptions of these tests. For example, Analysis of Variance (ANOVA) tests assume that the dependent variable populations have the same variance and are normally distributed (Little *et al.*, 1991), and as such normality tests should be conducted on the data prior to conducting ANOVA tests. The distinction between the normality and non-normality of data and what should be done in the case of non-normality will be discussed in Chapter 5 using an example application.

3.3 COMPUTATION OF MEASURES OF EFFECTIVENESS

This section describes how the efficiency, energy, emission and safety Measures of Effectiveness are computed using GPS second-by-second speed estimates.

3.3.1 COMPUTATION OF DELAY

The computation of the average trip speed from second-by-second speed measurements involves summing up all speed measurements and dividing by the number of observations. On the contrary, the estimation of delay is more challenging and involves the computation of instantaneous delays (d_i), as computed using Equation 3.1. This computation estimates the delay as the difference in time for a vehicle to travel at free-speed (u_f) versus traveling at the instantaneous speed measurement (u_i) for the distance traveled at u_i for the duration of the time increment (typically 1 second). The total delay for the entire trip can then be computed as the sum of all instantaneous delay estimates. It should be noted that when the instantaneous speed is less than the free-speed the delay is positive while it is negative when it exceeds the free-speed. Consequently, a vehicle may recuperate a portion of the delay it incurred by traveling at higher speeds at later instants of the trip.

$$d_i = \Delta t \left(-\frac{u_i}{u_f} \right) \quad \forall i \quad (3.1)$$

Where:

Δt : is the time increment in data collection (typically 1-second increment)

Equation 3.1 requires the estimation of the facility free-speed in order to compute vehicle delays, which is utilized to establish the base reference for computing vehicle delays. It should be noted that the use of a different free-speed results in different delay estimates, however as long as the free-speed is identical across scenarios relative differences will be consistent.

It should be noted that the estimation of a facility free-speed is fairly simple and involves driving a vehicle along the facility at extremely low levels of congestion. Using floating car procedures, the vehicle should attempt to overtake as many vehicles as overtake it, thus ensuring that it travels at a speed that is consistent with the general traffic. The average speed of the vehicle represents an estimate of the facility free-speed when it is not constrained by a traffic signal or other vehicles.

3.3.2 COMPUTATION OF VEHICLE STOPS

The definition of vehicle stops and computation of vehicle stops certainly differs depending on the literature source. The proposed methodology develops a new approach for estimating vehicle stops in real-time using instantaneous speed measurements. Specifically, the number of vehicle stops along a trip is computed as the sum of instantaneous partial stops. The proposed procedure for estimating vehicle stops computes partial stops every time increment as the ratio of the instantaneous speed reduction to the facility free-speed, as indicated in Equation 3.2.

$$S_i = \frac{u_i - u_{i-1}}{u_f} \quad \forall i \quad \ni u_i < u_{i-1} \quad (3.2)$$

Consequently, a reduction in speed from free-speed to a speed of zero would constitute a complete stop while a reduction in speed from a speed equal to half the free-speed to a speed equal to one quarter the free-speed would constitute 0.25 of a stop. Using this convention, the total number of stops along a trip can be computed as the sum of the partial stops for each observation period (each second).

3.3.3 COMPUTATION OF VEHICLE FUEL CONSUMPTION AND EMISSIONS

The proposed methodology uses energy and emission models that were developed by Ahn *et al.* (1999) and Rakha *et al.* (2000). However, prior to describing how these models were utilized within the proposed methodology, a brief background of the models is provided.

The primary sources of motor vehicle emissions are exhaust emissions from chemical compounds that leave the engine through the tail pipe system, and crankcase and evaporative emissions from the fueling system (mainly volatile organic compounds (VOCs) which include HC emissions) (TRB, 1995). For gasoline vehicles, exhaust emissions originate as a result of the combustion of fuel in the engine (engine-out emissions) and are then reduced by passing through the catalytic converter (tail pipe or exhaust emissions). Currently, diesel-powered engines do not use catalytic converters.

CO and HC emissions are the product of incomplete combustion of motor fuels and, in the case of HCs, of fuel vapors emitted from the engine and fuel system (TRB, 1995). NO_x emissions are the product of high-temperature chemical processes that occur during the combustion itself. Particulate Matter (PM), another compound mainly found in diesel exhaust, are formed primarily from incomplete combustion of diesel fuel and lubrication oil (TRB, 1995).

The air/fuel (A/F) ratio, which is controlled by the carburetor or fuel injection system, is the most important variable affecting the efficiency of the catalytic converter and thus the exhaust emissions. CO and HC emissions are highest under fuel-rich conditions, and NO_x is highest under fuel-lean conditions. Fuel-rich conditions occur during cold-start conditions, and under heavy engine loads (e.g. during rapid accelerations, on steep grades, or at high speeds) (TRB, 1995). In addition, malfunctions in the catalytic converter may result in high emissions (high emitters).

The current state-of-practice in estimating vehicle emissions is based on the average speed. However, research has demonstrated that the use of average speed alone is insufficient in estimating vehicle emissions. For example, although the Environmental Protection Agency (EPA) MOBILE5 model would indicate that a slowing of traffic typically increases emissions,

empirical research indicates the opposite in many cases. Research in Germany has shown that the greater the speed of vehicles in built-up areas, the higher is the incidence of acceleration, deceleration, and braking, all of which increase air pollution (Newman and Kenworthy, 1992).

Consequently, the proposed methodology utilizes microscopic HC, CO, and NO_x models that were developed as part of the MMDI evaluation using data collected at the Oak Ridge National Lab (ORNL). Sample plots of the models are illustrated in Figure 3.2.

These microscopic emission models were validated by applying the models to second-by-second speed estimates of the FTP city and fuel economy cycles. The results demonstrate that the microscopic models produce emissions that are consistent in magnitude with the MOBILE5 model estimates.

The ORNL data that were utilized to develop the fuel consumption and emission models were gathered on a dynamometer in the form of look-up tables that included the steady-state fuel consumption and emission rates as a function of the vehicle's instantaneous speed and acceleration. The emission data included hydrocarbon (HC), carbon monoxide (CO), and oxides of nitrogen (NO_x) emissions. A total of eight light duty vehicles of various weights and engine sizes were utilized (West *et al.*, 1997). These eight vehicles are representative of current internal combustion (IC) engine technology, as demonstrated in Table 3.2. Specifically, the average engine size for all vehicles is 3.3 liters, the average number of cylinders is 5.8, and the average curb weight is 1497 kg (3300 lbs). Industry reports show that the average sales-weighted domestic engine size for 1995 was 3.5 liters, with an average of 5.8 cylinders (Ward *et al.*, 1995 and EPA, 1993).

The fuel consumption and emission rates were provided for a range of speeds from 0 to 120 km/h (75 mph) at increments of 1.1 km/h (0.69 mph) and for a range of accelerations from -1.5 m/s² (-5 ft/s²) to 3.6 m/s² (12 ft/s²) at increments of 0.3 m/s² (1 ft/s²). These data included typical driving conditions that ranged from decelerating (acceleration less than zero) to idling (acceleration and speed equal to zero) to acceleration (acceleration greater than zero).

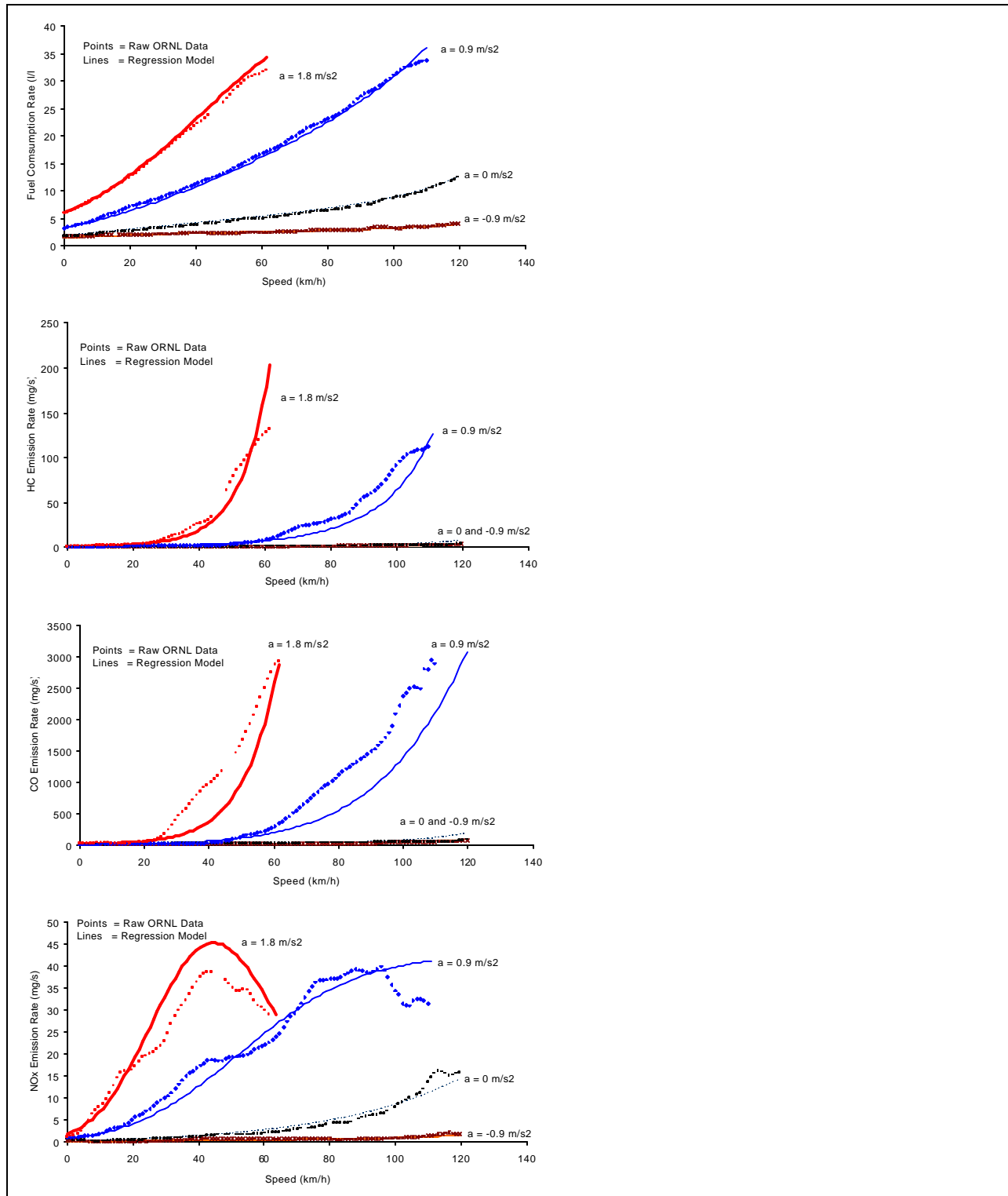


FIGURE 3.2 REGRESSION FIT FOR FUEL CONSUMPTION, HC, CO AND NO_x EMISSIONS (COMPOSITE VEHICLE)

TABLE 3.2 TEST VEHICLE AND INDUSTRY AVERAGE SPECIFICATIONS

(Source: West, *et al.* 1997)

Year	Make/Model	Engine	Curb Weight kg (lbs.)	Rated HP kW (HP)	City/Highway EPA Fuel Economy km/L (mpg)
Light-Duty Vehicle (LDV)					
1988	Chevrolet Corsica	2.8L Pushrod V6, PFI	1209 (2665)	97 (130)	8/12 (19/29)
1994	Oldsmobile Cutlass Supreme	3.4L DOHC V6, PFI	1492 (3209)	157 (210)	7/11 (17/26)
1994	Oldsmobile Eighty Eight	3.8L Pushrod V6, PFI	1523 (3360)	127 (170)	8/12 (19/29)
1995	Geo Prizm	1.6L OHC I4, PFI	1116 (2460)	78 (105)	11/13 (26/30)
1993	Subaru Legacy	2.2L DOHC Flat I4, PFI	1270 (2800)	97 (130)	9/12 (22/29)
	5-Car Average	2.8L, 5.2 Cylinders	1322 (2915)	111 (149)	
1995	LDV Industry Average	2.9L, 5.4 Cylinders	1315 (2900)		
Light Duty Trucks (LDT)					
1994	Mercury Villager Van	3.0L Pushrod V6, PFI	1823 (4020)	113 (151)	7/10 (17/23)
1994	Jeep Grand Cherokee	3.0L Pushrod I6, PFI	1732 (3820)	142 (190)	6/9 (15/20)
1994	Chevrolet Silverado Pickup	5.7L Pushrod V8, TBI	1823 (4020)	149 (200)	6/9 (14/18)
	3-Truck Average	4.2L, 6.7 Cylinders	1793 (3953)	134 (180)	
1995	LDT Industry Average	4.6L, 6.5 Cylinders			
Overall Average					
	8-Vehicle Average	3.3L, 5.8 Cylinders	1497 (3300)	119 (160)	
1995	Industry Average	3.5L, 5.8 Cylinders			

Some of the speed/acceleration combinations were unachievable by the vehicles (e.g. high accelerations at high speeds). In general the number of data points ranged from 1300 to 1600 depending on the power of the vehicle (maximum number of potential points was 1980 points [110 speed bins × 18 acceleration bins]).

Utilizing the data for the eight vehicles, composite fuel consumption and emission surfaces were derived by averaging across the eight vehicles (West *et al.*, 1997). The composite vehicle fuel

consumption data varied fairly linearly when the vehicle was cruising or decelerating, however, the relationship was significantly non-linear for higher levels of acceleration (acceleration greater than or equal to 1.2 m/s^2). In terms of emissions, the HC and CO surfaces appeared to be very similar except for the fact that CO emissions were much higher (up to 2500 mg/s in the case of CO versus 60 mg/s in the case of HC). The NO_x surface appeared to be more non-linear than the HC and CO surfaces when the vehicle was decelerating or cruising.

As shown in Figure 3.2, the ORNL data demonstrated a linear decay in the maximum acceleration as a function of the vehicle speed. It should be noted that deriving the maximum acceleration from the residual tractive force results in a non-linear function, however a linear relationship does provide a reasonable approximation. Consequently, the models that were developed using the ORNL are valid for the data range covered by the field data. These models produce unrealistic energy and emission estimates for speed/acceleration combinations outside these bounds as will be demonstrated in Chapter 4. Consequently, it is paramount that robust forms of data smoothing be applied to the instantaneous speed and acceleration measurements in order to ensure that the data are within the feasible range of typical vehicles.

3.3.4 COMPUTATION OF CRASH RISK

The evaluation of the safety impacts of alternative ITS scenarios was based on regression models that predict the expected frequency of 14 different crash types every second based on the facility type that the vehicle is traveling on. In addition, the expected damage and injury levels, per crash event, are estimated based on the instantaneous speed each vehicle is traveling at each second (Avgoustis *et. al.*, 2000), as was described in Chapter 2.

The crash rates, in each of the above applications of the safety computational method, were derived from the General Estimates System (GES) national crash database of more than 6,000,000 annual crashes. This crash database was subsequently supplemented with vehicle exposure data, which were stratified by facility type. The merging of crash frequencies with exposure data resulted in crash rates per unit distance and per unit time for different facility types. The conversion, from crash frequencies into crash frequencies by damage and injury level, was performed by considering speed dependent damage and injury levels for each of the 14

different crash types. Again, as was the case for efficiency, energy and emissions, the safety model was applied to the second-by-second GPS.

3.4 TRAFFIC GROWTH AND INDUCED TRAFFIC DEMAND

The proposed approach attempts to quantify changes in demand through the use of traffic and tube counts. Again, as was the case with the speed profiles, statistical tests using ANOVA techniques are applied to statistically verify changes in traffic demand. It should be noted, however, that the proposed approach does not identify the cause of any changes in traffic demand instead it establishes the statistical validity of these changes. Consequently, a change in traffic demand is not necessarily a result of the traffic-flow improvement project. It should be noted, however, the likelihood that these observed differences occur as a result of the project under consideration decreases as the time lag between the two data collection efforts increases.

3.5 ANALYSIS OF IMPACTS ON NETWORK

As described earlier, GPS data and tube & turning volume counts can be utilized to analyze benefits from traffic signal coordination. However, there is a problem in using traffic counts directly for analysis of network impact because traffic counts usually cover a part of network or just a corridor. For the analysis, Synthetic Origin-Destination estimation technique is introduced for an analysis of network impact.

An Origin-Destination (O-D) trip table represents number of trips between each given origin and destination zone. Many transportation organizations utilize the trip tables for planning purposes. Furthermore, accurate and fast O-D trip table generation techniques are needed, in the planning, operation and maintenance of ITS.

O-D tables can be obtained at the step of trip distribution in travel demand forecasting. If link counts are utilized in obtaining an O-D table, it is called synthetic O-D trip table. In O-D trip table estimation process, traffic flow can be static or dynamic. Most O-D trip tables in practice are based on static traffic flow. In synthetic O-D trip table estimation process, maximum entropy techniques are very popular and widely used.

Synthetic O-D estimation can be formulated in terms of an objective function as shown in Equation 3.3 and a constraint of flow-continuity.

$$\text{Maximize : } Z(T_{ij}, t_{ij}) = \frac{T!}{\prod_{ij} (T_{ij}!)} \prod_{ij} \left(\frac{t_{ij}}{\sum_{ij} t_{ij}} \right)^{T_{ij}} \quad (3.3)$$

Where:

T = the total number of trips in the network,

T_{ij} = trips from i to j ,

t_{ij} = seed matrix from derived from a previous study or survey.

The objective function is to find a trip matrix that is considered as the most likely with a flow-continuity constraint. However it is very difficult to solve the problem. Therefore, various solvers are utilized to obtain an O-D matrix that satisfies the objective function and the constraint. They are Microsoft Excel Solver, MATLAB, and Queens-OD using Stirling's approximation. The detail description of Synthetic O-D estimation process and techniques can be found in Paramahamsan (1999).

Among various solvers mentioned above, QueensOD is a solver for O-D estimation utilizing observed link flows, turning percentages, and link travel times. QueensOD utilizes the concept of maximum likelihood estimation method in order to estimate O-D demands. QueensOD is a stand-alone software although it shares file formats with the INTEGRATION, a microscopic simulation model developed by the late Dr. Michael Van Aerde.

As shown in Figure 3.3, QueensOD requires traffic volume and geometric characteristics. With observed link flow and turning movement counts before and after a traffic flow improvement project, QueensOD is able to produce estimated link flows and O-D matrix of a study network for before and after conditions, respectively. Based on estimated traffic flow data sets, ANOVA analysis can be performed to check any statistically significant difference in MOEs between before and after conditions.

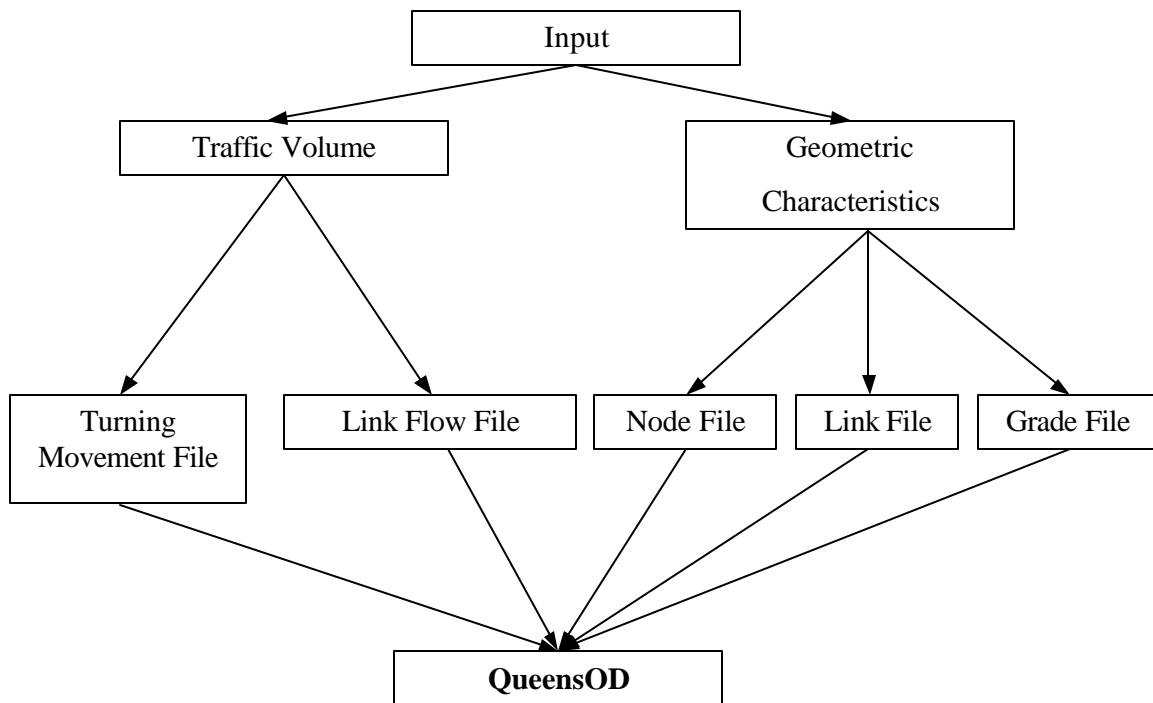


FIGURE 3.3 QUEENSOD PROCESS
 (Source: Diekmann, 2000)

3.6 SUMMARY OF PROPOSED APPROACH

The proposed methodology attempts to quantify the impact of traffic-flow improvement projects on different MOEs using field data. This approach can be utilized to quantify short-term project impacts, and, with caution, could be utilized to evaluate medium-term impacts. However, the level of confidence in the conclusions that are derived from the methodology decrease as a function of the time lag between the after and before data collection efforts.

The methodology requires a minimum of two data collection efforts, namely a "before" and an "after" data collection effort. The before data collection effort serves as a base case for the project evaluation. Each data collection effort involves two sources of data. The first of these data sources includes instantaneous vehicle speed measurements. These speed measurements can be collected using fairly inexpensive GPS technology. The second data source includes link and turning movement counts that can be gathered using fairly inexpensive traffic and turning movement counters.

Using the instantaneous vehicle speed measurements instantaneous acceleration levels are computed. The approach uses these data to compute instantaneous vehicle delay, stops, energy consumption, emissions (HC, CO and NO_x), and crash risk. Robust smoothing techniques are applied in order to ensure that speed/acceleration combinations are consistent with vehicle dynamics, as will be described in Chapter 4. ANOVA tests are utilized to statistically evaluate the significance of changes in vehicle speed profiles and traffic volumes, as described in Chapters 5 and 6, respectively. Furthermore, if there is any statistically significant change in before and after traffic flow, then network impact can be analyzed using an approach introduced in the previous section.

Chapter 4: SMOOTHING TECHNIQUES

While delay, queue lengths, and vehicle stops can be easily observed in the field, vehicle fuel consumption and emissions cannot be observed as easily. As a result, these measures are typically determined through simulation. Alternatively, fuel consumption and vehicle emissions can also be estimated using time series of speed and acceleration data collected in the field through the use of Global Positioning System (GPS) technologies. However, as with any field data collection system, the accuracy of the parameters estimated from the collected information greatly depends on the quality of that information. First, the accuracy of any given evaluation greatly depends on the measurement accuracy of the equipment used. This is an element that can be addressed through a careful selection and calibration of the equipment used to conduct an evaluation. Second, any grossly erroneous data that is not screened can lead to unrealistic vehicle fuel consumption and vehicle emission estimates. This is an important element that should not be overlooked as such errors can occur with any equipment used and can seriously undermine the validity of an evaluation and affect the credibility of the agency conducting the evaluation.

This chapter is to illustrate some problems caused by erroneous GPS measurements when estimating vehicle fuel consumption and emissions and to propose solutions to address these problems. As a solution to the mentioned problem, this chapter attempts more specifically to determine a data filtering technique that is best suited for the automatic removal of such erroneous and suspicious data.

To determine an appropriate data filtering technique, this chapter first presents how fuel consumption and vehicle emissions can be estimated from typical GPS data. A case study that will be used to illustrate the problems created by erroneous data is then introduced in the following section. The third section then presents not only the impacts that erroneous GPS measurements can have on fuel consumption and vehicle emission estimates, but also describes the region of feasible acceleration that is used later in the filtering techniques. The fourth section follows with an evaluation of various data smoothing techniques that can be used to reduce the

impacts of erroneous measurements. Finally, the fifth and last section presents the summary and general conclusions of this chapter.

4.1 ESTIMATION OF MEASURES OF EFFECTIVENESS USING GPS DATA

GPS technologies can be used to record the speed of a vehicle at regular intervals. From this information, the instantaneous acceleration level of a vehicle at each recording point can be determined using the backward difference formulation that is presented in Equation 1.

$$a_t = \frac{u_t - u_{t-\Delta t}}{\Delta t} \quad (4.1)$$

where:

- a_t = Instantaneous acceleration of vehicle at time t (m/s^2),
- u_t = Instantaneous speed of vehicle at time t (m/s),
- Δt = Interval between observations at times t and $t-\Delta t$ (s).

Equation 4.1 determines the acceleration of a vehicle at time t using a backward-difference approach, i.e., observations from previous intervals. Alternatively, a forward-differential approach, in which the measurements at time t and $t+I$ are used instead of time t and $t-I$, or a central-differential approach, in which the measurements are made with measurements at time $t-I$ and $t+I$, could be used. In particular, central difference schemes have been shown to provide accuracy levels that are at least one order of magnitude better than those obtained with either backward or forward schemes (Burden and Faires, 1997). However, since both central and forward schemes always require a knowledge of speed measurements at future recording points to calculate the acceleration level at any given time t , they cannot be applied to real-time processes. For this reason, this chapter primarily utilizes the backward difference scheme of Equation 4.1 in computing vehicle acceleration levels. It should be noted, however, that a comparison of the three acceleration computation schemes is presented with the associated impacts on vehicle fuel consumption and emission estimates.

