Modeling Microscopic Driver Behavior under Variable Speed Limits: A Driving Simulator and Integrated MATLAB-VISSIM Study

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ABSTRACT – ACADEMIC

Variable speed limits (VSL) are dynamic traffic management systems designed to increase the efficiency and safety of highways. While the macroscopic performance of VSL systems is well explored in the existing literature, there is a need to further understand the microscopic behavior of vehicles driving in VSL zones. Specifically, driver compliance to advisory VSL systems is quantified based on a driving-simulation experiment and introduced into a broader microscopic behavior model. Statistical analysis indicates that VSL compliance can be predicted based upon several VSL design parameters. The developed two-state microscopic model is calibrated to driving-simulation trajectory data. A calibrated VSL microscopic model can be utilized for new VSL control and macroscopic performance studies, adding an increased dimension of realism to simulation work. As an example, the microscopic model is implemented within VISSIM (overriding the default car-following model) and utilized for a safety-mobility performance assessment of an incident-responsive VSL control algorithm implemented in a MATLAB COM interface. Examination of the multi-objective optimization frontier reveals an inverse relationship between safety and mobility under different control algorithm parameters. Engineers are thus faced with a decision between performing multi-objective optimization and selecting a dominant VSL control objective (e.g. maximizing safety versus mobility performance).

Modeling Microscopic Driver Behavior under Variable Speed Limits: A Driving Simulator and Integrated MATLAB-VISSIM Study

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ABSTRACT – GENERAL AUDIENCE

Variable speed limits (VSL) are dynamic traffic management systems designed to increase the efficiency and safety of highways. While the system performance of VSL systems is well explored in previous research, there is a need to further understand the individual behavior of vehicles driving under VSL control. Specifically, driver compliance to advisory VSL systems is modelled based on a driving-simulation experiment. Low compliance equates to poor VSL performance so it is important for engineers to have the ability to predict compliance based on VSL design conditions. The compliance model is introduced into a driver behavior model that quantifies and predicts the driver decision process on VSL controlled highways. The driver behavior model parameters are set using data obtained from the driving-simulation experiment. Utilization of the developed driver behavior model will increase the accuracy of future simulation work on VSL system performance. In this study, the model is implemented within a traffic simulation software to conduct an assessment of the trade-offs between safety and mobility VSL performance for different VSL control designs. An accident is modelled in the simulation software, and VSL is utilized to respond to and alleviate the incident. Simulation results indicate an inverse relationship between safety and mobility performance – indicating that engineers must select a primary objective when selecting VSL control design parameters.

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ATTRIBUTIONS

Dr. Montasir Abbas oversaw this process, offering research advice and technical instruction. He also served as editor and corresponding author on the two papers submitted to the ASCE Journal of Transportation Engineering and the IEEE 20th International Conference on Intelligent Transportation Systems. Dr. Rakha and Dr. Hotle offered contributing advice and feedback at the midpoint of this research process.

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CHAPTER 1: INTRODUCTION

1.1. Background

The four million miles of roads crossing the United States carried 3.2 trillion miles of people and goods travel in 2016. According to the Infrastructure Report Card published by the American Society of Civil Engineers (ASCE), congestion exists on forty percent of the nation's urban interstates. The average driver spent forty-two hours in traffic in 2016, contributing to a total waste of 3.1 billion gallons of fuel and an economic cost of $160 billion [1]. As federal, state, and local governments work to improve infrastructure and reduce congestion, it has become increasingly clear that solutions must be explored beyond the traditional approach of increasing capacity by building new lanes and roads. A primary hindrance is the lack of funding – ASCE reports a $293 billion backlog of system expansion and enhancement projects [1]. Additionally, on many of the urban congested interstates throughout the country, the urban environment physically prevents roadway expansion as development lies immediately adjacent to the right-of-way. Finally, research has repeatedly confirmed the evidence of induced traffic demand. Capacity improvement projects, designed to relieve traffic, almost always results in a higher volume of traffic. One empirical study states that average roadway improvements induce the following levels of traffic: an extra 10% in the short term, an extra 20% in the long term, and potential for double these levels in peak periods [2].