Using the GPS-measured instantaneous speeds and the corresponding calculated instantaneous accelerations, the fuel consumed and pollutants emitted by a vehicle during a given trip can be estimated using microscopic energy and emission models. The main advantage of using such

models is that they offer the possibility to consider all observed speed variations within a recorded trip. While the determination of delay at signalized intersections typically only require knowledge of the major deceleration and acceleration events, all speed variations, particularly those occurring at high speed, could have a significant incidence on vehicle fuel consumption and emissions. In particular, such models could fully reflect differences in MOEs for trips with similar average speeds but involving different speed profiles.

Equation 4.2 indicates the generic form of the microscopic model that was used in this study. This model was developed using fuel consumption and emission data that were collected by the Oak Ridge National Laboratory (West *et al.*, 1997) and which provided steady-state fuel consumption and emission rates of hydrocarbon (HC), carbon monoxide (CO) and oxides of nitrogen (NO_x) for eight light-duty vehicles that were deemed representative of a 1995 U.S. vehicle fleet (Ahn *et al.*, 1999 and Rakha *et al.*, 2000). While efforts are continuing to develop and enhance these models, evaluations have already shown the ability of the models to follow very closely field observed trends of increasing fuel consumption with higher speeds and sharper accelerations, as well as to predict vehicle emissions that are consistent with field measurements (Ahn *et al.*, 2000).

$$\ln(MOE_e)_t = \begin{cases} \sum_{i=0}^3 \sum_{j=0}^3 (L_{i,j}^e \times \bar{u}_t^i \times a_t^j) & \text{for } a \geq 0 \\ \sum_{i=0}^3 \sum_{j=0}^3 (M_{i,j}^e \times \bar{u}_t^i \times a_t^j) & \text{for } a < 0 \end{cases} \quad (4.2)$$

where:

- MOE_e = Instantaneous fuel consumption or emission rate at time t (ml/s or mg/s),
- $L_{i,j}^e$ = Regression coefficient for MOE "e" at speed power " i " and acceleration power " j " for positive accelerations,
- $M_{i,j}^e$ = Regression coefficient for MOE "e" at speed power " i " and acceleration power " j " for negative accelerations,
- u_t = Instantaneous average speed at time t (km/h),
- a_t = Instantaneous acceleration at time t (km/h/s).

4.2 CASE STUDY

As part of the Phoenix Metropolitan Model Deployment Initiative, GPS speed and acceleration data were collected to evaluate the Scottsdale/Rural Road Signal Coordination Project (Rakha *et al.*, 2000), and more specifically, to evaluate the impacts of re-timing three traffic signals at the

boundary between the cities of Tempe and Scottsdale. While changes at only three intersections were considered, speed and acceleration data were collected over the entire length of the Scottsdale/Rural Road study corridor, which covered 21 intersections and extended over 9.6 kilometers.

As part of this data collection effort, four cars were equipped with GPS Placer 450 receivers and ran along the corridor from one end to the other. The vehicles were driven for three days (Tuesday through Thursday), before and after the signal timings were changed. The data collection effort characterizing the before conditions took place in January 1999, while the after data collection effort was conducted a month later, in February, after the signal timings were changed. Within each data collection effort, the GPS runs were conducted during the AM peak (7:00-9:00 A.M.), Midday (11:00 A.M. to 1:00 P.M.), and PM peak (4:00 to 6:00 P.M.) control periods. In total, 141 runs were made for the before period while 160 runs were made for the after period, yielding a total of 301 runs.

For each run, information about the test vehicle's position, its velocity and its heading were collected on a second-by-second basis, which represents the highest data acquisition frequency for current state-of-practice GPS receivers. Since the GPS receivers that were utilized in the study did not consider any differential correction and since Selective Availability (SA) error was still in effect at the time the data collection effort took place, the accuracy of the collected position and speed information was determined to be 58 m and 1 m/s, respectively.

4.3 GPS DATA RELIABILITY ISSUES

4.3.1 OVERVIEW

Current state-of-practice GPS nominal position accuracy is specified with a 25-m spherical error probability, while nominal velocity accuracy is specified with a 0.1 m/s error probability (Trimble Navigation Ltd., 1996 and 1998). These errors are attributed to a certain number of sources, the majority of which are associated with the way distances between a satellite and a GPS receiver are measured. Since distances are measured by calculating the time it takes for a signal to travel between a satellite and a receiver, any delay in the signal transmission thus results in distance overestimation and inaccuracies in the position and velocity estimates of

objects. Such delay in signal transmission can be caused by signals bouncing off various local obstructions such as mountains, buildings, bridges and other infrastructures before reaching the receiver. Charged particles and water vapor in the upper atmosphere may also slow the signal down. Other sources of error can further be traced to errors in the transmitted location of a satellite and errors within a receiver caused by thermal noise, software accuracy and inter-channel biases. Finally, for measurements made before May 2, 2000, additional errors could also be attributed to the Selective Availability policy, which deliberately introduced, for strategic reasons, a time-varying noise in the satellite time measurements. As a result of Selective Availability, location accuracy was downgraded from a 25-m error probability to a 100-m error, while velocity accuracy was reduced from 0.1 to 1 m/s accuracy.

To improve the accuracy of GPS measurements, differential correction techniques can be used. Differential GPS uses error correction factors that are based on satellite monitoring stations placed at known locations and transmitted to differential GPS receivers through a general broadcast to enhance the accuracy of measurements. Differential GPS eliminates virtually all measurement errors in GPS readings and enables highly accurate position and velocity calculation. For instance, with differential GPS positions the accuracy is within 2 meters under Selective Availability. With Selective Availability turned off, much greater precision is now possible; however, the extent of these improvements has not yet been fully evaluated.

Whether differential GPS is used or not, erroneous measurements are still observed as a result of losing the signal between the GPS receiver and the satellites. As an example, Figure 4.1 illustrates the speed and acceleration profiles that were obtained for one of the test runs along the Scottsdale/Rural Road corridor. In both profiles, a closer examination of the GPS measurements reveals two suspicious observations: one at about time 400 seconds and another around 600 seconds. In both cases, it is observed that the measured vehicle speed drops significantly, almost to zero, before returning to its original level over an extremely short period. Such sudden changes are reflected in the acceleration profile through the two high deceleration/acceleration peaks that can be observed near times 400 and 600 seconds. More detailed description of this issue will be presented in Section 4.3.3.

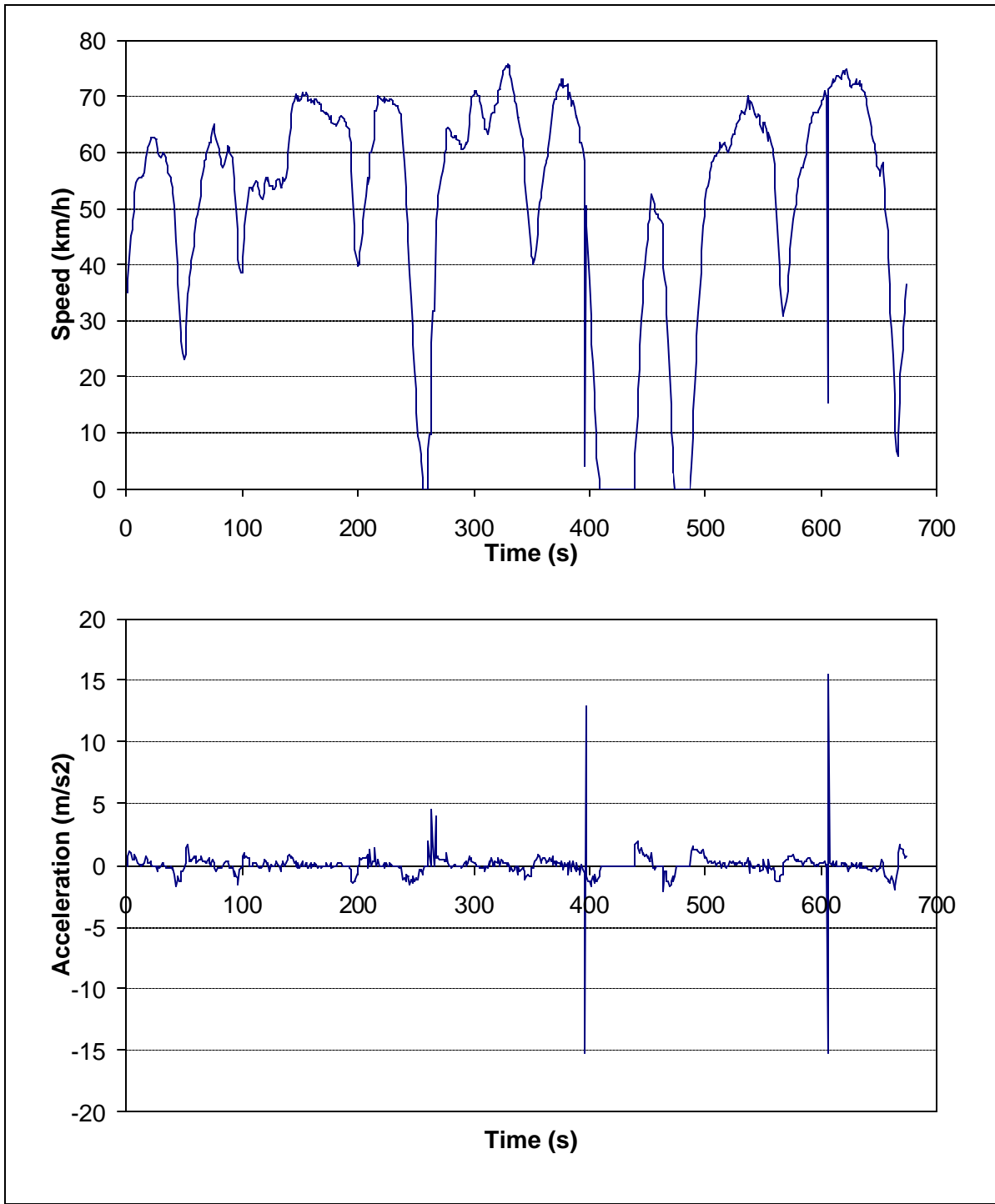


FIGURE 4.1 SAMPLE GPS SPEED AND ACCELERATION PROFILES

4.3.2 ESTIMATION OF VEHICLE ACCELERATIONS

As mentioned earlier vehicle acceleration levels can be estimated from speed measurements using numerical differentiation techniques given that acceleration is the differential of the vehicle speed.

These techniques include backward-difference, forward-difference, and central-difference formulations (Burden *et al.*, 1997). The literature indicates that the error using the central-difference formulation is approximately half the error of the backward-difference or forward-difference formulations. In addition, to these three types of formulations, a number of sub-formulations are available based on the number of data points that are required to solve the differential equation. For example, Equation 4.3 is called a three-point central-difference formulation (even though the third point u_i does not appear), while Equation 4.4 is a five-point central difference formulation, which involves evaluating the function at two additional points. The literature indicates that the five-point formulation improves the accuracy of estimation by an order of 1 (Burden *et al.*, 1997).

As part of this research effort various backward, forward and centered-difference formulations were tested on the sample trip profile of Figure 4.1. The resulting minimum and maximum acceleration levels were reduced from approximately 15 m/s^2 for the backward and forward formulations to approximately 8 m/s^2 for the three-point centered difference formulation, as summarized in Table 4.1. While the use of the centered-difference formulation reduces the acceleration error significantly, the acceleration estimates are still considerably beyond feasible vehicle acceleration levels. Consequently, there is a need to smooth the GPS data in order to ensure data validity. The application of the smoothing techniques that are described in the subsequent sections using the different differential formulations resulted in minor differences in energy and emission estimates (less than 5%). Consequently, the backward formulation was utilized for subsequent analyses because it provides an opportunity to apply the proposed algorithms in real-time given that it only uses measurements that were collected before “ t ”.

$$a_t = \frac{u_{t+\Delta t} - u_{t-\Delta t}}{2\Delta t} \quad (4.3)$$

$$a_t = \frac{u_{t-2\Delta t} - 8u_{t-\Delta t} + 8u_{t+\Delta t} - u_{t+2\Delta t}}{12\Delta t} \quad (4.4)$$

TABLE 4.1 COMPARISON OF ACCELERATION ESTIMATES FOR SAMPLE TRIP

	Backward 2- Point	Backward 3- Point	Centered 3- Point	Centered 5- Point	Forward 2- Point
Mean (m/s²)	0.0006	-0.0008	-0.0005	1.0571	-0.0004
Std. Dev. (m/s²)	1.29	3.91	0.80	1.02	1.29
Minimum (m/s²)	-15.14	-40.91	-7.88	-8.43	-15.14
Maximum (m/s²)	15.49	55.46	7.80	10.81	15.49

4.3.3 FEASIBLE SPEED/ACCELERATION REGION

As was demonstrated in Table 4.1 unrealistic accelerations were observed for the sample trip of Figure 4.1, as summarized in Table 4.2. The rows of Table 4.2 represent the different speed bins while the columns represent the different acceleration levels, and the values in the bins represent the number of observations for each speed/acceleration combination. The shaded areas on both sides of the table illustrate the regions of infeasible speed/acceleration combinations for an average automobile.

Figure 4.2 illustrates how the feasible speed/acceleration region was derived for a typical vehicle. In the figure, the data points represent the estimated maximum speed/acceleration combinations for a composite vehicle reflecting the average characteristics of the eight light-duty vehicles that were tested at the ORNL.

TABLE 4.2 RAW ACCELERATION DATA

		Acceleration (m/s ²)																											
		< -6	-6.0	-5.5	-5.0	-4.5	-4.0	-3.5	-3.0	-2.5	-2.0	-1.5	-1.0	-0.5	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0	5.5	6.0	> 6.0	
Speed (km/h)	0	1								4	8	3	47	1	3	2													
	10	1								3	4	1				3	2												
	20									1	6	4	2	1	1	7								1					
	30									1	2	8	5	6	9	10	3	2											
	40									2	8	8	9	12	21	4							1						
	50										6	9	42	69	18														1
	60										1	7	109	110	13	3													
	70												27	40	1														1
	80																												
	90																												
	>100																												

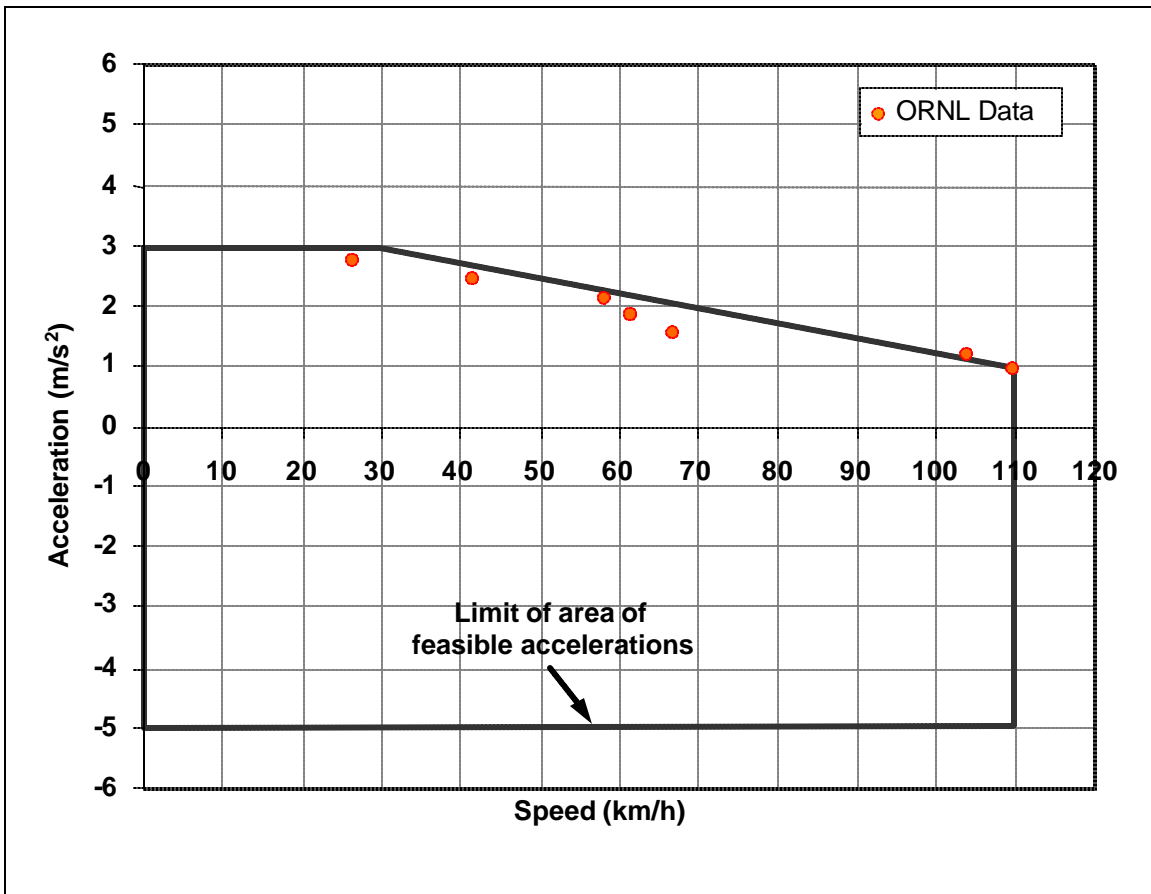


FIGURE 4.2 ACCELERATION CONSTRAINTS

The ORNL data indicated a linear decaying relationship between the vehicle's maximum acceleration rate and its speed for speeds in excess of 30 km/h. To generate a region of maximum feasible accelerations, a linear relationship was thus assumed to link an acceleration of 3 m/s^2 at a speed of 30 km/h with an acceleration of 1 m/s^2 at a speed of 110 km/h. As shown in the figure, this relationship ensured that all data points fell within the feasible speed/acceleration domain, or at least reasonably close to its limits. To complete the region, it was finally assumed that vehicles do not typically accelerate at rates higher than 3 m/s^2 and do not decelerate at rates higher than -5 m/s^2 , which corresponds to 50% of the force of gravity. This limit was determined based on studies in the Human Factors area that have shown that drivers could decelerate at rates of up to 60% the force of gravity under very extreme conditions. It should be noted that the energy and emission models that were developed using the ORNL data should not be utilized for speed/acceleration observations outside these feasible bounds. Consequently, this chapter presents smoothing schemes that ensure speed/acceleration data are within the feasible bounds of the models.

Table 4.2 demonstrates that the majority of speed/acceleration observations that were made along the Scottsdale/Rural road corridor fell within the predicted feasible domain and did not exceed 50 percent of the vehicle's maximum feasible acceleration at any given speed. When comparing the speed and acceleration profiles of Figure 4.1 to the acceleration data of Figure 4.2, it is then obvious that the suspicious recorded accelerations and decelerations are outside the typical range of operation of a passenger car. For instance, while Figure 4.2 indicates maximum practical accelerations of about 3.0 m/s^2 and maximum decelerations of about -5.0 m/s^2 , acceleration and deceleration rates of 15.0 and -15.0 m/s^2 , respectively, are observed in the acceleration profile of Figure 4.1.

The implications of such unrealistic observations on the performance evaluation of a signalized system can be significant. In particular, while erroneous speed and acceleration data might only have a small impact on delay, vehicle stop and queuing estimates, such data are likely to have major impacts on vehicle fuel consumption and emissions. In the former case, the low impact on delay is due to the fact that an error in speed measurements incurs a minor error for a single observation. However, errors in speed measurements result in significant errors in fuel

consumption and vehicle emission estimates as a result of errors in both the acceleration and speed levels of the vehicle. As an example, Table 4.3 indicates for a sample of 20 trips the total fuel consumption and vehicle emission estimates that are obtained after applying the microscopic energy and emission models of Equation 4.2 to the measured GPS speeds and accelerations. In the table, the estimates for the profiles of Figure 4.1 are included in the results for eighth run. Obviously suspicious fuel consumption and emission rates are produced for at least 8 of the 20 runs. In particular, it is observed that the results from these seven runs are so out of range that they significantly impact the MOE estimates, thus clearly demonstrating the need to filter GPS data before utilizing the energy and emission models.

TABLE 4.3 ESTIMATED FUEL CONSUMPTION AND EMISSIONS FOR RAW DATA

Trip	Obs+	Obs-	Max. Acceleration (m/s ²)	Max. Deceleration (m/s ²)	Avg	Standard Deviation	Fuel (l)	HC (gm)	CO (gm)	NOx (gm)
1	3	1	7.52	-5.93	-0.001	0.754	3,269,017.25	9,999.54	2,393.20	3,362.51
2	10	2	7.52	-8.59	0.005	0.942	6,538,035.50	13,165.55	6,555.83	7,269.99
3	10	3	7.31	-6.85	-0.002	0.932	3,279,639.75	6,795.60	9,824.83	17,167.63
4	0	0	2.35	-1.94	-0.006	0.570	1.12	1.28	15.84	3.05
5	4	0	7.98	-3.53	-0.006	0.768	1.55	9,808.85	16.84	3,288.68
6	1	0	3.12	-2.61	-0.002	0.668	1.23	1.47	16.37	3.51
7	0	0	2.71	-2.05	-0.003	0.661	1.21	1.51	16.66	3.44
8	4	2	15.50	-15.14	0.000	1.290	6,538,035.00	13,227.40	6,553.91	6,540.92
9	4	1	5.27	-6.90	0.017	0.794	86,370.88	6,906.94	3,285.18	9.89
10	0	0	1.28	-1.79	-0.006	0.407	1.00	0.98	14.93	2.28
11	0	0	1.59	-3.17	0.004	0.577	1.14	1.14	16.52	8.44
12	0	0	2.28	-2.56	-0.003	0.608	1.19	1.23	16.38	3.17
13	0	0	1.87	-2.12	0.002	0.601	1.31	1.36	17.34	3.47
14	1	0	2.43	-2.38	0.001	0.648	1.24	4.32	16.79	3.33
15	1	0	3.27	-2.53	-0.001	0.701	1.24	259.40	17.18	3.75
16	0	0	2.38	-2.07	0.009	0.735	1.38	1.70	18.04	4.48
17	0	0	2.48	-3.99	0.004	0.710	2.27	1.76	17.66	6,542.00
18	1	0	2.79	-2.40	0.000	0.628	1.22	2.93	15.98	3.40
19	2	0	3.43	-3.30	0.003	0.660	1.25	15.95	16.21	3.58
20	0	0	2.05	-1.97	0.006	0.618	1.23	1.27	17.03	3.30
Average							985,555.90	3,010.01	1,443.14	2,211.54

4.4 EVALUATION OF GPS DATA FILTERING TECHNIQUES

In this section, five different smoothing techniques are presented and evaluated on the basis of their ability to remove suspicious speed and acceleration data from GPS measurements without significantly altering the underlying trends. These techniques include data trimming, Simple Exponential (SE) smoothing, Double Exponential (DE) smoothing, Epanechnikov Kernel (EK) smoothing, and Robust Kernel (RK) and Simple Exponential (RSE) smoothing.

4.4.1 DATA TRIMMING

The data trimming approach removes data that fall outside the feasible bounds of the energy and emission model domain of application and replaces these data by speed/acceleration combinations that fall on the feasible boundary. As an example, a simple application of the technique to the acceleration data of Figure 4.1 would remove all observations falling either in the right or left shaded area of Table 4.2 and replacing them with maximum acceleration or deceleration rates for the identified speed. In this case, all unrealistic deceleration rates would be replaced by a rate of -5.0 m/s^2 , while unrealistic accelerations would be replaced by rates varying between 3.0 and 1.5 m/s^2 , depending on the speed associated with each observation.

Equations 4.5 and 4.6 summarize the data trimming technique. The technique computes the speed at instant “ t ” based on the speed in the previous period and the acceleration rate at instant “ t ”, as summarized in Equation 4.5. The acceleration, in turn, is computed using the two-point backward-difference formulation that was described earlier. If the speed/acceleration combination is infeasible, the data combination is replaced by the boundary acceleration at the measured speed using Equation 4.6.

$$u_t^s = u_{t-\Delta t}^s + a_t^s \Delta t \quad (4.5)$$

$$a_t^s = f_{trimming}(u_t^r, a_t^r) \quad (4.6)$$

where:

- a_t^r = Instantaneous raw acceleration of vehicle at time t (m/s^2),
- a_t^s = Instantaneous smoothed acceleration of vehicle at time t (m/s^2),
- u_t^r = Instantaneous raw speed of vehicle at time t (m/s),
- u_t^s = Instantaneous smoothed and/or trimmed speed of vehicle at time t (m/s),
- Δt = Measurement interval duration (s).

Figure 4.3 demonstrates the effect of the technique on the speed and acceleration profiles of Figure 4.1. The figure demonstrates that the trimming technique is efficient in removing all unrealistic acceleration and deceleration observations from the data set. These include some outlier accelerations around 250 seconds as the vehicle accelerates from a complete stop, as well as an outlier deceleration/acceleration combination at time 400 seconds. In the lower diagram, some of the undesirable effects of the technique can also be observed. The diagram compares the speed profile that is generated using the trimmed acceleration data to the original GPS speed measurement profile. The figure clearly demonstrates that a simple trimming of acceleration data results in a vehicle speed profile that underestimates vehicle speeds until the vehicle makes a full stop and has its speed returned to zero.

In Figure 4.3, it should be noted that the error in the speed profile would have been larger if the outlier acceleration had been ignored altogether, as this would have effectively replaced an interval with maximum feasible acceleration with an interval with zero acceleration (constant speed). Alternatively, the outlier could have been replaced with average adjacent readings. While this approach can be used with data points that are closely spaced, it is questionable when data points are further apart, because of the larger uncertainty that is associated with speed variations between the data points. Based on these considerations, the adoption of a trimming technique that constrains outliers to fit within the feasible speed/acceleration range appear to be a reasonable choice for application with the microscopic energy and emission models that were described earlier.

In an attempt to address the problem illustrated in Figure 4.3, a modified data trimming technique was devised. In this modified smoothing technique, which is expressed mathematically by Equations 4.5 through 4.7, the instantaneous acceleration used in the smoothing process was adjusted prior to the application of the data trimming technique to reflect the changes introduced by the technique between the raw and smoothed speed profiles, as demonstrated in Equation 4.7. This adjustment ensures that the trimming procedure closely replicates the measured speed profile, and thus, closely replicates the integral of the acceleration profile.

$$a_t^{r^*} = u_t^r - u_t^s \quad (4.7)$$

where:

$a_t^{r^*}$ = Adjusted instantaneous raw acceleration of vehicle at time t (m/s²),

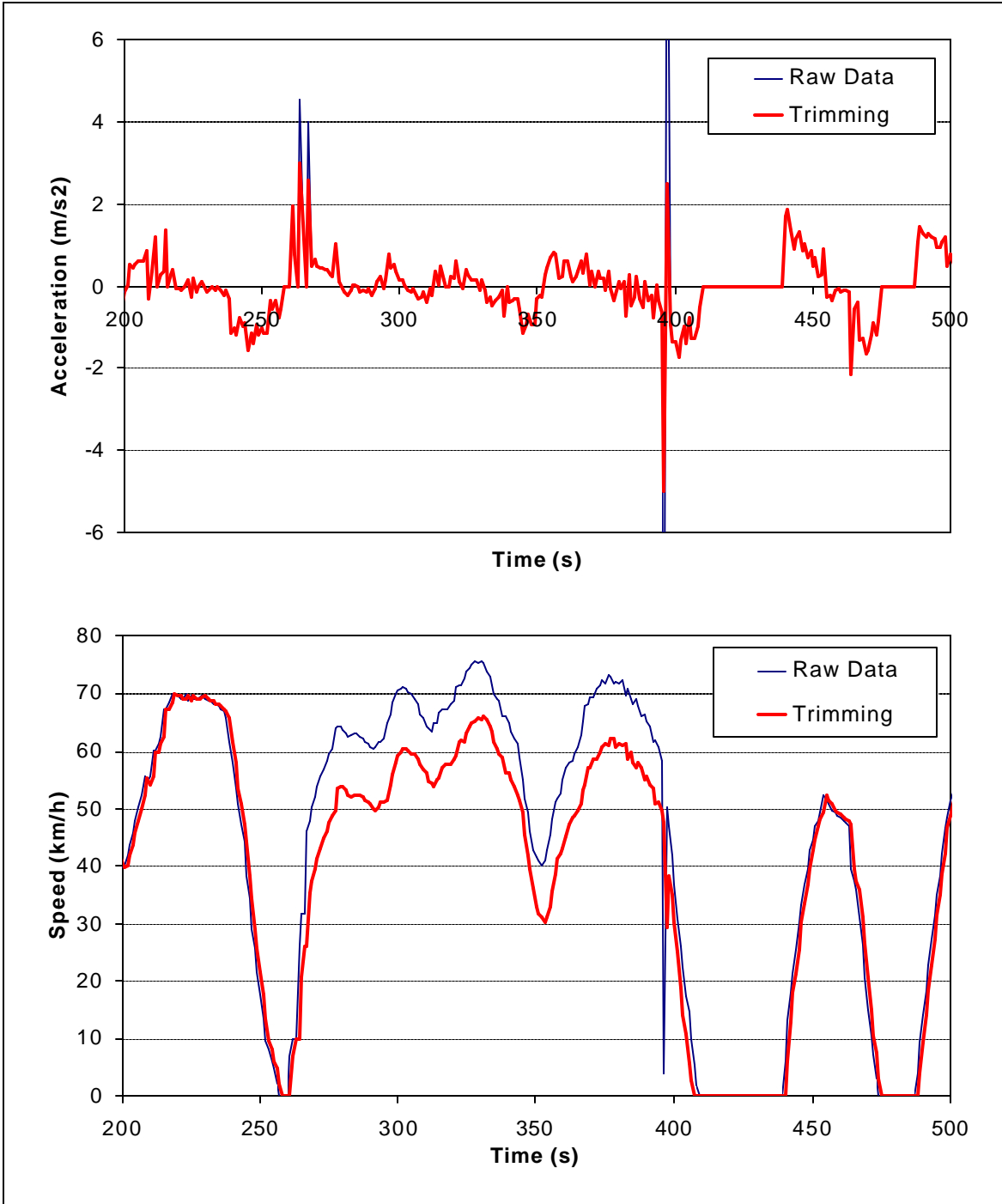


FIGURE 4.3 SPEED AND ACCELERATION PROFILES AFTER DATA TRIMMING WITHOUT ACCELERATION ADJUSTMENT

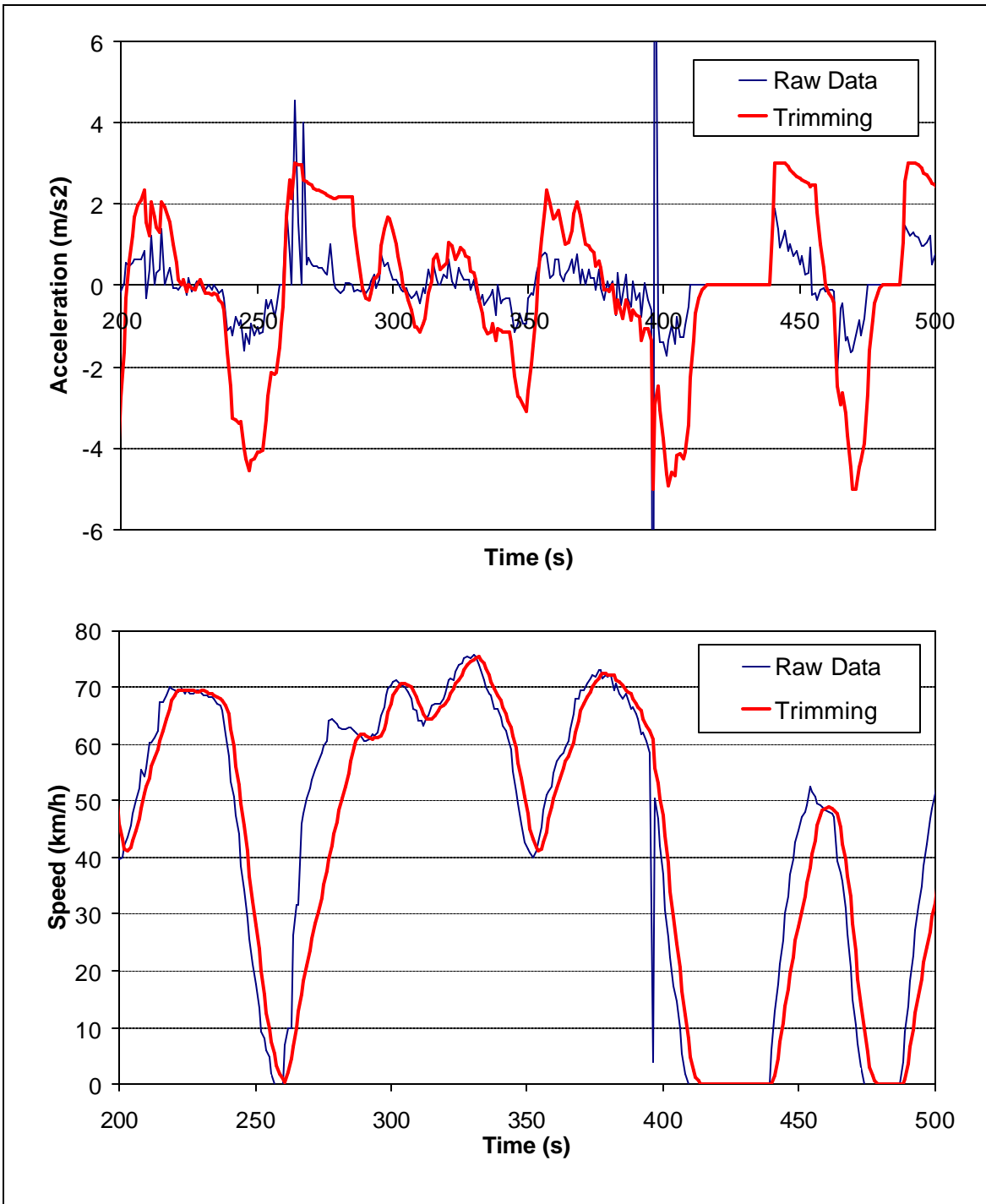


FIGURE 4.4 SPEED AND ACCELERATION PROFILES AFTER DATA TRIMMING WITH ACCELERATION ADJUSTMENT

Figure 4.4 illustrates the effects of the modified data trimming technique on the profiles of Figure 4.1. The figure clearly demonstrates that the modified trimming technique results in a much better agreement between the raw and trimmed speed profiles. However, it is also shown

that the technique was not able to completely remove the sudden deceleration/acceleration observation that was recorded at approximately 400 seconds. In addition, while only valid accelerations and decelerations are produced by the technique, there is in this case much less agreement between the raw and smoothed acceleration profiles. It is also observed that the modified technique causes speed changes in the smoothed profile to lag behind the observed changes, especially during sharp accelerations.

Based on the above results, it appears that both versions of the data trimming technique are not suitable for smoothing applications of GPS measurements. The above conclusion is confirmed when looking at the fuel consumption and vehicle emission estimates associated with the smoothed profiles. As an example, Table 4.4 summarizes the fuel consumption and vehicle emission estimates that are produced by the microscopic energy and emission model of Equation 4.2 for each of the 20 runs of Table 4.3 when the model is applied to the trimmed acceleration and speed estimates. The results demonstrate that while the fuel consumption and vehicle emission estimates are much improved when compared to those produced with the raw speed and acceleration data, clearly unrealistic estimates are still obtained for seven of the 20 runs.

TABLE 4.4 ESTIMATED FUEL CONSUMPTION AND EMISSIONS AFTER DATA TRIMMING

Trip	Obs+	Obs-	Max. Acceleration (m/s ²)	Max. Deceleration (m/s ²)	Avg	Standard Deviation	Fuel (l)	HC (gm)	CO (gm)	NOx (gm)	MSE
1	0	0	2.76	-5.00	-0.010	0.683	1269.84	26.69	18.07	3362.54	0.21
2	0	0	3.00	-5.00	-0.011	0.773	947.53	26.30	173.50	4002.30	0.30
3	0	0	3.00	-5.00	-0.013	0.832	224.44	21.76	299.91	13196.49	0.22
4	0	0	2.35	-1.94	-0.006	0.570	1.12	1.28	15.84	3.05	0.00
5	0	0	3.00	-3.53	-0.017	0.704	1.58	5.12	16.89	3288.73	0.21
6	0	0	3.00	-2.61	-0.002	0.667	1.23	1.47	16.37	3.51	0.00
7	0	0	2.71	-2.05	-0.003	0.661	1.21	1.51	16.66	3.44	0.00
8	0	0	3.00	-5.00	-0.009	0.661	24.28	8.75	176.19	3275.13	0.86
9	0	0	3.00	-5.00	0.011	0.737	2.10	4.67	317.92	3.61	0.15
10	0	0	1.28	-1.79	-0.006	0.407	1.00	0.98	14.94	2.28	0.00
11	0	0	1.59	-3.17	0.004	0.577	1.14	1.14	16.52	8.44	0.00
12	0	0	2.28	-2.56	-0.003	0.608	1.19	1.23	16.38	3.17	0.00
13	0	0	1.87	-2.12	0.002	0.601	1.31	1.36	17.34	3.47	0.00
14	0	0	2.34	-2.38	0.001	0.647	1.24	3.29	16.79	3.34	0.00
15	0	0	2.36	-2.53	-0.003	0.691	1.26	3.37	17.19	3.77	0.05
16	0	0	2.38	-2.07	0.009	0.735	1.38	1.70	18.04	4.48	0.00
17	0	0	2.48	-3.99	0.004	0.710	2.27	1.76	17.66	6542.00	0.00
18	0	0	2.79	-2.40	0.000	0.628	1.22	2.93	15.98	3.40	0.00
19	0	0	2.68	-3.30	0.001	0.649	1.26	4.31	16.24	3.62	0.04
20	0	0	2.05	-1.97	0.006	0.618	1.23	1.27	17.03	3.30	0.00
Average							124.39	6.04	61.77	1686.00	0.1

4.4.2 EXPONENTIAL SMOOTHING

The literature summarize the main forecasting and smoothing techniques as moving average models, exponential smoothing models, regression models, time series models, and Bayesian forecasting models (Montgomery *et al.*, 1976). The latter three models are more suitable for long-term forecasting, because they require an extensive number of data points to identify the appropriate model satisfactorily. For example, the Box-Jenkins time series model requires a minimum of 50 observations to forecast efficiently. Exponential smoothing methods are probably the most widely used procedures for smoothing discrete time series in order to forecast the immediate future (Montgomery *et al.*, 1976). This popularity is attributed to the simplicity, the computational efficiency, the ease of adjusting its responsiveness to changes in the process being forecast, and the reasonable accuracy of these methods (Montgomery *et al.*, 1976 and McLeavy *et al.*, 1985).

Forecasting systems that employ exponential smoothing assume that the time series of interest arises from some underlying stable process which depends only or primarily on time, and that the successive observations consist of this deterministic component plus a random error or noise component. If the smoothing constant is relatively small, more weight is given to the historical data, while if the smoothing constant is relatively large, more weight is put on the more recent observations.

The exponential smoothing techniques can be divided into non-adaptive and adaptive methods. In the non-adaptive smoothing techniques, the smoothing constant does not change, resulting in the assumption of a constant underlying time series. In the adaptive techniques, the smoothing constant is varied, thus permitting the model to adapt itself to changes in the underlying time series. This section explores more specifically the use of two non-adaptive exponential smoothing techniques to resolve some of the issues associated with GPS data. The first technique is known as Simple Exponential (SE) smoothing, while the second is known as Double Exponential (DE) smoothing. Furthermore, a robust SE method is developed as part of this research effort that varies the smoothing constant in such a manner as to ignore outlier observations. This robust smoothing method is a form of an adaptive exponential smoothing

approach. The two non-adaptive smoothing methods that were tested in this research effort are described in the following sections, while the robust smoothing technique is described later in this chapter.

Simple Exponential Smoothing

SE smoothing models assume that the mean of the underlying process remains constant with time, as defined by the general model of Equation 4.8.

$$a_t = b + E_t \quad (4.8)$$

where:

- a_t = Vehicle acceleration at time t ,
- b = Expected mean in time series process,
- E_t = Random component having a mean of 0 and standard deviation S_E ,

Based on this model, smoothed data are then generated from a time series of raw observations using Equation 4.9. When applying Equation 4.9, the literature suggests the use of a smoothing constant α that ranges between 0.01 and 0.30. By using larger values of α , one increases the responsiveness of the model to newly observed data. However, one also decreases the stability of the smoothed data by responding to the data noise. Similarly, the selection of lower values for the smoothing constant α reduces the responsiveness of the model while increasing its stability. In this study, a value of 0.30 was used, after tests with various parameter values indicated that such values appeared to produce the best overall smoothing results when considering the resulting smoothed acceleration profile and the calculated smoothed speed profile derived from the smoothed acceleration observations.

$$a_t^s = \alpha a_t^r + (1 - \alpha) a_{t-\Delta}^s \quad (4.9)$$

where:

- a_t^r = Raw vehicle acceleration at time t ,
- a_t^s = Smoothed vehicle acceleration at time t ,
- α = Smoothing constant (dimensionless parameter ranging from 0 to 1).

Figure 4.5 illustrates the effects of applying the SE smoothing technique to the acceleration data of Figure 4.1 using a scheme similar to Equations 4.5 and 4.6, where Equation 4.9 replaces Equation 4.6. The figure demonstrates that the technique was able to produce a smoothed acceleration profile that follows relatively well the general trends in the acceleration profile

based on the raw GPS measurements despite some obvious flattening of peaks and valleys in the smoothed profile. However, it also shows that the technique was not able to completely ignore the suspicious deceleration/acceleration event recorded near time 400 seconds and produced a smoothed speed profile in which the speed variations are offset in time when compared to the changes observed in the profile based on GPS measurements.

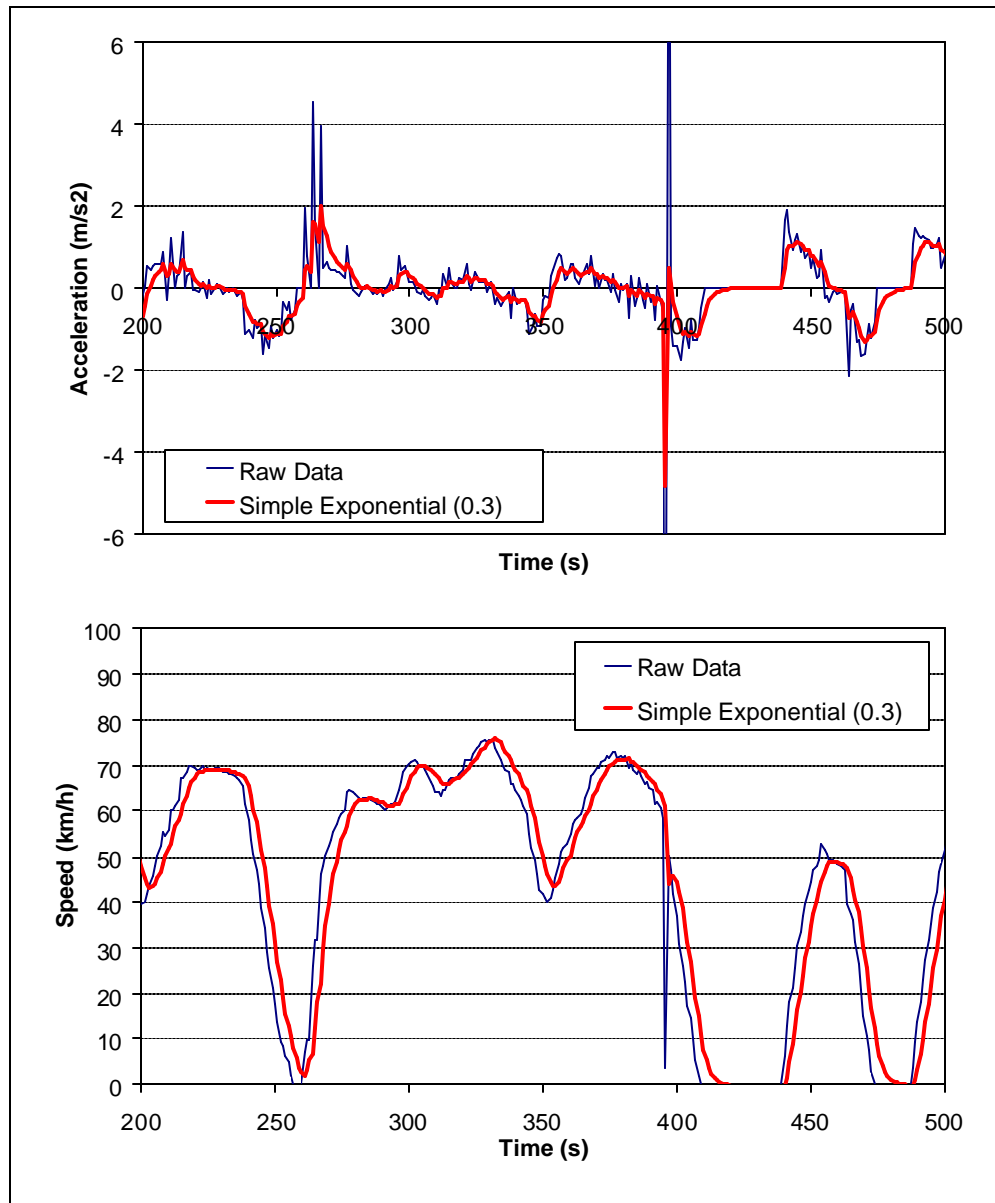


FIGURE 4.5 SPEED AND ACCELERATION PROFILES AFTER SIMPLE EXPONENTIAL SMOOTHING

The flattening of peaks and valleys in the smoothed profile explain the results of Table 4.5, which summarizes the estimated total fuel consumption and vehicle emissions for the twenty trips of Table 4.3 after application of the simple exponential data smoothing technique. In this case, while the fuel consumption and vehicle emission estimates are much improved when compared to the raw data and data trimming estimates of Table 4.3 and Table 4.4, unusually high estimates are still obtained for three of the recorded trips. These few unusual estimates are again enough to cast some doubts regarding the ability of the SE smoothing technique to ensure that GPS measurements are within the feasible range of the energy and emission models.

TABLE 4.5 ESTIMATED FUEL CONSUMPTION AND EMISSIONS AFTER SIMPLE EXPONENTIAL SMOOTHING

Trip	Obs+	Obs-	Max. Acceleration (m/s ²)	Max. Deceleration (m/s ²)	Avg	Standard Deviation	Fuel (l)	HC (gm)	CO (gm)	NOx (gm)	MSE
1	0	0	1.425	-1.811	-0.003	0.468	1.143	1.119	16.027	2.631	0.49
2	0	0	2.191	-2.750	0.001	0.555	1.201	1.527	16.694	3.245	0.63
3	1	0	2.514	-2.168	-0.005	0.568	1.334	5.450	17.631	3.451	0.62
4	0	0	1.387	-1.422	-0.009	0.453	1.073	1.078	16.104	2.660	0.29
5	1	0	2.802	-2.206	-0.009	0.559	1.378	146.228	17.738	3.794	0.44
6	0	0	1.505	-1.846	-0.002	0.518	1.189	1.212	16.575	3.020	0.35
7	0	0	1.730	-1.632	-0.006	0.553	1.189	1.309	17.248	3.301	0.30
8	0	0	1.979	-4.808	-0.002	0.547	3.043	2.213	63.346	3272.907	0.98
9	1	0	3.170	-2.291	0.024	0.609	1.296	1.530	17.343	3.791	0.45
10	0	0	0.820	-1.244	-0.009	0.278	0.974	0.920	14.982	2.043	0.25
11	0	0	0.769	-1.604	0.004	0.398	1.087	1.063	16.892	2.613	0.35
12	0	0	1.136	-1.486	-0.001	0.414	1.148	1.143	16.796	2.752	0.37
13	0	0	1.124	-1.271	0.004	0.456	1.311	1.362	18.275	3.379	0.33
14	0	0	1.231	-1.349	0.004	0.470	1.227	1.285	17.846	3.210	0.37
15	0	0	1.368	-1.480	-0.002	0.493	1.237	1.414	18.150	3.501	0.41
16	0	0	2.150	-1.328	0.017	0.560	1.395	1.969	19.357	4.294	0.42
17	0	0	1.660	-1.385	0.010	0.487	1.324	1.436	18.209	3.516	0.44
18	0	0	1.169	-1.464	0.000	0.432	1.155	1.179	17.011	2.913	0.38
19	0	0	1.460	-1.577	0.008	0.471	1.239	1.333	17.613	3.335	0.40
20	0	0	1.163	-1.397	0.013	0.467	1.234	1.276	18.100	3.244	0.34
Average							1.309	8.802	19.597	166.68	0.43

Double Exponential Smoothing

DE smoothing models assume that the mean of the underlying process changes linearly with time according to the general model of Equation 4.10.

$$a_t = b_1 + b_2 \cdot t + E_t \quad (4.10)$$

where:

- a_t = Vehicle acceleration at time t ,
- b_1, b_2 = Constants, which may be estimated using regression techniques,
- E_t = Random component having a mean of 0 and standard deviation S_E .

In this technique, smoothed data are generated from a set of raw observations by performing a double smoothing. The first smoothing applies Equation 4.11 to the set of raw data, while the second smoothing applies Equation 4.12 to the results of Equation 4.11.

$$a_t^{s_1} = \mathbf{a}a_t^r + (1-\mathbf{a})a_{t-\Delta t}^{s_1} \quad (4.11)$$

$$a_t^s = \mathbf{a}a_t^{s_1} + (1-\mathbf{a})a_{t-\Delta t}^s \quad (4.12)$$

where:

- a_t^r = Raw vehicle acceleration at time t ,
- $a_t^{s_1}$ = Intermediate smoothed acceleration from first smoothing process at time interval t ,
- a_t^s = Final smoothed acceleration from second smoothing process at time interval t ,
- \mathbf{a} = Smoothing constant (dimensionless parameter ranging from 0 to 1).

As was the case with the SE smoothing, a smoothing constant of 0.3 was utilized in the DE smoothing.

Figure 4.6 illustrates the effects of applying the DE smoothing technique to the acceleration data of Figure 4.1. In this case, a scheme similar to Equations 4.5 and 4.6 was utilized with the exception that Equation 4.6 was replaced by Equations 4.11 and 4.12.

When compared to the SE smoothing, this technique does not provide better compliance between the raw and smoothed acceleration profiles, as well as between the raw and smoothed speed profiles. While the technique was able to remove all unrealistic accelerations and decelerations and to almost entirely ignore the suspicious sudden deceleration/acceleration event recorded near time 400 seconds, it excessively flattened the peaks and valleys in the smoothed acceleration profile. This excessive flattening could explain the increasing offset observed between the raw and smoothed speed profiles, as well as the suspiciously high fuel consumption and vehicle emission estimates that can be observed in Table 4.6. In this case, the errors in both the fuel consumption and emission estimates are particularly much greater than those associated with the

profiles produced by the data trimming and the simple exponential smoothing techniques. These errors clearly indicate the inability of the DE smoothing technique to remove outlier GPS data.