Given these obstacles to increasing physical capacity of highways, new solutions are being proposed and implemented to increase the efficiency of highways, thus maximizing existing capacity. These solutions are significantly cheaper than infrastructure expansion and require little to no additional right-of-way. Among a larger subset of solutions known as Active Traffic Management is a technique known as Variable Speed Limits (VSL) [3]. VSL are dynamic, electronically controlled speed limits that adjust to reflect changes in traffic and weather conditions. Safety and mobility improvement are the two primary VSL objectives. VSL improves safety by slowing traffic speed through incident areas and by smoothing traffic speed (speed harmonization) [3]. Mobility improvements propagate from VSL's ability to prevent breakdown formation – most often by regulating inflow to a bottleneck region. VSL shifts critical occupancy to a higher value, thus enabling higher traffic flows than no-VSL control at the same occupancy levels [4].

1.2. Thesis Objectives

This thesis aims to answer several questions which are defined in greater detail in the following chapters. First, there is a need to understand how drivers react and behave to VSL systems – in other words, the microscopic behavior of drivers operating under VSL. Macroscopic effects of VSL have been well studied, but microscopic behavior, specifically predicting driver compliance to VSL, has been under-developed. Driver compliance to VSL is vital to VSL performance as low compliance will neglect any safety or mobility benefits, and may in fact worsen conditions due to increased speed deviation. Secondly, it is understood in the literature that there are performance tradeoffs between safety and mobility when optimizing VSL design. This multi-objective optimization frontier will be quantified under a VSL control algorithm for drivers following the developed microscopic behavior; and conclusions will be drawn concerning the optimal design for different design objectives.

1.3. Thesis Organization

The remainder of this thesis is organized into four chapters. The next chapter consists of relevant literature review – surveying and expanding upon the literature reviews conducted in the following two manuscripts. These two submitted journal manuscripts are chapters three and four which cover the conducted research including literature review, methodology, model formulation, and data analysis. Titled “Predicting Driving Behavior under Variable Speed Limits,” the first of these two manuscripts has been submitted for review to the ASCE (American Society of Civil Engineers) Journal of Transportation Engineering Part A. The second manuscript, titled “Safety and Mobility Trade-off Assessment of a Microscopic Variable Speed Limit Model, has been submitted for review to the IEEE (Institute of Electrical and Electronics Engineers) 20th International Conference on Intelligent Transportation Systems. The final chapter of this thesis consists of general conclusions and remarks on future work.

Background References

[1] ASCE, "2017 Infrastructure Report Card," 2017.

[2] P. Goodwin, "Empirical evidence on induced traffic: A review and synthesis," *Transportation,* vol. 23, 1996.

[3] W. Ackaah and K. Bogenberger, "Advanced Evaluation Methods for Variable Speed Limit Systems," *Transportation Research Procedia,* vol. 15, pp. 652-663, 2016.

[4] M. Papageorgiou, E. Kosmatopoulos, and I. Papamichail, "Effects of Variable Speed Limits on Motorway Traffic Flow," *Transportation Research Record: Journal of the Transportation Research Board,* vol. 2047, pp. 37-48, 2008.

CHAPTER 2: LITERATURE REVIEW

2.1. Literature Synthesis

The literature survey conducted in this thesis covers two main topic areas within the broader topic of VSL. First, the issue of microscopic driver behavior under VSL, specifically driver compliance, is explored. Second, a review of different types of VSL control algorithms is conducted. Examining VSL research that incorporates driver compliance, some studies assume ideal conditions, i.e. 100% of drivers comply with the posted VSL, while others test a series of compliance levels, e.g. 10%, 50%, 100%. Additional studies have developed driver compliance in greater detail. In one study, several compliance levels were translated into new speed distribution curves within the microscopic traffic simulation software, VISSIM [1]. Simulation of a VSL control model based on a real time crash risk evaluation model produced insignificant performance benefits for scenarios with a low VSL compliance level. Scenarios with medium and high VSL compliance levels saw reduced crash risk, improved speed homogeneity, and decreased travel time [1]. In another study that developed speed distributions corresponding to four compliance levels, it was noted that as compliance increased, there was a corresponding non-linear increase in safety performance. The largest safety improvement occurred with an increase from low to moderate compliance. A steady increase in travel time corresponding to an increase in compliance level was also shown in simulation. The increase in travel time results from a higher percentage of vehicles adhering to a lower speed limit value (the VSL), and then returning to base speed only when so informed by a new sign [2]. A third study that developed speed distributions used field data to develop speed distributions for aggressive, compliant, and defensive drivers under six unique speed limits. VISSIM simulation revealed the potential for increasing VSL compliance to decrease travel time and collision probability, and to increase vehicle throughput. However, results also indicated the difficulty of multi-objective VSL optimization as trade-offs were observed between safety and mobility depending on objective function [3]. While all of these studies accounted for driver compliance, each of them incorporated compliance into the existing microscopic driving behavior built into the chosen simulation software.