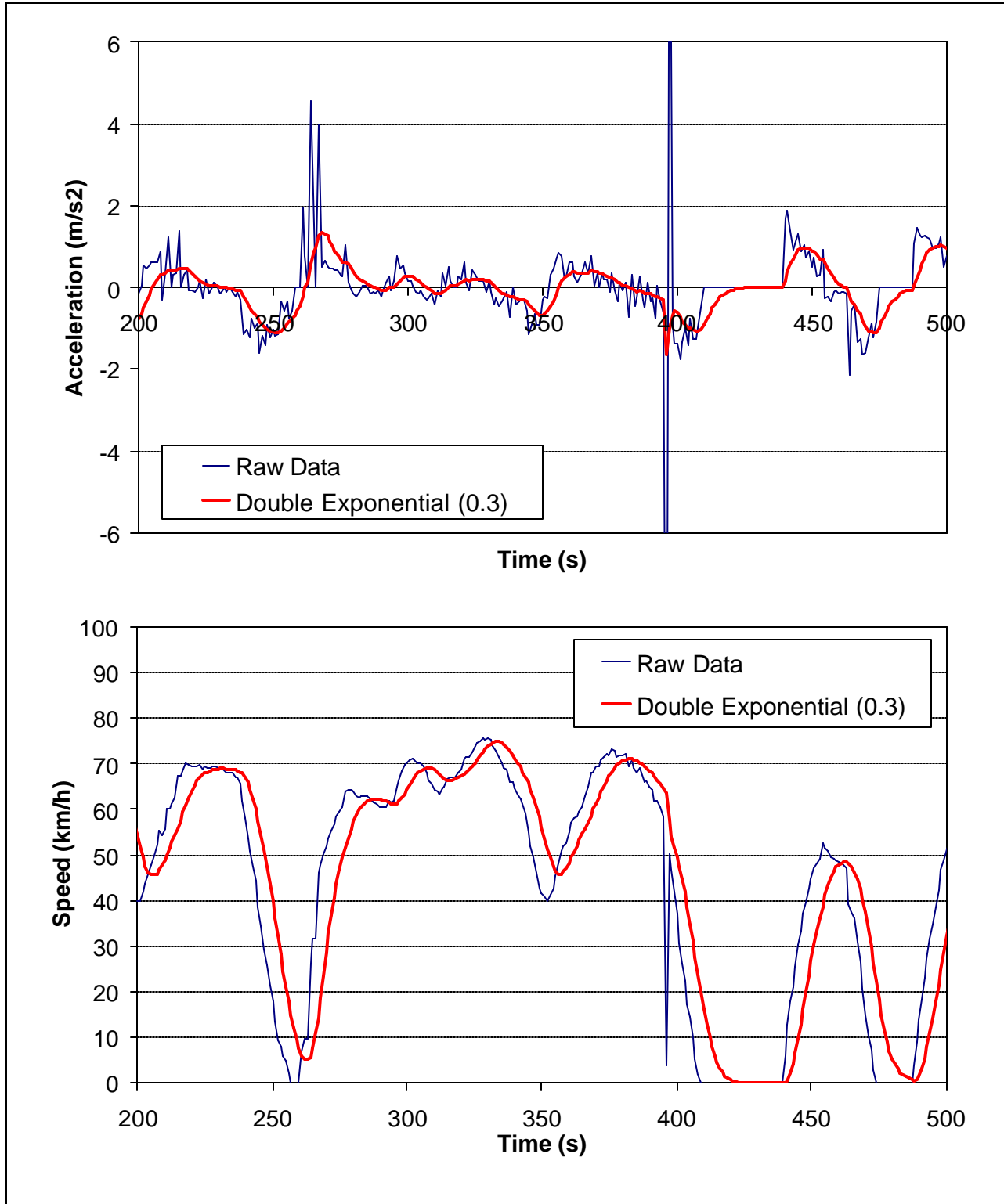


FIGURE 4.6 SPEED AND ACCELERATION PROFILES AFTER DOUBLE EXPONENTIAL SMOOTHING

TABLE 4.6 ESTIMATED FUEL CONSUMPTION AND EMISSIONS AFTER DOUBLE EXPONENTIAL SMOOTHING

Trip	Obs+	Obs-	Max. Acceleration (m/s ²)	Max. Deceleration (m/s ²)	Avg	Standard Deviation	Fuel (l)	HC (gm)	CO (gm)	NOx (gm)	MSE
1	1	0	2.601	-3.461	0.000	0.655	1.266	16.724	15.587	924.492	0.35
2	6	0	4.656	-4.973	0.006	0.790	3.558	128.911	145.003	3,273.666	0.46
3	2	0	4.246	-4.033	-0.003	0.785	1.753	3271.973	17.149	3,275.488	0.44
4	0	0	2.009	-2.024	-0.006	0.586	1.104	1.152	15.911	2.987	0.19
5	3	0	4.708	-3.507	-0.006	0.754	1.508	3428.439	16.738	3,028.198	0.30
6	0	0	2.459	-2.785	-0.003	0.691	1.241	1.403	16.281	3.563	0.24
7	0	0	2.285	-2.034	-0.003	0.702	1.214	1.663	16.558	3.548	0.20
8	5	2	4.273	-9.325	0.001	0.842	6,538,035.000	9909.828	6,554.132	6,541.257	0.72
9	3	0	3.174	-3.919	0.013	0.782	1.338	6.174	17.189	3.862	0.31
10	0	0	1.389	-1.918	-0.009	0.414	1.003	0.975	15.011	2.305	0.16
11	0	0	1.562	-2.955	0.003	0.626	1.193	1.306	17.036	4.329	0.23
12	0	0	1.97	-2.493	-0.009	0.628	1.221	1.402	16.464	3.500	0.25
13	0	0	1.941	-2.068	-0.002	0.647	1.357	1.568	17.327	4.019	0.21
14	0	0	2.114	-2.265	-0.001	0.695	1.306	1.879	16.882	3.935	0.25
15	0	0	2.202	-2.306	-0.003	0.744	1.344	3.282	16.780	4.244	0.27
16	0	0	2.15	-2.228	0.004	0.791	1.476	2.431	17.731	5.288	0.27
17	0	0	2.078	-2.412	-0.001	0.727	1.413	1.765	17.538	4.427	0.30
18	0	0	1.921	-2.361	-0.004	0.640	1.240	1.595	16.354	3.759	0.26
19	0	0	2.258	-2.764	-0.001	0.679	1.301	1.981	16.322	3.919	0.27
20	0	0	1.873	-2.153	0.003	0.670	1.284	1.486	17.143	3.875	0.23
Average							326,903.106	839.297	349.957	855.033	0.3

4.4.3 KERNEL SMOOTHING

Kernel smoothing methods use weight sequences to determine the underlying trend of a series of observations. In these methods, each observation around a given data point is assigned a weight relative to its position to the data point in question (Simonoff *et al.*, 1996 and Hardle *et al.*, 1997). These weights are then used to compute a weighted average representing the underlying trend. In this section, two specific smoothing methods are reviewed: the Epanechnikov Kernel method and the Robust M-Kernel method.

Epanechnikov Kernel (EK) smoothing

EK smoothing methods use the parabolic density function defined by Equations 4.13 and 4.14 to assign weights to observations around a given data point x .

$$K(z) = \begin{cases} 0.75(1 - z^2) & \text{if } |z| \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad (4.13)$$

$$z = \frac{t - t_{i\Delta t}}{\Delta t} \quad (4.14)$$

where:

- $K(z)$ = Kernel density function,
- t = Data point at which the underlying trend is estimated,
- $t - t_{i\Delta t}$ = Relative position of data point i in relation to data point under consideration,
- Δt = Bandwidth of density function.

In this model, the bandwidth parameter Δt controls the width of the density function and thus, how many observations surrounding a data point t will be included in the trend line estimation. As a result, the selection of a larger bandwidth parameter typically results in more smoothing, as more data points are used to compute the underlying trend, while the selection of a smaller bandwidth results in less smoothing. For this study, the impacts of assigning values of 0, 1, 2, 3 and 4 to the bandwidth parameter Δt were analyzed before determining that a value of 3 produced the best overall results. This yielded the data smoothing process of Equations 4.15 and 4.16.

$$u_i^s = u_{i-\Delta t}^s + a_i^s \Delta t \quad (4.15)$$

$$a_i^s = 0.75^2 a_{i-\Delta t}^r + 0.75 a_i^r + 0.75^2 a_{i+\Delta t}^r \quad (4.16)$$

Figure 4.7 illustrates the effects of applying the EK smoothing technique of Equations 4.15 and 4.16 to the data of Figure 4.1. The upper diagram in the figure indicates that the technique was able to follow the various trends of changing accelerations and decelerations, in addition to removing all unrealistic acceleration and deceleration observations. However, the diagram also indicates that the technique was not able to remove the suspicious deceleration/acceleration event that occurred at approximately 400 seconds. This inability to completely ignore the suspicious event explains why a single estimate appears to be out of range in the data of Table 4.7 after applying the EK smoothing technique to the trips of Table 4.3. The table indicates that the only suspicious estimate is the 12.98g of CO emissions for the eighth trip, which is illustrated in Figure 4.7. In this case, it is thus logical to conclude that the source of error in the estimation of

HC emissions is the inability of the technique to fully remove the suspicious deceleration/acceleration event at approximately 400 seconds.

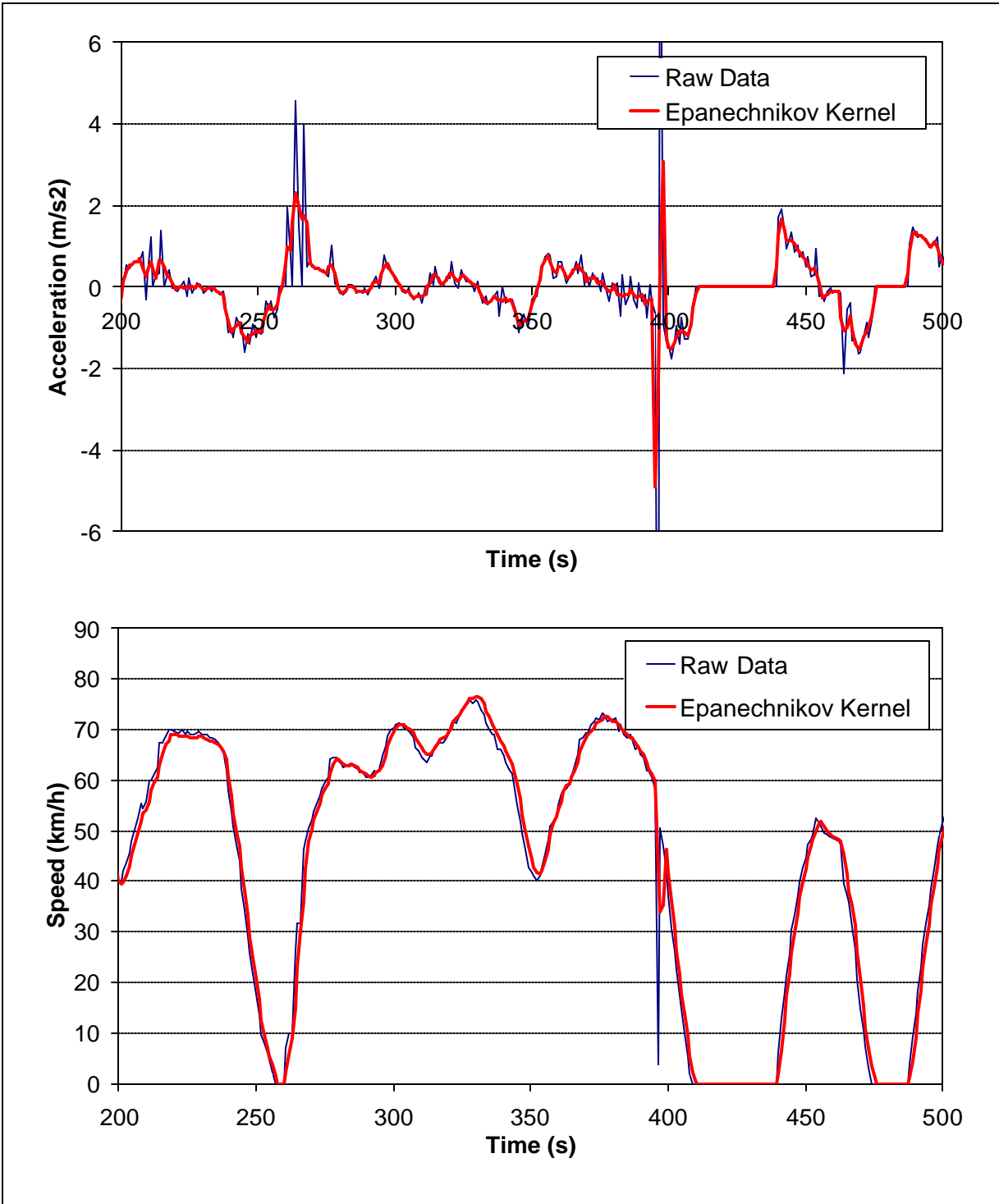


FIGURE 4.7 SPEED AND ACCELERATION PROFILES AFTER KERNEL SMOOTHING

TABLE 4.7 ESTIMATED FUEL CONSUMPTION AND EMISSIONS AFTER KERNEL SMOOTHING

Trip	Obs+	Obs -	Max. Acceleration (m/s ²)	Max. Deceleration (m/s ²)	Avg	Standard Deviation	Fuel (l)	HC (gm)	CO (gm)	NOx (gm)	MSE
1	0	0	1.68	-1.87	0.00	0.51	1.13	1.09	15.44	2.56	0.53
2	0	0	2.15	-1.76	0.00	0.60	1.17	1.39	15.94	3.10	0.68
3	0	0	1.96	-1.83	0.00	0.60	1.29	1.67	16.66	3.13	0.66
4	0	0	1.62	-1.52	-0.01	0.49	1.05	1.03	15.55	2.51	0.25
5	0	0	2.10	-2.84	-0.01	0.61	1.35	1.59	16.87	4.86	0.40
6	0	0	1.89	-2.14	0.00	0.56	1.16	1.15	15.84	2.83	0.29
7	0	0	1.83	-1.67	0.00	0.59	1.15	1.21	16.47	3.08	0.22
8	1	0	2.30	-2.49	0.00	0.56	1.11	12.98	15.78	2.87	1.15
9	1	0	3.17	-1.83	0.02	0.64	1.24	1.35	16.41	3.43	0.40
10	0	0	1.00	-1.28	-0.01	0.32	0.97	0.91	14.62	2.01	0.19
11	0	0	1.16	-1.68	0.00	0.47	1.09	1.06	16.32	2.65	0.22
12	0	0	1.52	-1.47	0.00	0.48	1.12	1.09	15.71	2.61	0.27
13	0	0	1.38	-1.55	0.00	0.51	1.25	1.25	16.81	3.05	0.22
14	0	0	1.60	-1.65	0.00	0.54	1.18	1.20	16.41	2.96	0.26
15	0	0	1.67	-1.89	0.00	0.57	1.19	1.33	16.71	3.32	0.29
16	0	0	2.15	-1.63	0.01	0.62	1.30	1.49	17.48	3.86	0.28
17	0	0	1.66	-1.58	0.00	0.56	1.26	1.29	16.64	3.16	0.33
18	0	0	1.49	-1.75	0.00	0.50	1.12	1.13	15.84	2.77	0.30
19	0	0	1.46	-1.81	0.00	0.53	1.18	1.21	16.21	2.99	0.30
20	0	0	1.38	-1.70	0.01	0.53	1.18	1.19	16.65	2.97	0.21
Average							1.17	1.83	16.22	3.04	0.37

Robust-Kernel (RK) smoothing

RK smoothing techniques are designed to handle data sets with outlying data. The robustness of these methods is essentially achieved by ignoring grossly erroneous data that would otherwise

affect in an undesirable way the smoothing results. In this study, a form of a Robust M-Kernel smoothing method was developed. M-smoothers are characterized by the use of a non-quadratic loss function to reduce the influence of the outlying observations in the calculation of the weighted average estimates defining the underlying trend. The model used in this study is the same as the EK model of Equations 4.15 and 4.16, except for the fact that a weight of 0.0 is assigned to any observation falling outside the feasible speed/acceleration range defined in Figure 4.2.

Figure 4.8 illustrates the effects of applying the RK smoothing technique to the acceleration data of Figure 4.1. The figure clearly illustrates a good agreement between the smoothed and raw acceleration profiles, but not between the smoothed and raw speed profiles. As was the case with the data trimming technique, vehicle speeds are again underestimated as a result of ignoring outlier observations.

An adjustment of vehicle acceleration prior to the smoothing the acceleration data with the RK technique similar to the model of Equations 4.5 to 4.7 finally yields the diagrams of Figure 4.9. As observed, the adjustment of vehicle accelerations results in smoothed acceleration and speed profiles that closely matches the GPS measurements, while excluding outlier observations. Specifically, the RK smoothing does not respond to the suspicious deceleration/acceleration event that is observed at approximately 400 seconds without significantly altering the speed and acceleration profiles. This ability to produce valid smoothed profiles is further confirmed by the data of Table 4.8 for the 20 test runs. In this case, it can be observed that all fuel consumption and vehicle emission estimates fall closely to each other with no apparent suspicious or unreasonably high estimates. This result thus strongly indicates the validity of the technique.

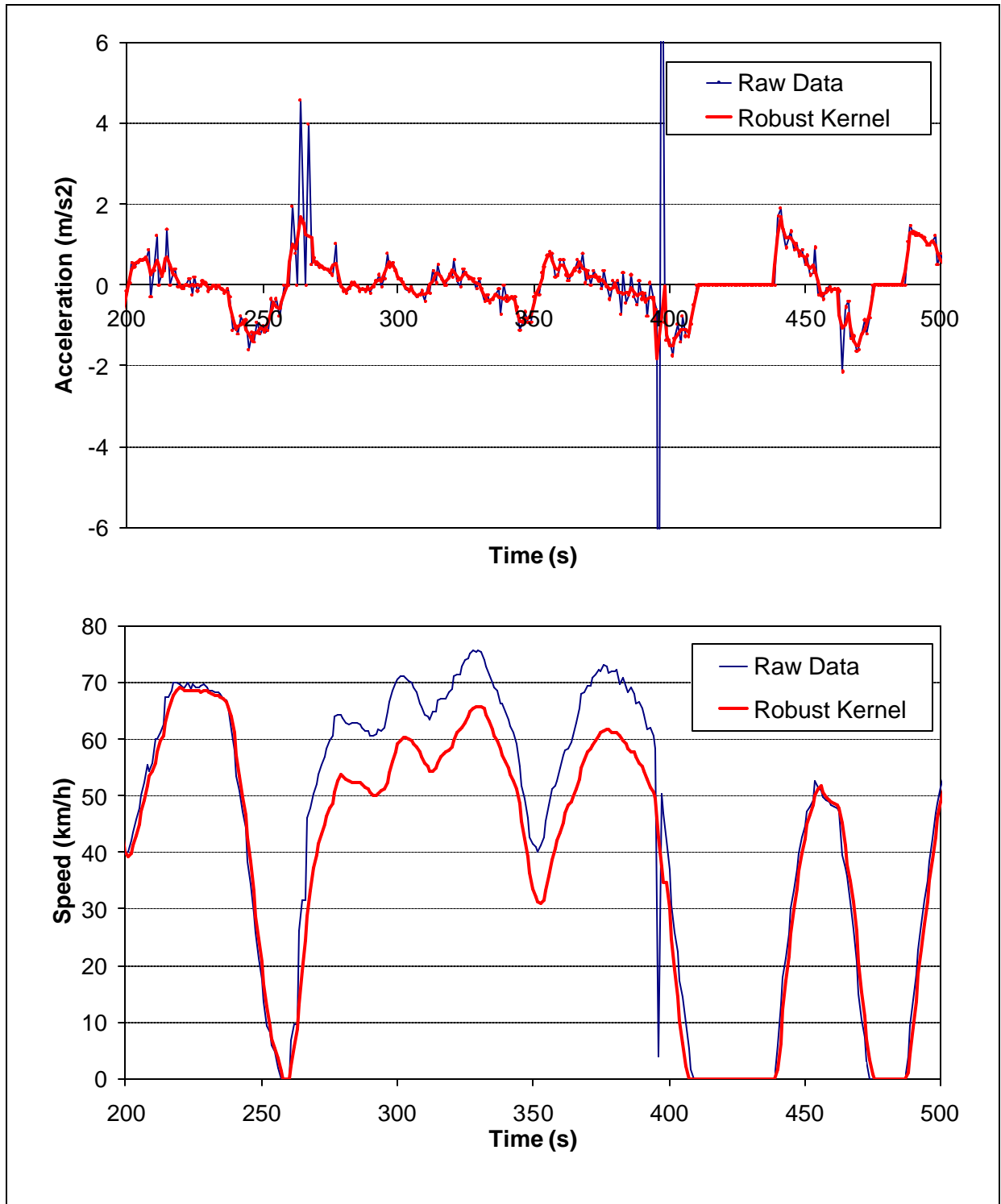


FIGURE 4.8 SPEED AND ACCELERATION PROFILES AFTER ROBUST KERNEL SMOOTHING WITH ACCELERATION ADJUSTMENT

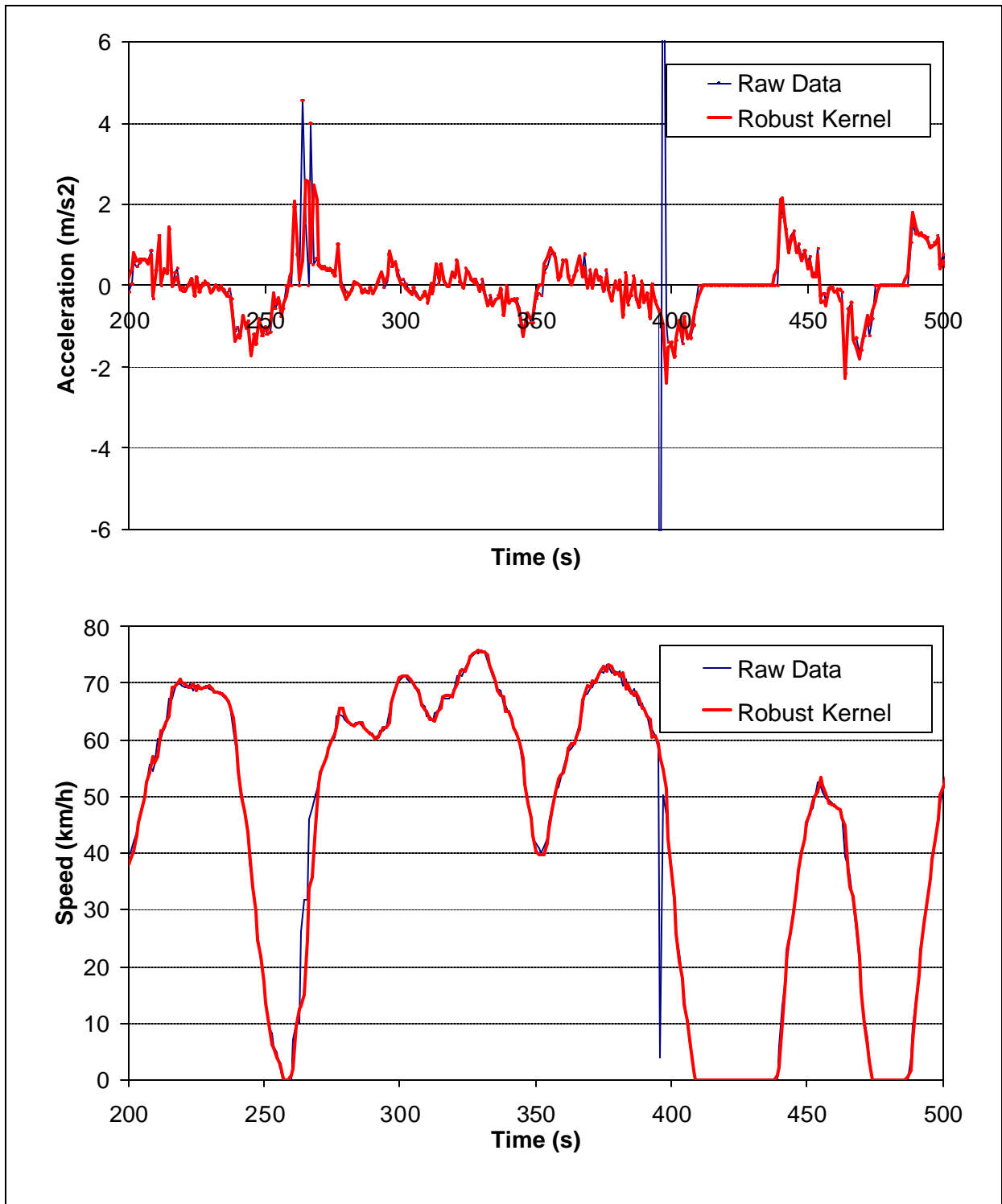


FIGURE 4.9 SPEED AND ACCELERATION PROFILES AFTER ROBUST KERNEL SMOOTHING WITH ACCELERATION ADJUSTMENT

TABLE 4.8 ESTIMATED FUEL CONSUMPTION AND EMISSIONS AFTER ROBUST KERNEL SMOOTHING

Trip	Obs+	Obs-	Max. Acceleration (m/s ²)	Max. Deceleration (m/s ²)	Avg	Standard Deviation	Fuel (l)	HC (gm)	CO (gm)	NO _x (gm)	MSE
1	0	0	1.8	-2.5	0.00	0.65	1.20	1.33	15.21	3.84	0.45
2	0	0	1.8	-2.5	0.00	0.73	1.23	1.46	15.50	4.34	0.78
3	0	0	1.8	-2.5	-0.02	0.75	1.37	1.59	16.23	4.82	0.68
4	0	0	1.8	-1.9	-0.01	0.59	1.10	1.23	15.50	2.97	0.12
5	0	0	1.8	-2.5	-0.02	0.71	1.38	1.59	16.51	4.51	0.43
6	0	0	1.8	-2.5	-0.01	0.68	1.21	1.32	15.78	3.53	0.19
7	0	0	1.8	-1.9	-0.01	0.68	1.18	1.31	16.23	3.35	0.15
8	0	0	1.8	-2.4	0.00	0.62	1.13	1.19	15.66	3.04	1.17
9	0	0	3.0	-2.5	0.01	0.75	1.29	1.54	15.98	3.86	0.46
10	0	0	1.6	-1.9	-0.01	0.45	0.99	0.96	14.60	2.22	0.12
11	0	0	1.8	-2.5	0.03	0.65	1.09	1.12	14.93	3.28	0.24
12	0	0	1.7	-2.5	-0.02	0.65	1.15	1.16	15.43	2.91	0.18
13	0	0	1.8	-2.5	-0.02	0.64	1.25	1.27	16.28	3.28	0.15
14	0	0	1.8	-2.5	-0.02	0.68	1.19	1.26	15.73	3.17	0.22
15	0	0	1.8	-2.5	-0.02	0.71	1.20	1.34	15.90	3.62	0.26
16	0	0	2.2	-2.5	-0.02	0.77	1.30	1.57	16.31	4.04	0.20
17	0	0	1.8	-2.5	-0.02	0.75	1.30	1.37	16.11	4.03	0.24
18	0	0	1.7	-2.5	-0.01	0.65	1.18	1.29	15.26	3.93	0.22
19	0	0	1.8	-2.5	-0.02	0.68	1.20	1.34	15.37	3.43	0.28
20	0	0	1.8	-2.2	-0.01	0.66	1.18	1.21	16.03	3.07	0.18
Average							1.21	1.32	15.73	3.56	0.34

4.4.4 ROBUST SIMPLE EXPONENTIAL SMOOTHING

While the RK smoothing model does remove outlier points whilst smoothing the vehicle speed and acceleration profiles, it does require that the method be applied off-line given that it uses observations in the future (e.g. $t+\Delta t$). In an attempt to develop a robust smoothing procedure that can be applied in real-time, a robust exponential smoothing procedure was developed. The model uses Equation 4.9 with a smoothing constant that is set to zero when an observation falls outside the feasible regime of Figure 4.2. The speed and acceleration profiles demonstrate that the proposed model using a smoothing factor of 0.5 follows the raw speed and acceleration profiles without responding to outlier observations, as illustrated in Figure 4.10. The fuel consumption for the test trip was 1.138 liters with vehicle emissions of HC, CO, and NO_x of 1.377, 16.066, and 3.019 grams, respectively. These MOE estimates are consistent with the RK method estimates for trip 8 of Table 4.9. Consequently, the robust SE method is proposed for use with GPS data because it provides a procedure that is robust, smoothes data noise, and can be applied in real-time.

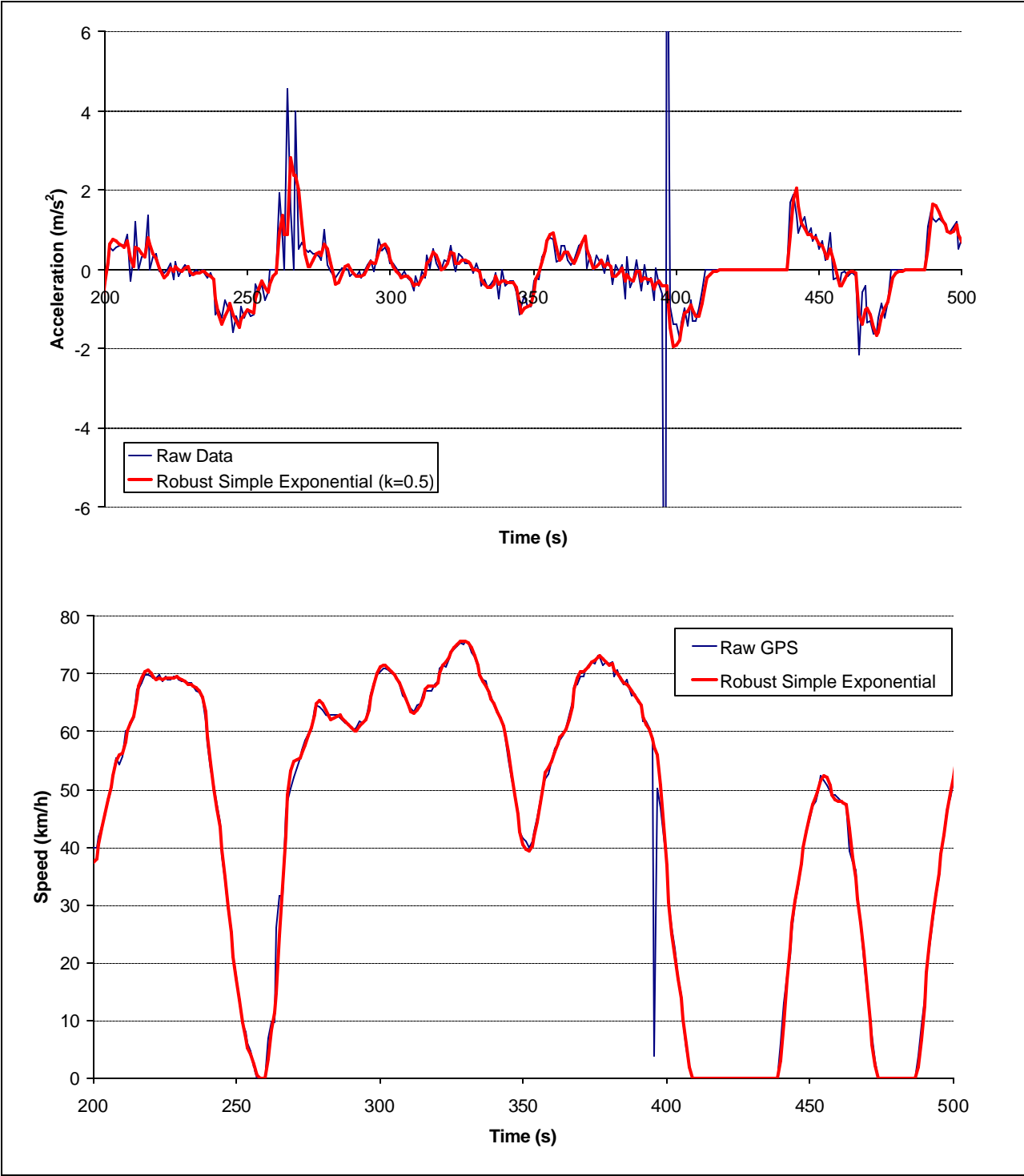


FIGURE 4.10 SPEED AND ACCELERATION PROFILES AFTER ROBUST SE SMOOTHING WITH ACCELERATION ADJUSTMENT

TABLE 4.9 ESTIMATED FUEL CONSUMPTION AND EMISSIONS AFTER ROBUST KERNEL SMOOTHING FOR PROFILES WITH MEASUREMENT ERROR

Trip	Obs+	Obs-	Max. Acceleration (m/s ²)	Max. Deceleration (m/s ²)	Standard Deviation	Fuel (l)	HC (g)	CO (g)	NOx (g)	MSE
1	0	0	1.500	-2.5	-0.019	0.881	1.41	1.99	16.92	1.21
2	0	0	1.500	-2.5	-0.019	0.881	1.41	1.99	16.92	1.21
3	0	0	1.496	-2.5	-0.011	0.896	1.43	2.04	17.05	1.23
4	0	0	1.500	-2.5	-0.017	0.897	1.42	1.95	17.16	1.23
5	0	0	1.494	-2.5	-0.024	0.889	1.42	1.98	17.32	1.23
6	0	0	1.499	-2.5	-0.021	0.919	1.44	2.10	16.81	1.29
7	0	0	1.499	-2.5	-0.016	0.880	1.40	1.93	16.98	1.18
8	0	0	1.496	-2.5	-0.019	0.898	1.43	2.03	17.22	1.27
9	0	0	1.491	-2.5	-0.014	0.914	1.45	2.06	17.36	1.24
10	0	0	1.500	-2.5	-0.017	0.918	1.44	2.07	17.19	1.19
Average						0.897	1.43	2.01	17.09	1.23

4.4.5 SENSITIVITY OF FILTERING METHODS TO DATA VARIATIONS

To evaluate the sensitivity of the filtering methods considered in this chapter to variations in speed and acceleration measurements, these methods were applied to speed profiles reflecting typical GPS measurement errors. To conduct this evaluation, ten test profiles were specifically generated from the data of Figure 4.1 (Trip 8 in Table 4.2), by assigning an error to each speed measurement. The error that was assigned was assumed to correspond to a normal distribution with a mean corresponding to the measured speed and a standard deviation of 1 m/s which corresponds to the accuracy of the GPS unit.

After applying each smoothing technique the ten test profiles, results similar to those of the eighth sample trip in Table 4.3 through Table 4.8 were observed for all ten randomly modified profiles. While the speed and acceleration estimates from each of the ten initial test profiles yielded highly unrealistic vehicle fuel consumption and/or emission estimates due to the presence of suspicious sudden changes in speed measurements, the application of the various smoothing methods significantly improved the estimates, with the best results again obtained with the robust M-Kernel smoothing method. As an example, Table 4.8 illustrates the results of the application of the M-Kernel smoothing method to each of the ten test profiles. The method resulted in fairly similar fuel consumption and emission estimates despite the added variability in the speed data. While higher fuel consumption and emissions are obtained when compared to

those associated with the original profile in Table 4.8, these higher estimates are attributable to the higher fuel consumption and emissions that are typically associated with increased speed variability.

4.5 SUMMARY AND CONCLUSIONS

This chapter demonstrated the issues associated with the use of GPS data for estimating vehicle fuel consumption and emissions and to propose solutions to these problems. In addition, this chapter investigated more specifically the impact of erroneous GPS speed measurements on energy and emission estimates and attempted to determine a data filtering technique that is best suited for the automatic removal of erroneous and suspicious data from GPS speed measurements.

Through a case study, it was first determined that the use of raw GPS data could result in unrealistically high fuel consumption and emission estimates if erroneous data are not removed from the original GPS measurements. Following this analysis, this chapter investigated the ability of six data smoothing techniques to remove erroneous and suspicious data from a given data set containing second-by-second GPS speed measurements without significantly altering the underlying trend. These techniques included data trimming, Simple Exponential smoothing, Double Exponential smoothing, Epanechnikov Kernel smoothing, and Robust Kernel and Simple Exponential smoothing. After having applied the data smoothing techniques to a number of observed speed profiles and evaluated the fuel consumption and vehicle emissions using the resulting smoothed profiles, the following observations were made:

- Simply trimming points outside the feasible speed/acceleration region generally improves fuel consumption and emission estimates. However, the estimates might remain unrealistically high for some trips.
- The simple Exponential smoothing technique improves the fuel consumption and vehicle emission estimates over data trimming technique. However, unrealistically high estimates are still obtained for some trips. In addition, the smoothed speed profiles produced by the technique appear to lag in their reaction to observed changes.
- The Double Exponential smoothing technique does not improve fuel consumption and vehicle emissions over the Simple Exponential smoothing technique. The technique

produces on the contrary much worse estimates, mostly because of the flattening of peaks and valleys that results from the application of this technique.

- The Epanechnikov Kernel smoothing technique with a bandwidth parameter of 3 produces smoothed acceleration profiles that are generally consistent with the observed data. However, the method is still unable to completely remove all suspicious data and can consequently still produce unrealistic fuel consumption and vehicle emission estimates.
- The robust M-smoothing technique with a bandwidth parameter of $h=3$ appears to be the best technique when applied in tandem with an acceleration adjustment model. This technique was able to remove all suspicious and erroneous data from the original data set without altering the underlying trends
- The robust Simple Exponential smoothing technique that was developed in this thesis was able to remove all suspicious and erroneous data from the original data set without altering the underlying trends. Both robust smoothing techniques produced realistic fuel consumption and vehicle emission estimates for all trips studied.

Chapter 5: IMPACTS OF TRAFFIC SIGNAL COORDINATION: FIELD RESULTS

The objective of this thesis is to develop a field evaluation methodology for quantifying network-wide efficiency, energy, emission, and safety impacts of operational-level transportation projects. Chapter 3 presented a proposed methodology for the field evaluation of the efficiency, energy, environmental, and safety impacts of traffic-flow improvement projects based on GPS second-by-second data. Next, Chapter 4 illustrated some problems caused by erroneous GPS measurements when estimating vehicle fuel consumption and emissions and to propose solutions to address these problems. As a solution to the mentioned problem, Chapter 4 recommended the robust M-smoothing technique with a bandwidth parameter of $h=3$ and the robust Simple Exponential smoothing technique to remove all suspicious and erroneous data from the original data set without altering the underlying trends. Based on smoothed data using the robust technique, this chapter statistically compares the various estimated MOEs for the before and after traffic signal coordination scenarios on Scottsdale/Rural Road in Phoenix, Arizona for all periods. The study area and procedures of collection are first described, before comparing the various MOEs for all periods for the before and after traffic signal coordination. Finally, the impacts of traffic signal coordination on the Southern/Baseline Avenue Corridor are also analyzed using statistical techniques for AM & PM peak periods only due to limited GPS data measurements.

5.1 EVALUATION OF SCOTTSDALE/RURAL ROAD TRAFFIC SIGNAL COORDINATION PROJECT

This section presents the study area, the before/after signal timings, and the procedures of GPS data collection for the evaluation of the impacts of traffic signal coordination along the Scottsdale/Rural Road Corridor.

5.1.1 STUDY AREA

The study area consists of a 9.6-kilometer section of Scottsdale/Rural Road that traveled the City of Tempe to the South (Rural Road) and the City of Scottsdale to the North (Scottsdale Road), as illustrated in Figure 5.1.

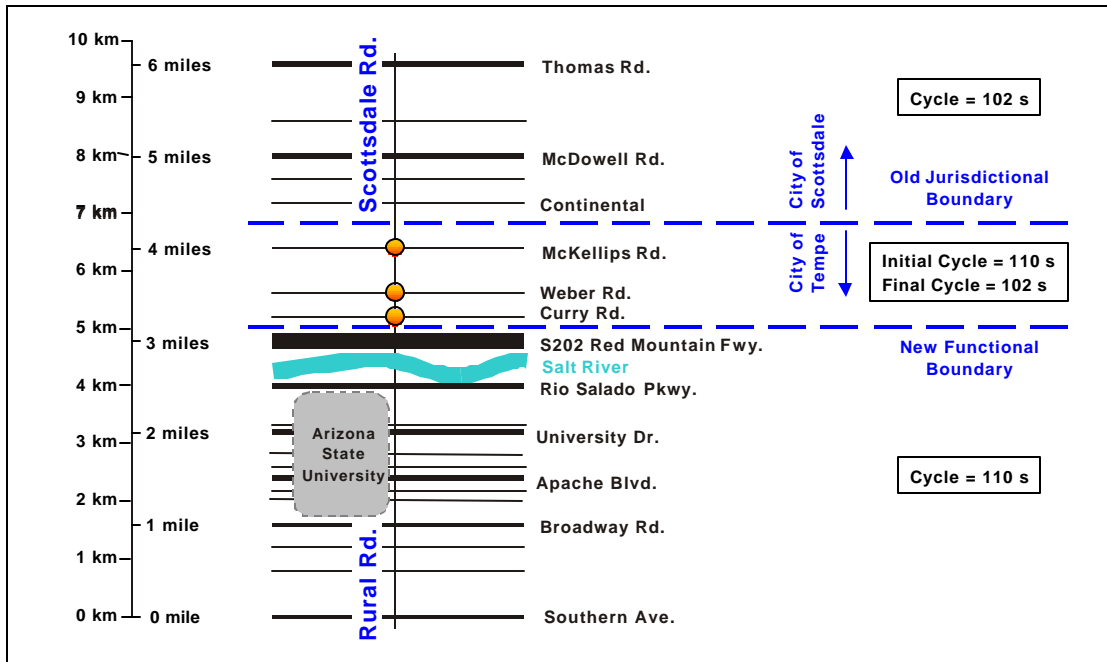


FIGURE 5.1 SCOTTSDALE/RURAL ROAD STUDY CORRIDOR

The 9.6-kilometer section includes a railway crossing (near University Drive) and a total of 21 traffic signals, 16 located in the City of Tempe and 5 in the City of Scottsdale. The traffic signals within each city operated at different cycle lengths resulting in a break in traffic signal coordination at their boundary. Specifically, the traffic signals in the City of Tempe operated at a cycle length of 110 seconds while the signals in the City of Scottsdale operated at a cycle length of 102 seconds. Ideally, both cities should operate at a common cycle length in order to improve traffic progression. However, that was not possible due to other confounding factors. Therefore, an attempt was made to improve traffic progression along the corridor by shifting the break in traffic signal coordination from the less efficient city boundary to a functional boundary where traffic signal coordination was less of an issue. This boundary shift was accomplished by changing the cycle length of three traffic signals at the intersections of Scottsdale/Rural Road with McKellips Road, Weber Road, and Curry Road.

5.1.2. BEFORE/AFTER SIGNAL TIMINGS

The three signals mentioned in the previous paragraph were re-timed independently for the AM, Midday and PM periods. Figure 5.2 illustrates the signal timings for the AM peak before and after making the signal changes.

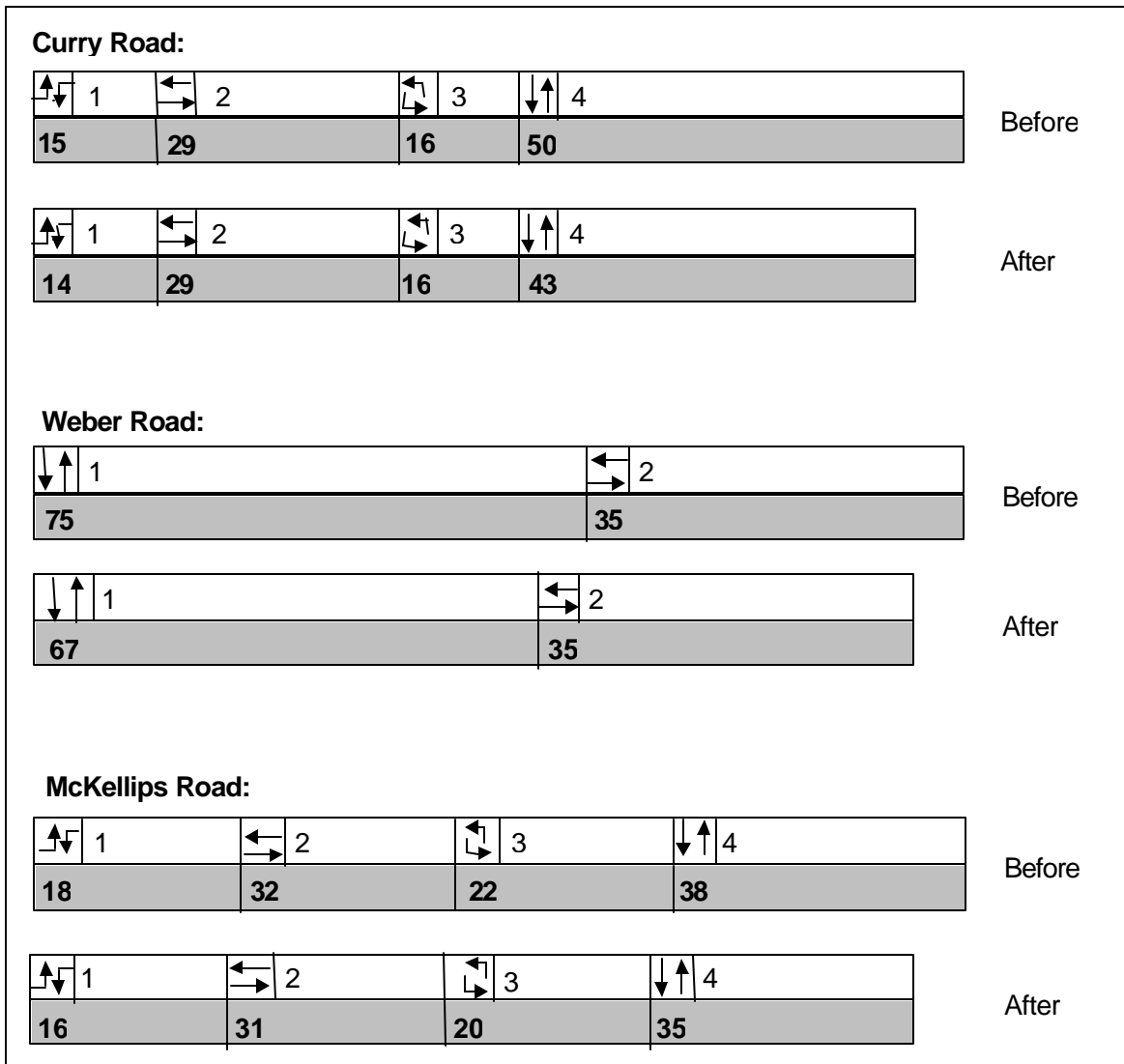


FIGURE 5.2 BEFORE/AFTER SIGNAL TIMINGS (AM PEAK PLAN)

The figure shows the phase sequencing of each traffic signal together with the duration of each phase. For example, the traffic signal at the intersection of Rural Road and Curry Road included four phases and operated at a cycle length of 110 seconds for the before scenario versus 102 seconds for the after scenario. The four phases included an advanced left turn phase for the eastbound/westbound direction (Curry Road), followed by a through phase for the same direction. These two phases were then followed by two similar phases for the northbound/southbound direction (Scottsdale/Rural Road). Figure 5.2 indicates minor changes to the signal timings between the before and after scenarios for the AM peak. Small changes were

also implemented for the Midday and PM peak analysis periods. However, contrary to the intersection green splits, major changes were made to the traffic signal offsets. These changes are indicated in Table 5.1. Consequently, the focus of the signal changes was primarily on changing the traffic signal coordination along the corridor as opposed to changing the phase split at individual intersections.

TABLE 5.1 BEFORE AND AFTER TRAFFIC SIGNAL OFFSETS

Intersection	AM Peak Plan		PM Peak Plan		Off-Peak Plan	
	Before	After	Before	After	Before	After
Rural/S202	10	10	0	0	20	20
Rural/Curry	95*	41*	100*	58*	55*	37*
Rural/Weber	75	22	2	51	45	32
Rural/McKellips	36*	98*	46*	4*	0*	4*
Scottsdale/Continental	38	38	38	38	32	32

* Offsets refer to phase 4 in Figure 5.2

5.1.3 FIELD DATA COLLECTION

In order to evaluate the efficiency, energy, environmental and safety benefits of traffic signal coordination across a jurisdictional boundary, two data collection efforts were conducted within a month of one another (January 1999 and February 1999). It was felt that a month was a sufficient duration to confine the potential benefits to the changes in the signal coordination while still allowing enough time for the signal timings to be tested and fine-tuned. The data collection efforts were conducted during the mid-week period (Tuesday through Thursday) in order to reflect typical weekday traffic conditions. Mondays and Fridays were not considered because studies have shown that they are not necessarily reflective of typical weekday conditions (Rakha *et al.*, 1995). The only abnormal condition that occurred during the data collection effort was the occasional closing of the railway crossing near University Drive. Closings typically occurred during the before and after data collection efforts at approximately the same time during the PM peak (around 4:30 PM on Thursday). Given that the roadway was closed for both data collection efforts during the same analysis period it was felt that the closures would not bias the results.

The first of the data collection efforts involved collecting mainline and turning movement counts at a number of traffic signals before and after the signal timings were changed. The data set will be used in ANOVA analyses in Chapter 6. The second data collection effort included collecting second-by-second speed measurements from floating cars that traveled along Scottsdale/Rural Road corridor before and after the signal timings were changed. The floating cars, which were equipped with a Global Positioning System (GPS), attempted to travel at the average speed of the general traffic by overtaking as many vehicles as the number of vehicles that overtook them.

For the second data collection, three GPS-equipped vehicles were driven along the Scottsdale/Rural Road corridor for three days (Tuesday through Thursday) before and after the signal timing changes. The GPS runs were conducted during the AM peak (7:00 to 9:00 AM), Midday (11:00 to 1:00 PM), and PM peak (4:00 to 6:00 PM) periods. The GPS unit measured the vehicle's latitude and longitude, its heading, and its speed every second. It should be noted that the GPS unit that was utilized did not include any differential correction, which reduced the location accuracy from 2 meters to within 100 meters. However, the relatively low accuracy in locating the vehicle didn't affect the accuracy of the speed estimates because they were not computed from the vehicle location.

As indicated in Table 5.2, a total of 141 runs were conducted for the before conditions, while a total of 160 runs were conducted for the after conditions. Each run involved driving the 9.6-kilometer study section from one end to the other.

TABLE 5.2 CLASSIFICATION OF GPS BEFORE AND AFTER RUNS

Scenario	Northbound			Southbound			TOTAL
	AM Peak	Midday	PM Peak	AM Peak	Midday	PM Peak	
Before	26	26	17	27	27	18	141
After	29	27	26	27	26	25	160
Total	55	53	43	54	53	43	301

Using the GPS speed measurements it was possible to compute a vehicle's acceleration every second. Because the measured acceleration levels included some unrealistic observations (acceleration levels beyond the capabilities of the test vehicles), a form of robust Kernel

smoothing was applied to the acceleration levels. While the details of the data smoothing are discussed in Chapter 4, it is sufficient to mention that the estimates of fuel consumption based on the smoothed speed and acceleration levels were found to range from a minimum of 0.96 to a maximum 1.59 liters/trip. It should also be noted that these estimates were found to be consistent with estimates based on the Environment Protection Agency's standard Federal Test Procedure (FTP) drive cycles (Dion *et al.*, 2000).

5.1.4 FIELD DATA ANALYSIS

This section is to compute and statistically compare the various MOEs for the before and after scenarios. This section describes also the analysis that was conducted to evaluate the efficiency, energy, emission, and safety impacts of the traffic signal re-timing on Scottsdale/Rural Road.

The differences in the various MOEs, as computed from the GPS runs, were evaluated considering all three periods of analysis collectively and then separately. Furthermore, the analysis considered the localized impacts at the signalized approaches in addition to the impacts on the entire corridor.

5.1.4.1 Results for all Periods

The various MOEs were computed for each of the 301 trips and summarized by direction and period, as demonstrated in Table 5.3. The results indicate a 6 percent increase in the average speed between the after and before conditions when averaged over all three periods. This increase was in the range of 5 percent for the AM peak, and 31 percent for the PM peak in the southbound direction.

In order to statistically verify any difference in those MOE estimates, ANOVA tests were performed on the data considering three factors: before and after scenario, analysis period (AM, Midday, PM), and direction (northbound and southbound).

TABLE 5.3 MAINLINE MOE COMPARISON (AVERAGE MOES FOR ENTIRE 9.6-KILOMETER TRIP)

Scenario	Measure of Effectiveness	Northbound			Southbound			Average
		AM Peak	Midday	PM Peak	AM Peak	Midday	PM Peak	
Before	Speed (km/h)	45.4	43.5	38.5	47.5	46.9	29.5	41.9
	Stops/trip	6.6	6.6	7.3	6.4	6.2	10.0	7.2
	Fuel (l/trip)	1.15	1.16	1.23	1.14	1.14	1.39	1.20
	HC (g/trip)	1.17	1.17	1.23	1.19	1.17	1.38	1.22
	CO (g/trip)	15.4	15.2	15.5	15.6	15.3	15.7	15.4
	NO _x (g/trip)	3.13	3.06	3.17	3.18	3.13	3.39	3.18
	Crashes×10 ⁻⁶ /trip	24.8	25.7	29.0	23.7	24.0	37.4	27.4
After	Speed (km/h)	47.9	46.0	41.0	48.2	45.4	38.7	44.5
	Stops/trip	6.4	6.4	7.5	6.4	6.6	8.1	6.9
	Fuel (l/trip)	1.13	1.15	1.22	1.14	1.17	1.27	1.18
	HC (g/trip)	1.17	1.19	1.25	1.19	1.22	1.29	1.22
	CO (g/trip)	15.4	15.5	15.7	15.6	15.6	15.7	15.6
	NO _x (g/trip)	3.00	3.16	3.27	3.06	3.22	3.28	3.17
	Crashes×10 ⁻⁶ /trip	23.5	24.5	27.4	23.3	24.8	29.9	25.6

The ANOVA results indicated that:

- The difference in speed between the before and after scenarios was statistically significant (p=0.0001).
- The number of vehicle stops was reduced by 3.6 percent, from an average of 7.2 to 6.9 stops/trip, which was found to be a marginally statistically insignificant change (p=0.0615).
- Fuel consumption was reduced by 1.6 percent on average, from 1.20 to 1.18 liters/trip. These findings were found to be statistically significant (p=0.0146). This reduction represents an annual saving of 5.32 liters/year/trip (assuming a 261-workday year), or an average yearly weekday savings of 261,900 liters/year (using an average daily tube count of 50,000 vehicles).

- There were in overall no change in HC emissions, a statistically significant increase in CO emissions ($p=0.010$), and a statistically insignificant reduction in NO_x emissions.
- Finally, the total crash risk was reduced by 6.6 percent ($p=0.001$), from 27.4×10^{-6} to 25.6×10^{-6} crashes. These crash risks correspond to approximately 2.7 crashes per million vehicle kilometers for the before scenario, and 2.5 crashes per million vehicle kilometers for the after scenario. These crash rates also are consistent with average national rates for typical arterial roadways as identified in the General Estimates System (GES) database.

5.1.4.2 AM Peak Results

Averaging over the 26 AM peak northbound before runs and the 29 after runs, there appears to be a consistent increase in the average speed between the after and before scenarios, as illustrated in Figure 5.3. In the figure, the x-axis shows the distance along the trip with a gridline at each of the 21 traffic signals. The thick gridlines further identify the signals for which the timings were altered (McKellips Road, Weber Road and Curry Road) while the thick-hatched line indicates the location of the grade railway crossing near University Drive.

Comparing the northbound and southbound speed profiles, there appears to be a more significant increase in the average speed between the before and after scenarios in the southbound direction. Furthermore, the difference in speed is more pronounced in the section between McKellips Road and Curry Road for the southbound direction than it is for the northbound direction.

Given that the speed profile of a vehicle is a function of the moment, within a signal cycle, that the vehicle encounters a first signalized intersection, comparing individual speed profiles could be misleading. For this reason, comparisons were made using average speed profiles. For this analysis, the average speed profile over all trips during the AM period for the before scenario was computed, together with the 95 percent confidence limits, as illustrated in Figure 5.4. The figure demonstrates a significant level of variability in the speed profile, especially immediately upstream of signalized intersections. As it is observed, the confidence limits are generally wider upstream of signalized intersections, reflecting specific variations in vehicle arrival times within a signal cycle. The confidence limits for the mean shown in the figure were computed by dividing the confidence limits by the square root of the number of observations in the sample.

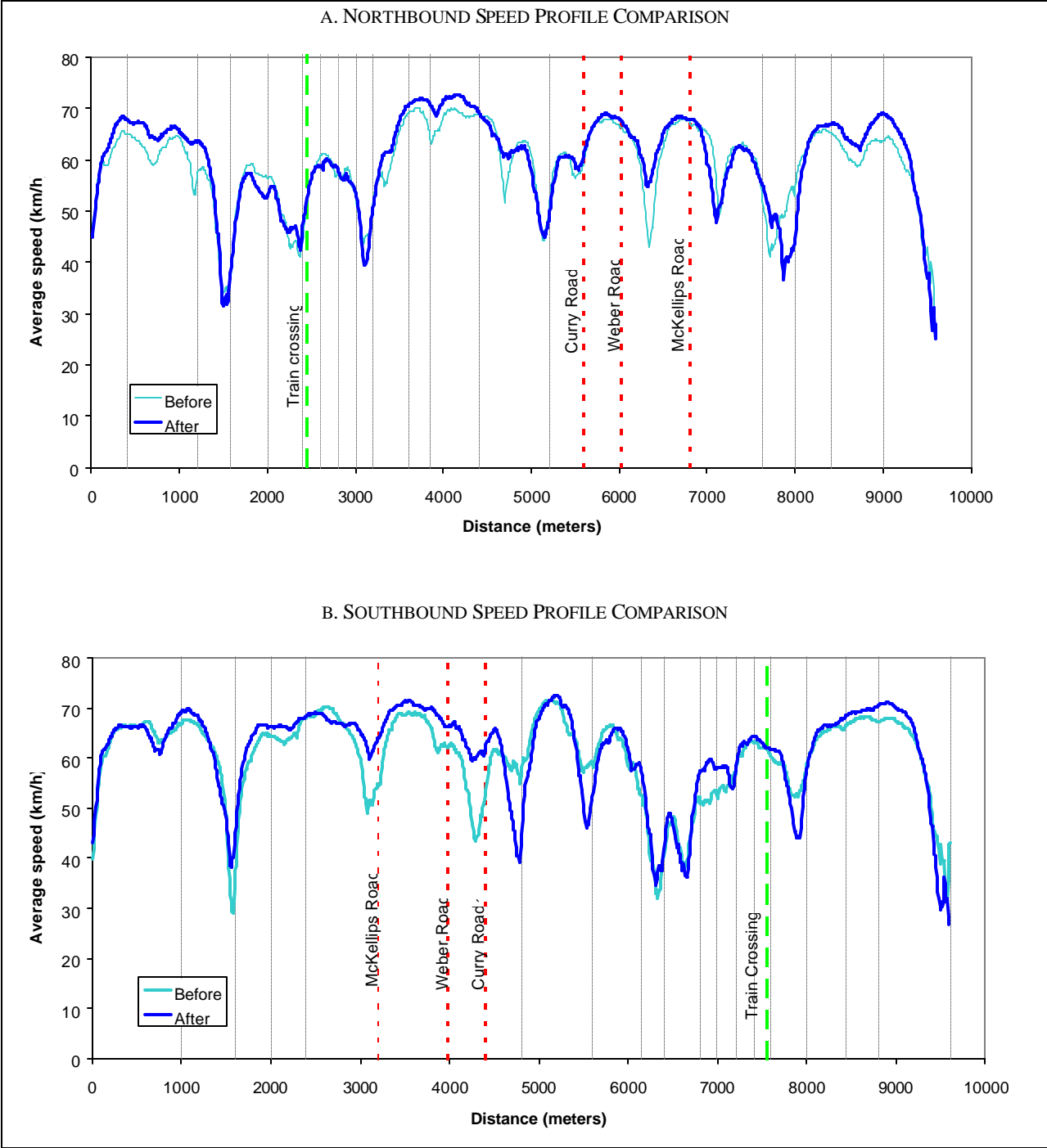


FIGURE 5.3 AM PEAK NORTHBOUND AND SOUTHBOUND SPEED PROFILE

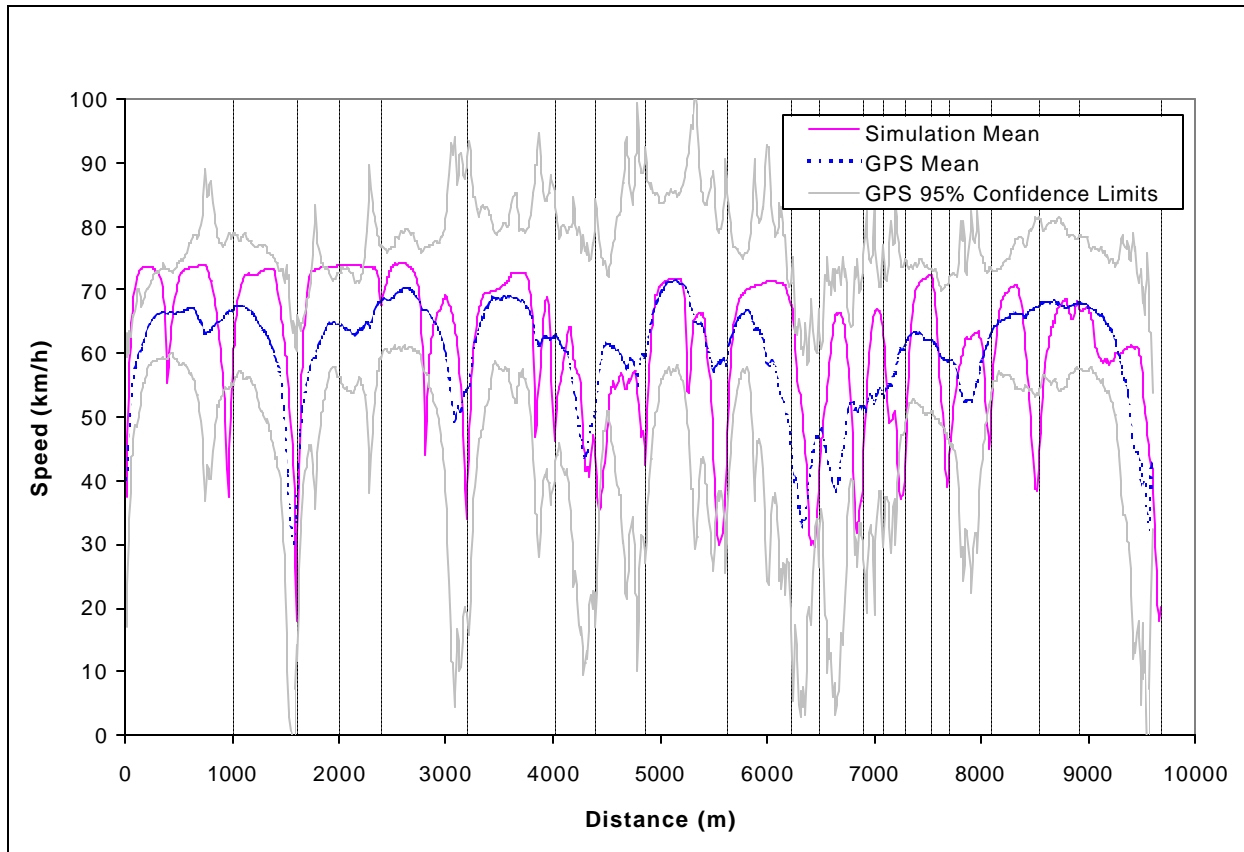


FIGURE 5.4 SPEED VARIABILITY IN FIELD DATA (SOUTHBOUND DIRECTION DURING AM PEAK)

The ANOVA results for the AM peak concluded that there was no statically significant difference between the before and after MOEs (5 percent level of significance), with the exception of the average speed that was found to be marginally statistically significant ($p=0.046$). Specifically, the average speed increased from 45.4 to 47.9 km/h in the northbound direction as a result of the traffic signal re-timing, and increased from 47.5 to 48.2 km/h in the southbound direction.

Additional ANOVA tests were performed on the computed MOEs at the signalized approaches for the AM before and after runs. Four factors were considered in the analysis: before/after scenario, direction of trip (northbound and southbound), intersection (18 unchanged and 3 re-timed) and period (AM, Midday, PM). The ANOVA tests concluded that there was a statistical difference between the before and after MOEs, with the exception to CO emissions and the expected number of fatal crashes for the approaches to the three signals that were re-timed.

Alternatively, for the traffic signals that were not re-timed, there was not enough statistical evidence to conclude that the differences in the computed MOEs were significant (5 percent level of significance).

Table 5.4 summarizes the changes in MOE between the before and after scenarios for each intersection for the AM peak period. The shaded cells in the table represent changes that are statistically significant at the 5 percent level of significance.

TABLE 5.4 PERCENT CHANGE IN MAINLINE MOES FOR AM PEAK

Intersection	Speed	Stops	Delay	Fuel	HC	CO	NO _x	Crashes
Thomas Road	-1	26	20	5	6	5	1	12
Oak Street	1	2	-7	2	5	2	9	-2
McDowell Road	3	13	-24	-6	-4	-4	-14	-13
Los Arcos Mall	5	-27	-25	-2	-4	3	-4	-6
Continental	1	12	-6	-1	-1	-2	-10	0
Mc Kellips Road	19	-40	-52	-10	-9	0	-11	-21
Weber Road	4	-34	-24	-6	-7	-2	-17	-6
Curry Road	13	-24	-21	-9	-9	-1	-14	-10
S 202	-6	30	16	0	0	-4	-11	7
Rio Salado Parkway	-1	23	6	4	7	3	9	0
6th Street	8	-23	-27	-5	-3	1	-1	-12
University Drive	-1	5	7	5	7	5	-3	5
Terrace Road	-2	-6	2	3	6	4	-1	1
Lemon Street	6	-3	-45	-9	-7	-3	2	-19
Apache Boulevard	1	20	15	2	2	0	-2	10
Spence Avenue	-2	-7	43	10	13	4	19	14
Vista del Cerro Drive	-3	20	29	8	8	5	13	8
Broadway Road	-5	17	-13	-1	1	-3	5	-8
Broadmar Street	6	-40	-29	-6	-5	-1	-22	-7
Alameda Drive	4	-24	-27	2	4	7	8	-3

Southern Avenue	-4	10	10	-4	-1	-9	-1	-2
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The table does indicate improvements at approaches to the signals that were re-timed (e.g., a 19% increase in average speed at the approaches to McKellips Road) and mixed results at the approaches to the signals that were not re-timed. Apart from the approaches to McKellips Road, there does not appear to be any statistically significant changes in the various MOEs between the before and after scenarios.

5.1.4.3 Midday Results

The ANOVA results for the Midday period concluded that there was no statistically significant difference between the before and after MOEs, except for the CO emissions and the estimated minor injury crash risk ($p=0.0002$ and 0.0252 , respectively). Although the average speed increased from 43.5 to 46.0 km/h in the northbound direction as a result of the traffic signal re-timing, and decreased slightly from 46.9 to 45.4 km/h in the southbound direction, these differences were not statistically significant.

Similar to the AM peak analysis, ANOVA tests were conducted on the Midday MOE estimates at the signalized approaches. The ANOVA tests concluded that there was no statistical difference between the before and after MOE estimates at the three re-timed traffic signals. Alternatively, the average speed, CO emissions, and estimated number of minor damage crashes were found to be higher for the after scenario. These differences were statistically significant.

Additional ANOVA tests were performed on the computed MOEs at the signalized approaches for the northbound and southbound directions. The ANOVA tests for northbound direction indicated that apart from the average speed at one intersection (McKellips Road), there was no statistical difference between the before and after scenarios. Alternatively, southbound direction experienced statistically significant reductions at the re-timed traffic signals for all MOEs, with the exception for CO emissions.

In summary, the benefits of the traffic signal coordination during the Midday analysis period were insignificant at the corridor level, but significant at the approach level, especially in the southbound direction.

5.1.4.4 PM Peak Results

The ANOVA results for the PM peak analysis period demonstrated statistically significant improvements in the various MOEs in the southbound direction. Specifically, the average speed increased insignificantly from 38.5 to 41.1 km/h in the northbound direction, while it increased significantly from 29.5 to 38.7 km/h in the southbound direction. These increases in average speed were observed along the entire corridor.

ANOVA tests for re-timed traffic signals were performed on the computed MOEs for the PM before and after runs. The ANOVA tests concluded that there was a statistical difference in delay and crash risk as a result of the traffic signal re-timing. For the 18 traffic signals that were not re-timed, there was enough statistical evidence to conclude that the differences in the computed MOEs were significant (5 percent level of significance), except for the CO and NO_x emission. However, these differences were mixed in direction. Furthermore, additional ANOVA tests concluded that the benefits of the signal re-timing were restricted to the southbound direction. Consequently, it appeared that the benefits of the signal coordination were confined to the approaches to the traffic signals that were re-timed and to the southbound direction. These benefits were not apparent when the entire corridor was considered.

5.2 FIELD EVALUATION OF SOUTHERN/BASELINE CORRIDOR TRAFFIC SIGNAL COORDINATION PROJECT

This section first describes the field data collection effort on Southern/Baseline Avenue. This description is then followed by a summary analysis of the GPS runs and a statistical analysis of the impact of the signal-retiming project on the corridor.

The Southern Avenue/Baseline corridor was selected as one of the smart corridors within the Phoenix MMDI proposal because it is one of the busiest east-west arterial corridors in the Phoenix Metropolitan area. Although the plan was to perform traffic signal coordination across

the jurisdictional boundary between the City of Mesa and the City of Tempe, this plan was not implemented. Nevertheless, the methodology used in this section can be applied to analyze operational ITS projects in other areas.

5.2.1 STUDY AREA

Figure 5.5 shows the Southern/Baseline corridor. The GPS car runs for the data collection covered an approximately 17.5-km section of the corridor that ran from Gilbert Road to the East to 48th street to the west.

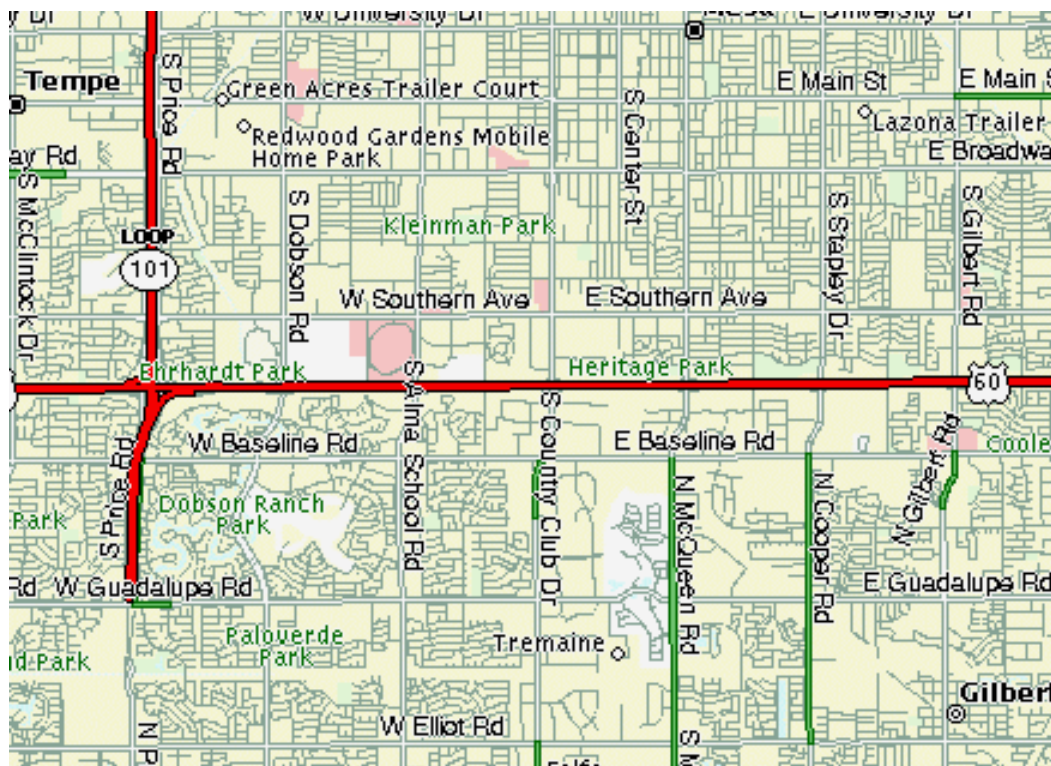


FIGURE 5.5 SOUTHERN/BASELINE CORRIDOR

(Source: <http://www.mapquest.com>)

5.2.2 FIELD DATA COLLECTION

Two floating car data collection efforts were made along the Southern/Baseline corridor. A total of 60 runs were made, with 38 runs conducted before the signal timings were changed and 22 runs after the signal timings were changed. During the after data collection effort, some construction work was being done on Southern Avenue and Gilbert Road, as well as on a section

of 300 m west of Baseline and Gilbert. The first of these data collection efforts was conducted from June 24 to 26, 1997 while the second was conducted from June 7 to 10, 1999. The data collection effort included collecting instantaneous speed measurements from floating cars that traveled along Southern Road, Baseline Road and Interstate 60 prior and after the signal timings were changed. These floating cars were equipped with a Global Positioning System (GPS) unit that measured the vehicle's speed every second. For the before study, two vehicles were used, while only one was used for the after study.

Specifically, a number of GPS-equipped vehicles were driven along the three parallel roadways of the study corridors for three days (Tuesday through Thursday) or four days (Monday through Thursday) before and after changing the signal timings. The GPS runs were conducted during the AM peak (7:00 to 9:00 AM) and the PM peak (4:00 to 6:00 PM). The GPS unit measured the vehicle's latitude and longitude location, its heading, and its speed every second. The speed was measured based on the shift in the GPS signal (Doppler technology). The vendor stated speed accuracy was 0.1 m/s.

5.2.3 FIELD DATA ANALYSIS

The efficiency, energy, emission and safety measures of effectiveness were computed for the 60 floating car runs that were conducted. Table 5.5 summarizes the results of this evaluation for both the AM and PM peak periods for both directions of travel along the Southern/Baseline corridor. A total of 34 GPS runs were made during the AM peak while a total of 26 runs were made during the PM peak, as summarized in Table 5.5.

As it can be observed in Table 5.5, the test vehicles experienced congestion in the westbound direction during the AM peak and in the eastbound direction during the PM peak. During the AM peak, an average speed of 60.11 km/h was observed for traffic in the westbound direction while vehicles traveled at 74.24 km/h in the opposing direction. For the PM peak period, a speed of 57.67 km/h was observed in the eastbound directions while traffic flowed westbound at 69.13 km/h. These results are consistent with the typical daily flow profile of the study corridor in Figure 5.6, in the sense that the AM peak occurs in the westbound direction while the PM peak occurs in the eastbound direction.

TABLE 5.5 SUMMARY RESULTS FOR TRIPS

	Variable	Sample Size	Mean	StdDev	Min	Max
AM Peak Eastbound	Speed (km/h)	13	74.24	24.00	49.35	103.38
	Stops	13	5.44	3.41	1.44	9.62
	Delay (s)	13	354.70	290.14	33.54	698.62
	Fuel (l)	13	2.00	0.24	1.67	2.26
	HC (g)	13	2.68	0.25	2.33	3.18
	CO (g)	13	36.30	7.44	28.98	48.62
	NO _x (g)	13	7.51	1.63	5.44	10.17
	Crash Risk (Crashes)	13	20.00	6.91	12.39	28.18
AM Peak Westbound	Speed (km/h)	21	60.11	17.49	34.46	97.83
	Stops	21	7.22	3.41	1.83	13.90
	Delay (s)	21	532.56	288.83	64.83	1236.79
	Fuel (l)	21	2.11	0.29	1.74	2.78
	HC (g)	21	2.66	0.35	2.08	3.52
	CO (g)	21	32.04	3.89	28.22	42.17
	NO _x (g)	21	8.01	1.80	5.82	11.87
	Crash Risk (Crashes)	21	24.01	6.74	13.03	40.06
PM Peak Eastbound	Speed (km/h)	13	57.67	22.92	32.55	91.13
	Stops	13	7.96	4.47	1.69	14.53
	Delay (s)	13	667.25	464.00	108.08	1328.66
	Fuel (l)	13	2.17	0.37	1.68	2.69
	HC (g)	13	2.66	0.20	2.30	2.98
	CO (g)	13	32.99	4.48	28.78	42.32
	NO _x (g)	13	7.93	1.44	5.29	10.24
	Crash Risk (Crashes)	13	26.98	10.77	14.01	41.97
PM Peak Westbound	Speed (km/h)	13	69.13	24.93	43.34	102.09
	Stops	13	5.43	3.46	0.88	9.77
	Delay (s)	13	438.72	322.54	40.15	870.80
	Fuel (l)	13	2.01	0.23	1.70	2.38
	HC (g)	13	2.53	0.18	2.21	2.78
	CO (g)	13	35.46	7.73	28.36	49.97
	NO _x (g)	13	7.04	1.23	5.59	9.29
	Crash Risk (Crashes×10 ⁻⁶)	13	21.96	7.68	12.41	31.96

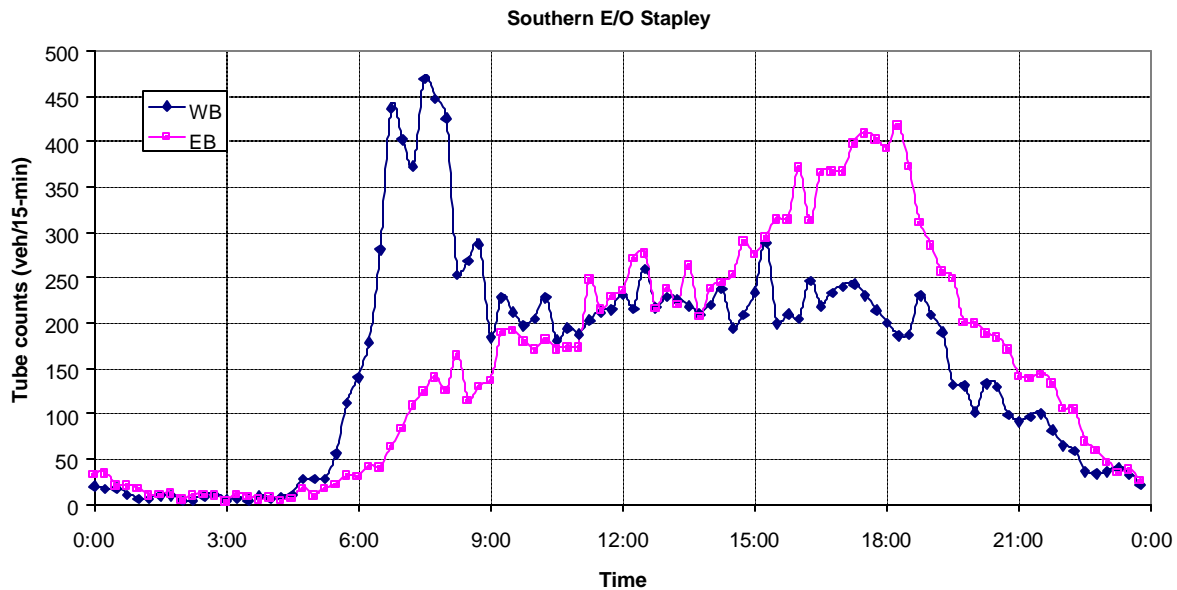


FIGURE 5.6 TEMPORAL VARIATION IN TRAFFIC FLOW ALONG SOUTHERN ROAD

Normality Test

As discussed in Chapter 3, before conducting an ANOVA test, a normality test should be done to check whether the dependent variable populations follow a normal distribution. The Shapiro-Wilk test was conducted in that purpose. This test produces a score ranging from 0 to 1. The closer the score is to 1, the more likely the data is normally distributed.

The distinction between the normality and non-normality of data and what should be done in the case of non-normality are two controversial issues. On the one hand, some researchers believe that the ANOVA technique is robust and can be used with data that do not conform to normality. On the other hand, other researchers believe that non-parametric techniques should be used whenever there is a question of normality. Research has shown that data that do not conform to normality due to skewness and/or outliers can cause an ANOVA to report more Type 1 and Type 2 errors (Ott, 1989).

Conover (1980) recommends the use of ANOVA on raw data and a ranked data analysis in experimental designs where no non-parametric test exists. If the results from both analyses are nearly identical then the parametric test is valid. If the rank-transformed analysis indicates

substantially different results than the parametric test, then the ranked data analysis should be used.

As a result, an approach using both an ANOVA on the normalized data and an ANOVA on rank-transformed data was adopted. Ranking of data was only conducted when the Shapiro-Wilk test was less than 0.85. As indicated in Table 5.6, the Shapiro-Wilk test exceeded 0.85 for most of the dependent variables that were considered except for the average speed and CO emissions. By rank-transforming the average speed and CO emissions it was ensured that these variables were normalized (Shapiro-Wilk value in excess of 0.85).

TABLE 5.6 SUMMARY RESULTS OF NORMALITY TEST

Variable	Shapiro - Wilk Statistic
Average Speed	0.85
Rank of Average Speed	0.94
Number of Vehicle Stops	0.94
Delay	0.91
Fuel Consumption	0.93
HC Emissions	0.97
CO Emissions	0.78
Rank of CO Emissions	0.94
NO _x Emissions	0.94
Number of Crashes	0.91

ANOVA Tests

In order to statistically verify any differences in the MOE estimates between the before and after case, two ANOVA tests were conducted. The first of these ANOVA tests analyzed the entire data set (60 trips) while the second test only considered the AM peak trips (34 trips).

In the first analysis four independent factors were considered in the ANOVA. The first of these factors was the period of travel (AM peak versus PM peak), as summarized in Table 5.7. The second factor included the roadway on which the runs were made. Three parallel routes were available along the Southern/Baseline corridor, including Southern Road, Baseline Road and Interstate 60. The third factor that was considered was the direction of travel (eastbound versus

westbound). The fourth and final factor was whether the trip was made before or after the signal timings were changed.

TABLE 5.7 FACTORS CONSIDERED IN ANOVA

Class	Levels	Description of Levels
Period of Travel	2	AM peak - PM peak
Roadway	3	Southern Road - Interstate 60 - Baseline Road
Direction of Travel	2	Eastbound - Westbound
Before/After Indication	2	Before - After

The results of the ANOVA indicate that the average speed was statistically different across the different roadways (FACIL variable), while the period of travel (PER variable), the direction of travel (DIR variable) or the before/after flag (FLAG variable) were not found to be statistically different, as demonstrated in Table 5.8.

The model provided a good fit to the data (coefficient of determination of 0.87). Interestingly although the direction of travel and period of travel individually were not significant, the interaction of period and direction was found to be significant. This finding is best explained using Figure 5.7.

TABLE 5.8 ANOVA RESULTS FOR SPEED VARIABLE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	21	25490.68798595	1213.84228505	12.06	0.0001
Error	38	3824.37649905	100.64148682		
Corrected Total	59	29315.06448500			
	R-Square	C.V.	Root MSE	SPD Mean	
	0.869542	15.52957	10.03202307	64.59950000	
Source	DF	Type III SS	Mean Square	F Value	Pr > F
PER	1	73.45003102	73.45003102	0.73	0.3983
FACIL	2	13983.83264232	6991.91632116	69.47	0.0001
FACIL*PER	2	339.63791566	169.81895783	1.69	0.1986
DIR	1	5.29347993	5.29347993	0.05	0.8198
DIR*PER	1	1956.24943080	1956.24943080	19.44	0.0001
FACIL*DIR	2	109.80238536	54.90119268	0.55	0.5840
FACIL*DIR*PER	2	1082.67752763	541.33876381	5.38	0.0088
FLAG	1	314.74188201	314.74188201	3.13	0.0850
FLAG*PER	1	3.26455514	3.26455514	0.03	0.8580
FLAG*FACIL	2	184.35561937	92.17780968	0.92	0.4088
FLAG*FACIL*PER	1	56.96577303	56.96577303	0.57	0.4565
FLAG*DIR	1	6.89344120	6.89344120	0.07	0.7950
FLAG*DIR*PER	1	228.31343376	228.31343376	2.27	0.1403
FLAG*FACIL*DIR	2	127.18685291	63.59342646	0.63	0.5371
FLAG*FACIL*DIR*PER	1	113.63403377	113.63403377	1.13	0.2947

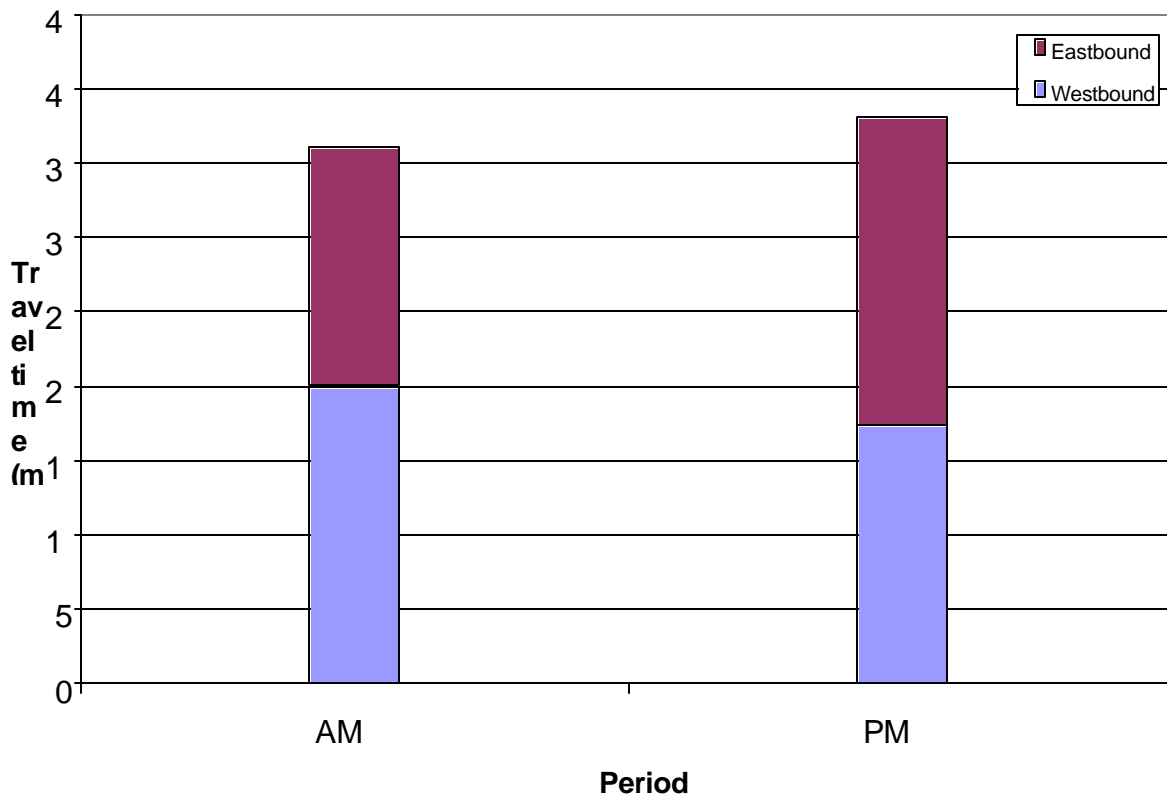


FIGURE 5.7 AVERAGE TRAVEL TIME AS A FUNCTION OF PERIOD AND DIRECTION OF TRAVEL

In the figure, it is observed that although the time to complete a round trip during each of the peaks is similar (in the range of 36 to 38 minutes), the breakdown of trip duration by direction is different during each of the periods. Specifically, during the AM peak the vehicles travel at lower speeds (higher travel time) in the westbound direction while they travel at lower speeds in the eastbound direction during the PM peak. Consequently, while singularly these variables are not significant, collectively they become significant.

Given that the average speed estimates failed the Shapiro-Wilk normality test, the estimates were rank-transformed. Comparing Table 5.8 to Table 5.9, it appears that the ANOVA of the rank-transformed data was consistent with the parametric analysis. In both analyses, the before and after conditions were not found to be statistically significantly different at a level of significance of 5 percent.

TABLE 5.9 ANOVA RESULTS FOR RANK OF SPEED VARIABLE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	21	15027.38333333	715.58968254	9.16	0.0001
Error	38	2967.61666667	78.09517544		
Corrected Total	59	17995.00000000			
	R-Square	C.V.	Root MSE	RSPD Mean	
	0.835087	28.97425	8.83714747	30.50000000	
Source	DF	Type III SS	Mean Square	F Value	Pr > F
PER	1	323.53051436	323.53051436	4.14	0.0488
FACIL	2	7541.00623727	3770.50311864	48.28	0.0001
FACIL*PER	2	252.37672723	126.18836362	1.62	0.2121
DIR	1	28.17599060	28.17599060	0.36	0.5516
DIR*PER	1	1216.91502721	1216.91502721	15.58	0.0003
FACIL*DIR	2	41.22906721	20.61453360	0.26	0.7694
FACIL*DIR*PER	2	171.63867086	85.81933543	1.10	0.3436
FLAG	1	312.50646566	312.50646566	4.00	0.0526
FLAG*PER	1	2.29086169	2.29086169	0.03	0.8649
FLAG*FACIL	2	112.51104002	56.25552001	0.72	0.4931
FLAG*FACIL*PER	1	76.48749284	76.48749284	0.98	0.3286
FLAG*DIR	1	16.82133026	16.82133026	0.22	0.6452
FLAG*DIR*PER	1	99.99247737	99.99247737	1.28	0.2649
FLAG*FACIL*DIR	2	404.06205889	202.03102945	2.59	0.0884
FLAG*FACIL*DIR*PER	1	43.29464306	43.29464306	0.55	0.4611

The results for the other MOEs, which are summarized in Table 5.10, were found to be similar to the average speed results. Specifically, all MOEs were found not to be statistically different between the before and after conditions at a level of significance of 5 percent, except for HC emissions. In particular, the HC emissions were found to be lower by 2 percent for the after conditions when compared to the before conditions.

In addition to comparing MOEs between the after and before conditions, a comparison was made across the different roadways, as summarized in Table 5.11.

TABLE 5.10 SUMMARY OF ANOVA RESULTS (ENTIRE DATA SET)

Dependent Variable	Root MSE	F Value	Pr > F
Speed	314.74	3.13	0.085
Rank of Speed	312.51	4.00	0.053
Stops	0.00	0.00	0.996
Delay	118833.11	3.92	0.055
Fuel	0.00	0.09	0.769
HC	0.31	5.01	0.031
CO	0.97	0.10	0.749
Rank of CO	74.75	1.49	0.229
NO _x	0.02	0.02	0.888
Crashes	56.18	3.80	0.059

TABLE 5.11 SUMMARY RESULTS FOR AM PEAK GPS RUNS

Variable	Roadway	Sample Size	Mean	SNK Grouping
Speed (km/h)	1	7	50.61	A
	2	13	51.87	A
	3	14	85.64	B
Stops	1	7	9.52	A
	2	13	8.49	A
	3	14	3.23	B
Delay (s)	1	7	699.90	A
	2	13	643.84	A
	3	14	180.40	B
Fuel (l)	1	7	2.34	A
	2	13	2.20	A
	3	14	1.81	B
HC (g)	1	7	2.91	A
	2	13	2.63	B
	3	14	2.57	B
CO (g)	1	7	31.33	A
	2	13	29.44	A
	3	14	38.74	B
NO_x (g)	1	7	9.69	A
	2	13	8.38	B
	3	14	6.36	C
Crash Risk (Crashes $\times 10^{-6}$)	1	7	28.13	A
	2	13	26.82	A
	3	14	15.61	B

The results indicate that estimated MOEs for Southern Road and Baseline Road (roadway 1 and 2) were similar, and that the MOEs for Interstate 60 (roadway 3) were statistically different from those from the arterials. This difference is indicated in Figure 5.8 and by the Student-Newman-Keuls (SNK) test. For example, the average speed on the arterials was in the range of 50 km/h while the average speed on the freeway was in the range of 85 km/h. This finding contradicts Wordrop's first principal, which states that travel times along utilized roadways exhibit equal travel times (user equilibrium).

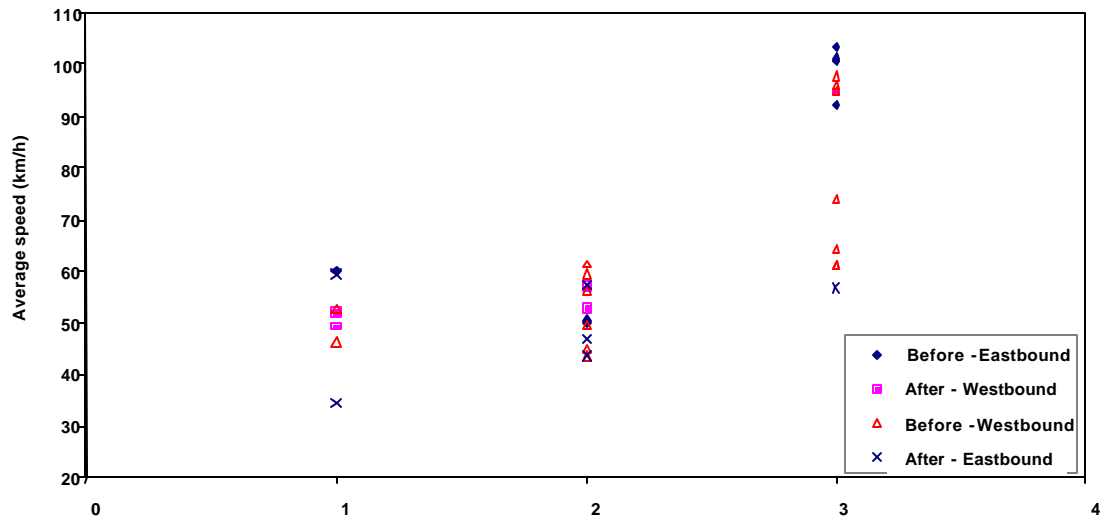


FIGURE 5.8 VARIATION IN AVERAGE SPEED DURING THE AM PEAK AS A FUNCTION OF ROADWAY

The ANOVA tests of the AM peak separately concluded the same results as did the ANOVA tests for the entire data set.

5.3 SUMMARY AND CONCLUSIONS

While these two case studies provide some insight as to the potential benefits of coordinating traffic signals across jurisdictional boundaries, more importantly it demonstrates the feasibility of using GPS second-by-second speed measurements for the evaluation of operational-level traffic improvement projects. Specifically, the use of statistical models allows for the evaluation of the efficiency, energy, emissions and safety benefits of operational-level traffic improvement projects without making investment in expensive equipment.

Based on a field evaluation of Scottsdale/Rural Road, the results showed that the mainline average speed increased by 6 percent when averaged over all three-analysis periods (AM peak, Midday, and PM peak). In addition, the number of vehicle stops was reduced by 3.6 percent on average, while the fuel consumption was reduced by 1.6 percent. The HC and NO_x emissions were found to remain constant, while the CO emissions increased by 1.2 percent. Finally, the crash risk was reduced by 6.7 percent. The data from all analysis periods showed statistically

significant localized benefits for some of the MOEs as a result of the signal re-timing. However, these benefits were statistically insignificant when the entire 9.6-kilometer mainline section of the corridor was considered. Therefore, networkwide impact analysis was not performed at this stage. If there is statistically significant difference in before and after MOEs then networkwide impact analysis is recommended.

The results of the Southern/Baseline Road field evaluation indicated that there did not appear to be any statistical difference (5 percent level of significance) between the before and after conditions. The field results do indicate a 2 percent reduction in HC emissions between the after and before scenario. At this point it is not clear why only HC emissions show this difference.

Chapter 6: ANALYSIS OF CHANGES IN DEMAND

In the previous chapter, we evaluated the benefits of coordinating traffic signal timings across jurisdictional boundaries. However, the evaluation was achieved only based on measurements from floating cars equipped with a GPS device.

Mainline and turning movement counts at a number of traffic signals, as the first of the data collection efforts mentioned in Chapter 5, were collected for quantifying any change in traffic demand of study area as a result of the signal timing change in January and February 1999, respectively. In order to identify the differences between before and after total volumes, Analysis of Variance (ANOVA) technique was utilized to establish any statistically significant differences. Specifically, statistical analyses for turning volume and tube count are beginning with ANOVA for overall effect and then more detailed level analyses are performed such as time-of-day effects and directional effect analyses.

This chapter analyzes tube count and turning using ANOVA technique to identify whether there is any statistically significant differences in traffic demand between before and after conditions.

6.1 TRAFFIC COUNTS

6.1.1 TUBE COUNTERS AND TURNING MOVEMENT COUNTERS

In this chapter, turning movement and tube counts were utilized to investigate statistically significant change on traffic demand between before and after traffic signal retiming. In order to collect tube count and turning volume information, several tube counters and turning movement counters were utilized in this thesis. Brief introduction about those devices are presented in the following section.

In order to evaluate the level of service of a roadway section, traffic data is essential and such information can be collected through three common ways: (1) image recording with video or film cameras, (2) traditional manual collection by people, and (3) automated collection with mechanical counters. Among these three ways, mechanical counters are preferred for obtaining daily traffic volumes (Papacosta *et al.*, 1993).

In this thesis, tube counters, one of kinds of mechanical counters, are utilized to obtain mid-link traffic volumes. The Figure 6.1 shows an application of a tube counter on a roadway.



FIGURE 6.1 AN APPLICATION OF A TUBE COUNTER
(Source: <http://www.jamartech.com/>)

Since tube counters can't provide turning movements information, several turning movement counters were utilized as shown in Figure 6.2. With the counter, it is possible to count vehicles and to track four movements (left, through, right, and other) from four approaches at an intersection.



FIGURE 6.2 USE OF A TURNING MOVEMENT COUNTER AT AN INTERSECTION
(Source: <http://www.jamartech.com/prod02.htm>)

6.1.2 TURNING MOVEMENT AND TUBE COUNTS

Turning movement counts were collected at seven intersections along the 9.6-kilometer section of the Scottsdale/Rural Road corridor. These counts were collected for the AM peak, Midday and

PM peak at 15-minute intervals for a single day (Wednesday) for the before and after conditions on January 27 and February 17, 1999, respectively. The intersections for which turning movement counts were collected included the intersections of Scottsdale/Rural Road with Southern Avenue, Broadway Road, University Drive, Curry Road, McKellips Road, McDowell Road, and Thomas Road. The total intersection counts at the different intersections were generally higher for the after conditions than for the before, while the northbound volumes were generally lower, and the southbound volumes generally higher. The statistical analysis of these differences is described later in this chapter.

In addition to the 15-minute turning movement counts, pneumatic-tube traffic counters were also installed at six locations: Lakeshore, Hermosa Street, Alameda Drive, Rio Salado Parkway, Weber Road, and Oak Street. The traffic counters collected 15-minute counts for three continuous days. Figure 6.3 illustrates the temporal variation in traffic volume at all six locations for the northbound and southbound directions for one of the analysis days (Wednesday). The figure demonstrates a peak in the northbound direction for the AM peak for all locations south of Arizona State University (ASU). Similarly, the southbound direction indicates a peak in traffic volume for the locations north of ASU during the AM peak. Consequently, it is evident from the temporal volume variation that ASU is a major trip attractor during the AM peak. The same peak that exhibits in the northbound direction exhibits itself during the PM peak in the southbound direction. Figure 6.3 (c) also illustrates that the average volume across all locations in either direction appeared to be similar for both the before and after conditions. Again, the differences in total volumes were tested using Analysis of Variance (ANOVA) techniques in order to establish any statistically significant differences, which are presented later in this chapter.

6.2 TRAFFIC COUNTS ANALYSIS

The first step in the evaluation of demand impacts of traffic signal coordination was to statistically quantify the difference in total intersection volume and tube counts between the before and after scenarios.

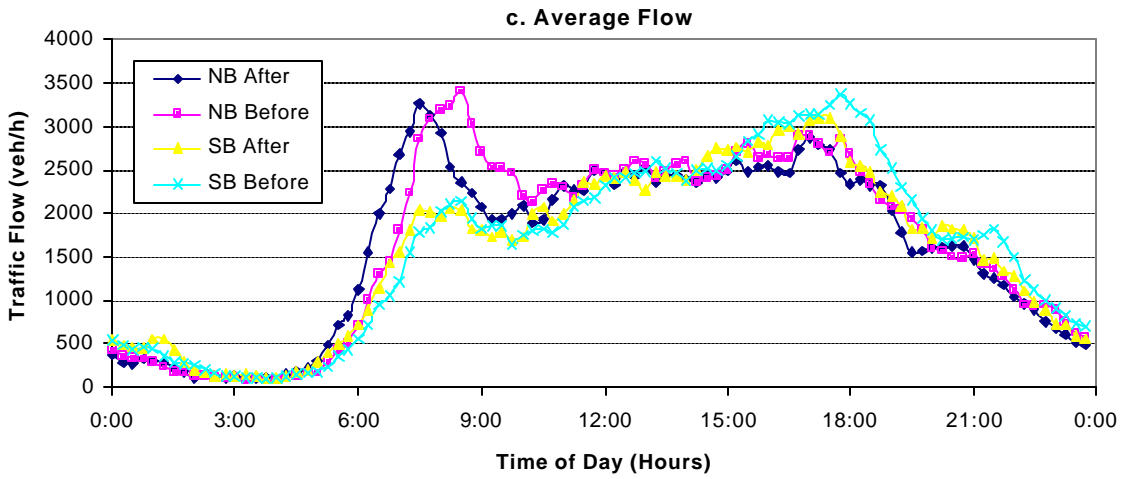
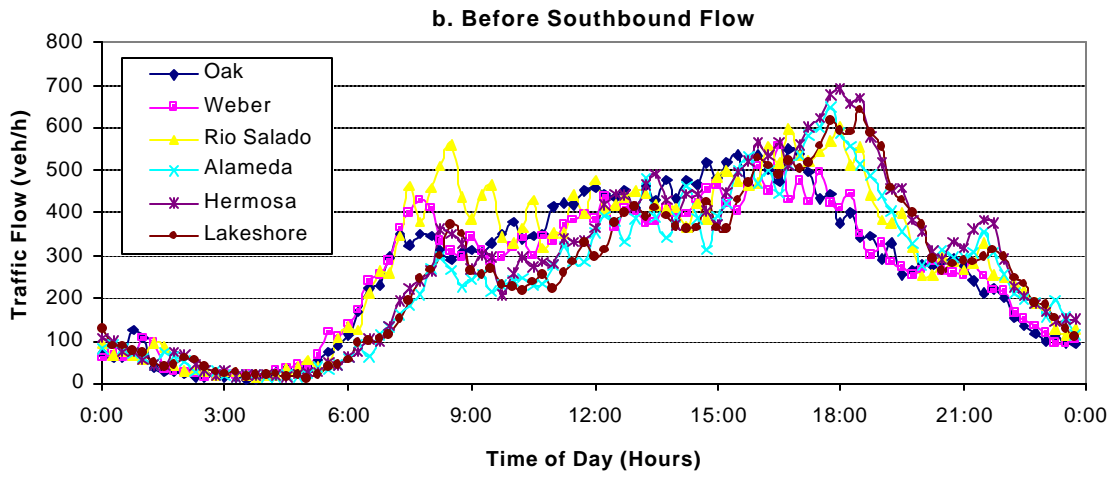
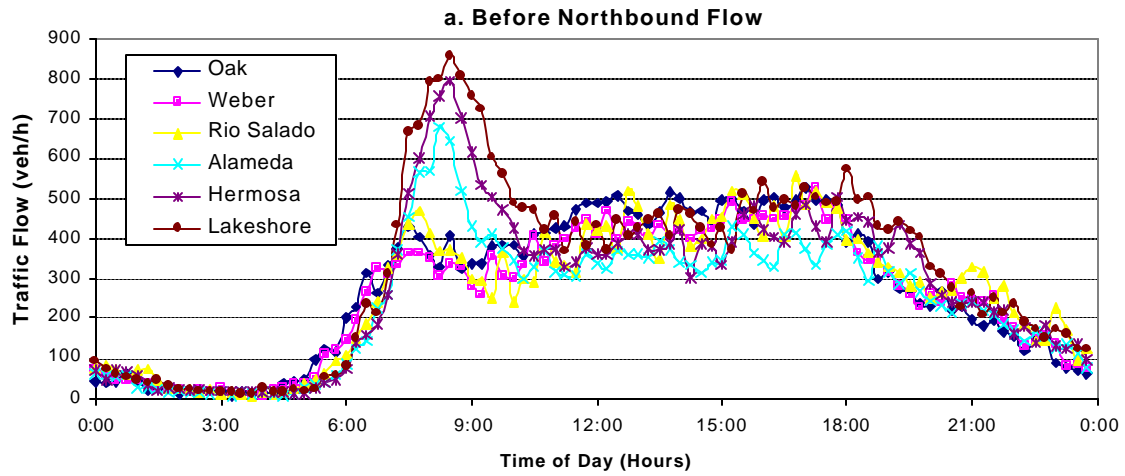


FIGURE 6.3 BEFORE/AFTER TEMPORAL VARIATION IN DEMAND

For traffic count analyses, ANOVA analysis starts with overall effect analysis and then proceed in more detailed level such as time-of-day effects and directional effects analyses. The first subsection presents turning movement count analysis for overall effects, time-of-day effects, and directional effects. Following turning movement analyses, tube count analyses are presented.

6.2.1 TURNING MOVEMENT COUNT ANALYSIS

Overall Effects

As shown in Table 6.1, average traffic flow for all periods for before traffic signal retiming is smaller than for after traffic signal coordination.

TABLE 6.1 AVERAGE TURNING VOLUME FOR ALL PERIODS FOR BEFORE AND AFTER

Average Turning Volume	Before	After
AM, Midday, and PM	2657	2732

In order to analyze statistically before and after variation of traffic flow, an ANOVA type of analysis that considered four factors was performed on the turning movement counts. The four factors included a before/after flag, the intersection location, the approach direction, and traffic movement from each approach. In detail, a total of seven intersections, two before/after conditions, and four directions of traffic movement were considered. The ANOVA analysis shown in Table 6.2 indicated that the intersection location, the approach direction, and period were statistically different. In addition, the interaction effect of the approach direction and period were statistically significant, i.e., traffic flow from each approach is very closely related with time of day. However, there did not appear to be a statistically significant difference (5 percent level of significance) in the approach flows between the before and after conditions.

TABLE 6.2 ANALYSIS OF VARIANCE TABLE

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	239259.52	0.76	0.3840
Intersection	6	6301058.51	20.08	<.0001
Approach	3	20074101.06	63.96	<.0001
Period	2	8185971.43	26.08	<.0001
Period*Approach	6	4976804.37	15.86	<.0001
Error	149	313845.4		

Consequently, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in change in demand.

Time-of-day effects

As shown in Table 6.3, after average turning volumes for AM, Midday, and PM are slightly bigger than before average turning volumes. In order to check any statistically significant change in traffic flow, the three factors of an ANOVA included the intersection location, a before/after flag, and the approach direction. The ANOVA analyses of Tables 6.4-6.6 indicated that both the intersection location and the approach direction were statistically different same as overall effect analysis. Also, there did not appear to be a statically significant difference (5 percent level of significance) in traffic for the before and after AM, Midday, and PM conditions, respectively.

TABLE 6.3 AVERAGE TURNING VOLUME FOR AM FOR BEFORE AND AFTER

Average turning volume by time-of-day	Before	After
AM	2354	2446
Midday	3111	3142
PM	2505	2608

TABLE 6.4 ANOVA FOR AM

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	119233.14	0.30	0.5840
Intersection	6	2143432.99	5.47	0.0003
Approach	3	10794383.00	27.54	<.0001
Error	45	391891.55		

TABLE 6.5 ANOVA FOR MIDDAY

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	14208.29	0.04	0.8405
Intersection	6	2583599.25	7.44	<.0001
Approach	3	10997876.43	31.67	<.0001
Error	45	347230.24		

TABLE 6.6 ANOVA FOR PM

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	146473.14	0.70	0.4080
Intersection	6	2243182.75	10.69	<.0001
Approach	3	8235450.38	39.23	<.0001
Error	45	209931.05		

Directional Effects

In addition to time-of-day effect ANOVA analysis, directional effects were analyzed. Like comparison of average turning volumes of a time-of-day for before and after, after average approach volumes from each direction are slightly increased than before condition as shown in Table 6.7. The considered three factors included the intersection location, a before/after flag, and time-of-day. The four directions of traffic approach included north, east, south, and west. As shown in Tables 6.8 – 6.11, ANOVA analyses indicated that both the intersection location and time-of-day were statistically different apart from an ANOVA analysis for approach from south. However, there did not appear to be a statistically significant difference (5 percent level of significance) in traffic flows between the before and after conditions for each approach.

TABLE 6.7 AVERAGE TURNING VOLUME FROM EACH APPROACH FOR BEFORE AND AFTER

Average Approach Volume	Before	After
From North	3140	3213
From East	2078	2160
From South	3391	3407
From West	2018	2149

TABLE 6.8 ANOVA FOR APPROACH FROM NORTH

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	55517.36	0.37	0.5455
Intersection	6	573928.52	3.86	0.0052
Time of day	2	9489599.74	63.81	<.0001
Error	32	148706.16		

TABLE 6.9 ANOVA FOR APPROACH FROM EAST

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	69540.02	2.44	0.1278
Intersection	6	4445631.02	155.29	<.0001
Time of day	2	2063887.71	72.55	<.0001
Error	32	28444.25		

TABLE 6.10 ANOVA FOR APPROACH FROM SOUTH

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	2916.667	0.01	0.9269
Intersection	6	679011.19	1.99	0.0966
Time of day	2	258173.596	0.76	0.4777
Error	32	341488.23		

TABLE 6.11 ANOVA FOR APPROACH FROM WEST

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	180583.71	0.97	0.3315
Intersection	6	4628330.38	24.92	<.0001
Time of day	2	11304723.50	60.88	<.0001
Error	32	185693.17		

6.2.2 TUBE COUNT ANALYSIS

Overall Effects

In this section, tube counts (mid-link traffic volumes) are utilized to analyze before and after variation of traffic flow. The table 6.12 shows that after average tube count is slightly smaller than before average tube count. In order to check whether there is any statistically significant difference in the traffic demand the before and after conditions or not, an ANOVA analysis technique was used. The five factors of an ANOVA analysis included the tube counter location, a before/after flag, direction, time-of-day, and tube counting day. A total of six locations, two before/after conditions, two directions of traffic movement, three tube counting days, and time-of-day (AM, Midday, and PM) were considered. The ANOVA result of Table 6.13 indicated that both the direction and time-of-day were statistically different. Same results were shown in GPS data and turning movement analyses. In addition, the interaction effect of direction and period

were statistically significant, which is similar to the ANOVA result for turning volume. However, there did not appear to be a statically significant difference (5 percent level of significance) in the traffic flows between the before and after conditions, which is consistent with turning volume analysis and GPS data analysis. Consequently, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any traffic demand change.

TABLE 6.12 AVERAGE TUBE COUNT FOR BEFORE AND AFTER

	Before	After
Average Volume	3403	3355

TABLE 6.13 ANOVA OF TUBE COUNTS FOR OVERALL EFFECTS ANALYSIS

Effect	Degree of freedom	Mean square	F-statistic	p-value
Direction	1	5482978.69	16.96	<.0001
Before & after	1	120889.35	0.37	0.5416
Day	2	165238.70	0.51	0.6006
Time of day	2	16547857.14	51.19	<.0001
Location	5	766475.83	2.37	0.0406
Direction*Time of Day	2	17277920.20	53.44	<.0001
Error	202	323292.9		

Time-of-day effects

Averaging AM tube counts of before and after, there appears to be a slight increase in the average volume between the before and after scenarios, as shown in Table 6.14. An ANOVA analysis that considered four factors was performed on the AM tube counts. The four factors included the tube counter location, a before/after flag, traffic directions (north and south), and three consecutive tube-counting days.

TABLE 6.14 AVERAGE TUBE COUNT FOR AM BETWEEN BEFORE AND AFTER

	Before	After
Average Volume (AM)	3054	3075

As shown in Table 6.15, the ANOVA result for AM indicated that both the location and the traffic direction were statistically different, but there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions. Thus, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any significant change in traffic volume.

TABLE 6.15 ANOVA OF TUBE COUNTS FOR AM

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	8213.35	0.01	0.9058
Direction	1	33071489.01	56.86	<.0001
Day	2	120842.06	0.21	0.8130
Location	5	1638062.31	2.82	0.0235
Error	62	581670.76		

Averaging MIDDAY tube counts of before and after as shown in Table 6.16, there appears to be a slight increase in the average volume between the before and after scenarios. An ANOVA type of analysis that considered four factors was performed on the MIDDAY tube counts. The four factors included the tube counter location, a before/after flag, traffic directions (north and south), and three consecutive tube-counting days. The ANOVA result for MIDDAY of Table 6.17 indicated that both the location and the traffic direction were statistically different, but there did not appear to be a statically significant difference (5 percent level of significance) in the tube counts between the before and after conditions. Thus, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any significant change in traffic volume.

TABLE 6.16 AVERAGE TUBE COUNT FOR MIDDAY BETWEEN BEFORE AND AFTER

	Before	After
Average Volume (Midday)	3114	3170

TABLE 6.17 ANOVA OF TUBE COUNTS FOR MIDDAY

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	57630.125	1.10	0.2983
Direction	1	664896.681	12.69	0.0007
Day	2	73307.792	1.40	0.2544
Location	5	767619.792	14.66	<.0001
Error	62	52375.573		

Unlike AM and Midday, averaging PM tube count before and after, there appears to be a decrease in the average volume between the before and after scenarios, as shown in Table 6.18. An ANOVA type of analysis that considered four factors was performed on the PM tube counts. The four factors included the tube counter location, a before/after flag, traffic directions (north and south), and three consecutive tube-counting days. As shown in Table 6.19, the ANOVA result for PM indicated that only the traffic direction was statistically different, but there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions. Consequently, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any significant change in traffic volume.

TABLE 6.18 AVERAGE TUBE COUNT FOR PM BETWEEN BEFORE AND AFTER

	Before	After
Average Volume (PM)	4041	3821

TABLE 6.19 ANOVA OF TUBE COUNTS FOR PM

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	870320.222	3.57	0.0635
Direction	1	6302433.389	25.86	<.0001
Day	2	160883.375	0.66	0.5204
Location	5	298622.167	1.23	0.3080
Error	62	243714.20		

Directional Effects

The average traffic volumes for northbound and southbound as shown in Table 6.20, indicate that the before average tube counts are slightly bigger than after average tube counts.

In order to check the difference in traffic demand statistically, an ANOVA type of analysis for investigating directional effect that considered three factors was performed on the tube counts. The three factors included the tube counter location, a before/after flag, and the three tube-counting days. A total of six locations, two before/after conditions, and three tube-counting days were considered. The ANOVA results of Table 6.21 for the northbound tube counts indicated that only the location was statistically different. However, all three factors of southbound tube counts ANOVA were determined statistically insignificant as shown in Table 6.22. As a result, there is no statistical evidence to indicate that the changes in traffic signal timings affected traffic volume.

TABLE 6.20 AVERAGE TUBE COUNTS FOR NORTH / SOUTH BOUND FOR BEFORE AND AFTER

Average Volume	Before	After
Northbound	3550	3516
Southbound	3245	3194

TABLE 6.21 ANOVA OF TUBE COUNTS FOR NORTHBOUND

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	51570.37	0.13	0.7243
Day	2	334100.73	0.81	0.4474
Location	5	1538023.08	3.73	0.0039
Error	99	412019.20		

TABLE 6.22 ANOVA OF TUBE COUNTS FOR SOUTHBOUND

Effect	Degree of freedom	Mean square	F-statistic	p-value
Before & after	1	70023.148	0.08	0.7750
Day	2	8024.694	0.01	0.9906
Location	5	721526.111	0.85	0.5198
Error	99	851989.57		

6.3 SUMMARY AND CONCLUSIONS

Based on the proposed approach in Chapter 3, this chapter analyzed changes in demand through the use of traffic and tube counts were collected in six mid-link locations and seven intersections. Specifically, statistical tests using ANOVA techniques were applied to statistically verify changes in traffic demand.

The ANOVA results of turning volume counts indicated that there is no statistically significant difference in turning volumes between the before and after conditions. Furthermore, the ANOVA results of tube counts also confirmed that there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions.

Based on those two ANOVA analyses, it can be concluded that there is no statistical evidence to indicate that the change in traffic signal timings resulted in change in traffic demand.

Chapter 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 CONCLUSIONS

This thesis presented a comprehensive approach for the field evaluation of operational-level traffic flow improvement projects. The approach is the first attempt to use GPS data for the field evaluation of operational level transportation projects. The approach was applied to evaluate operational traffic flow improvement projects such as traffic signal coordination along corridor.

The conclusions drawn from analyses of smoothing techniques and ANOVA analyses of GPS data are:

- GPS speed measurements may include significant errors as a result of loss of Satellite connections to the GPS receivers.
- Simply trimming data points outside the feasible speed/acceleration region generally improved fuel consumption and emission estimates. Nevertheless, the estimates might remain unrealistically high for some trips.
- The simple Exponential smoothing technique improved the fuel consumption and vehicle emission estimates over data trimming technique. However, unrealistically high estimates are still obtained for some trips.
- The Double Exponential smoothing technique did not improve fuel consumption and vehicle emissions over the Simple Exponential smoothing technique.
- The Epanechnikov Kernel smoothing technique with a bandwidth parameter of 3 produced smoothed acceleration profiles that are generally consistent with the observed data. However, the method is still unable to completely remove all suspicious data and can consequently still produce unrealistic fuel consumption and vehicle emission estimates.
- The robust M-smoothing technique with a bandwidth parameter of $h=3$ appears to be the best technique when applied in tandem with an acceleration adjustment model. The robust Simple Exponential smoothing technique, also, was able to remove all suspicious and erroneous data from the original data set without altering the underlying trends. Both robust smoothing

techniques produced realistic fuel consumption and vehicle emission estimates for all trips studied.

The proposed approach was applied to evaluate the impacts of re-timing traffic signals along an arterial corridor. The conclusions of the sample application include:

- ANOVA results of GPS data for all periods indicated that the difference in speed between the before and after scenarios was statistically significant ($p=0.0001$).
- The number of vehicle stops for all periods was reduced by 3.6 percent, from an average of 7.2 to 6.9 stops/trip, which was found to be a marginally statistically insignificant change ($p=0.0615$).
- Fuel consumption for all periods was reduced by 1.6 percent on average, from 1.20 to 1.18 liters/trip. These findings were found to be statistically significant ($p=0.0146$).
- For all periods there were in overall no change in HC emissions, a statistically significant increase in CO emissions ($p=0.010$), and a statistically insignificant reduction in NO_x emissions.
- The total crash risk for all periods was reduced by 6.6 percent ($p=0.001$), from 27.4×10^{-6} to 25.6×10^{-6} crashes. These crash risks correspond to approximately 2.7 crashes per million vehicle kilometers for the before scenario, and 2.5 crashes per million vehicle kilometers for the after scenario. These crash rates also are consistent with average national rates for typical arterial roadways as identified in the General Estimates System (GES) database.
- The GPS data from all analysis periods showed statistically significant localized benefits for some of the MOEs as a result of the signal re-timing. However, these benefits were statistically insignificant when the entire 9.6-kilometer mainline section of the corridor was considered.
- The ANOVA results for the AM peak GPS data indicated that there was no statically significant difference between the before and after MOEs (5 percent level of significance), with the exception of the average speed that was found to be marginally statistically significant ($p=0.046$). Specifically, the average speed increased from 45.4 to 47.9 km/h in the northbound direction as a result of the traffic signal re-timing, and increased from 47.5 to 48.2 km/h in the southbound direction. Additional ANOVA tests at the signalized approaches

for the AM before and after runs. Four factors were considered in the analysis: before/after scenario, direction of trip (northbound and southbound), intersection (18 unchanged and 3 re-timed) and period (AM, Midday, PM). The ANOVA tests indicated that there was a statistical difference between the before and after MOEs, with the exception to CO emissions and the expected number of fatal crashes for the approaches to the three signals that were re-timed. Alternatively, for the traffic signals that were not re-timed, there was not enough statistical evidence to conclude that the differences in the computed MOEs were significant (5 percent level of significance).

- The ANOVA results for the Midday period showed that there was no statistically significant difference between the before and after MOEs, except for the CO emissions and the estimated minor injury crash risk ($p=0.0002$ and 0.0252 , respectively). The ANOVA tests for the three re-timed traffic signals showed that there was no statistical difference between the before and after MOE estimates. Alternatively, the average speed, CO emissions, and estimated number of minor damage crashes were found to be higher for the after scenario. These differences were statistically significant. Additional ANOVA tests on the computed MOEs at the signalized approaches for the northbound and southbound directions. The ANOVA tests for northbound direction indicated that apart from the average speed at one intersection (McKellips Road), there was no statistical difference between the before and after scenarios. Alternatively, southbound direction experienced statistically significant reductions at the re-timed traffic signals for all MOEs, with the exception for CO emissions.
- The ANOVA results for the PM peak analysis period demonstrated statistically significant improvements in the various MOEs in the southbound direction. Specifically, the average speed increased insignificantly from 38.5 to 41.1 km/h in the northbound direction, while it increased significantly from 29.5 to 38.7 km/h in the southbound direction. These increases in average speed were observed along the entire corridor. ANOVA tests for re-timed traffic signals showed that there was a statistical difference in delay and crash risk as a result of the traffic signal re-timing.
- Based on GPS data analyses, for the 18 traffic signals that were not re-timed, there was enough statistical evidence to conclude that the differences in the computed MOEs were significant (5 percent level of significance), except for the CO and NO_x emission. However, these differences were mixed in direction. Furthermore, additional ANOVA tests concluded

that the benefits of the signal re-timing were restricted to the southbound direction. Consequently, it appeared that the benefits of the signal coordination were confined to the approaches to the traffic signals that were re-timed and to the southbound direction. These benefits were not apparent when the entire corridor was considered. Next, the ANOVA results of the Southern/Baseline Road field evaluation indicated that there did not appear to be any statistical difference (5 percent level of significance) between the before and after conditions. Especially, only HC emissions was decreased by 2 percent between the after and before scenario. However, it was not identified why only HC emissions show this difference.

To analyze any change in traffic demand of study area as a result of the signal timing change, ANOVA analyses were performed based on mainline and turning volume counts. The conclusions from the ANOVA analyses are as follows:

- The ANOVA results of turning movement counts for all periods indicated that the intersection location, the approach direction, and period were statistically different. In addition, the interaction effect of the approach direction and period were statistically significant, i.e., traffic flow from each approach is very closely related with time of day. However, there did not appear to be a statistically significant difference (5 percent level of significance) in the approach flows between the before and after conditions.
- The ANOVA analyses of time-of-day effects indicated that both the intersection location and the approach direction were statistically different same as overall effect analysis. Also, there did not appear to be a statically significant difference (5 percent level of significance) in traffic for the before and after AM, Midday, and PM conditions, respectively.
- ANOVA analyses of directional effects showed that both the intersection location and time-of-day were statistically different apart from an ANOVA analysis for approach from south. However, there did not appear to be a statistically significant difference (5 percent level of significance) in traffic flows between the before and after conditions for each approach.
- The ANOVA result of tube count analysis for overall effects indicated that both the direction and time-of-day were statistically different. Same results were shown in GPS data and turning movement analyses. In addition, the interaction effect of direction and period were statistically significant, which is similar to the ANOVA result for turning volume. However, there did not appear to be a statically significant difference (5 percent level of significance)

in the traffic flows between the before and after conditions, which is consistent with turning volume analysis and GPS data analysis. Consequently, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any traffic demand change.

- The ANOVA result for AM indicated that both the location and the traffic direction were statistically different, but there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions. Thus, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any significant change in traffic volume.
- The ANOVA result for MIDDAY indicated that both the location and the traffic direction were statistically different, but there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions. Therefore, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any significant change in traffic volume.
- The ANOVA result for PM indicated that only the traffic direction was statistically different, but there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions. Consequently, there is no statistical evidence to indicate that the changes in traffic signal timings resulted in any significant change in traffic volume.
- The ANOVA results for the northbound tube counts showed that only the location was statistically different. As a result, there is no statistical evidence to indicate that the changes in traffic signal timings affected traffic volume.

The ANOVA results of turning volume counts indicated that there is no statistically significant difference in turning volumes between the before and after conditions. Furthermore, the ANOVA results of tube counts also confirmed that there did not appear to be a statistically significant difference (5 percent level of significance) in the tube counts between the before and after conditions. Based on the ANOVA analyses, it can be concluded that there is no statistical evidence to indicate that the change in traffic signal timings resulted in change in traffic demand.

7.2 RECOMMENDATIONS FOR FURTHER RESEARCH

The recommendations for further research are suggested as follows:

- In collecting speed data using GPS device, speed data is totally determined by a test driver's driving style. Therefore, it is recommended to do further research on the interaction between test driver's driving style and data quality collected by the drivers.
- Some of the results presented in this thesis are based on data collected in Phoenix, Arizona. Therefore, more tests are needed to use the proposed methodology in this thesis for an evaluation of operational-level transportation projects in other cities.
- As mentioned in Chapter 3, further work is required to investigate the long-term impacts of operational-level traffic improvement projects because the approach in this thesis can be utilized to quantify short-term project impacts, and, with caution, could be utilized to evaluate medium-term impacts. In particular, more research is required to quantify the induced demand incurred by traffic flow improvement projects.
- The emission model utilized in this thesis includes some limitations such as the current emission models only estimate vehicle exhaust emissions for hot stabilized conditions. Cold start emissions and ambient temperature are not considered in the model. In addition, the model cannot be applied beyond the vehicle speed and acceleration boundaries that were used in its calibration. Therefore, further research is required to develop an emission model that is sensitive to ambient temperature and cold start emissions.
- As discussed in Chapter 3, if there is a statistically significant difference in MOEs between before and after an operational-level traffic-flow improvement project, O-D estimation techniques can be used for estimating link flows based on ATR counts and turning movement counts. With the estimated link flow, various MOEs can be produced for before and after conditions. Therefore, it is recommended that O-D estimation techniques be used in estimating link flows when the differences in MOEs for before and after a traffic flow improvement project are statistically significant. Then, ANOVA techniques can be utilized to identify any statistical significance in differences of MOEs at network level for before and after traffic flow improvement projects.
- Prior to transportation data collection, usually, appropriate data size should be determined by reasonable ways because the collection and processing of traffic data requires significant time and resources. To determine reasonable sample size, the distribution of samples in a population should be assumed (most common assumption is that the population is normally

distributed). In addition, the acceptable limits of error for the sample should be chosen (usually $\alpha = 0.05$). Based on an assumed distribution of a population and the acceptable limits of error for the sample, appropriate GPS floating car runs can be determined using a statistical technique. Therefore, further research on determining reasonable sample size should be pursued.

- The comprehensive approach shown in this dissertation includes GPS data collection step that is often time-consuming work although GPS data provides start and finish times, length and duration, and all travel routes of a GPS run. In addition, data reduction process also requires significant time because GPS data is very huge and the post processing of the data is time-consuming work. For that reason, a more efficient data reduction application should be developed to provide a convenient user interface within a GIS.

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VITA

Heung Gweon Sin was born in Seoul, Korea on March 28, 1963. He graduated from the Myongji University in Korea, with a BS in Industrial Engineering in 1985. In 1989, he received a Master in City Planning degree with specialization in Transportation Planning at Seoul National University in Seoul, Korea. After completion of graduate study, he worked with Korea Transport Institute as a researcher from October 1992 to October 1993.

He received a Master of Science degree in Civil Engineering with specialization in Transportation Engineering at Purdue University in West Lafayette, Indiana. In 1996, he then came to Virginia Polytechnic Institute and State University for his Ph.D. in Civil Engineering. In February 2001, he joined Urbitran Associates Inc. in New York, New York.