Several other research studies focused more on understanding VSL microscopic driver behavior as a whole. A series of scenarios containing different VSL and VMS (Variable Message Signs) designs were conducted in a driving simulator experiment. These scenarios included differences in traffic volume, VMS text, and VSL speed change. Statistical analysis of participants' driving behavior showed that VSL successfully smoothed speed transitions preceding breakdown regions. However, a driver behavior model was not developed from the results in this study [4]. A VSL microscopic model assuming 100% driver compliance was produced in another study. This two-state longitudinal acceleration model relies on safety constraints (such as vehicle headway) to switch between car-following and speed limit tracking [5]. One of the objectives of this thesis is to combine driver compliance and VSL microscopic behavior into a single model that can be utilized to improve the quality of future VSL simulation research.

In regards to VSL control strategies there are three main algorithm types: threshold calibration, model predictive control, and feedback control. Analysis of an existing flow-based threshold system on a highway in Sweden proposed shifting the threshold design from mobility to safety focused. In particular, an indicator variable for speed homogenization, coefficient of variation of speed (CVS), was proposed as the new VSL activation threshold [6]. CVS, defined as the ratio of all vehicles' standard deviation of speeds to mean of speeds, was originally proposed as an accident prediction indicator [7]. Existing field data from the Swedish highway system already indicated that CVS increased in the five to ten minutes preceding an accident, thus making CVS a strong variable upon which to base speed homogenization [6]. Other threshold-based VSL control algorithms have been based on crash likelihood [8], occupancy [9], and traffic parameters (flow, speed, and density) [10]. The crash likelihood thresholds were constructed from a regression model that considers lateral and longitudinal speed variance across traffic. Simulation results of this VSL model produced safety benefits but also increased travel time [8]. The occupancy-based model enabled higher flows in overcritical conditions on the highway by shifting critical occupancy [9]. The traffic parameter threshold model utilized shockwave prediction methods to result in higher traffic flows and reduced variance in critical conditions (peak of flow-density graph) [10].

The second type of VSL control algorithm, model predictive control, relies on macroscopic traffic models to predict the future state of the traffic system. Control can then be implemented in the present time step to alleviate problems before they actually arise. Two studies predicted the creation of shockwaves and activated VSL to suppress the negative traffic conditions contributing to the shockwave. Simulation in both studies showed successful shockwave suppression and improvements in traffic mobility measures [11, 12]. An additional study suppressed detected shockwaves by utilizing VSL to control the downstream traffic inflow. Besides shockwave suppression, positive results included reduction in travel time and speed homogenization [13, 14].

Feedback algorithms, the final type of VSL control, focus on improving bottleneck situations in the traffic system. Based upon Mainstream Traffic Flow Control (MTFC) principles, VSL is utilized to move congestion upstream from the bottleneck location [15]. Various controllers have been designed for single [15, 16] and multiple [17] point bottlenecks. The basic logic of the controller is to select the VSL which will achieve critical density in the traffic flow. System detectors and a macroscopic traffic model are utilized to compute the optimum flow and subsequently the optimum VSL to achieve the critical density. Simulation results revealed travel time reductions of 15-20% for single bottlenecks, and 18-21% [15, 16] for multiple point bottlenecks [17]. While most previous studies have reported performance measures for the system's optimized design, this thesis quantifies the multi-objective optimization performance frontier (safety versus mobility) for a particular control algorithm.

Literature References

[1] Yu, R., and Abdel-Aty, M. (2014). "An optimal variable speed limits system to ameliorate traffic safety risk." *Transportation Research, Part C*, 46(Journal Article), 235-246.

[2] Hellinga, B., and Mandelzys, M. (2011). "Impact of Driver Compliance on the Safety and Operational Impacts of Freeway Variable Speed Limit Systems." *Journal of Transportation Engineering*, 137(4), 260-268.

[3] Qiu, T. Z., Fang, J., Hadiuzzaman, M., Karim, M. A., and Luo, Y. (2015). "Modeling Driver Compliance to VSL and Quantifying Impacts of Compliance Levels and Control Strategy on Mobility and Safety." *Journal of Transportation Engineering*, 141(12), 4015028.

[4] Lee, C., and Abdel-Aty, M. (2008). "Testing Effects of Warning Messages and Variable Speed Limits on Driver Behavior Using Driving Simulator." *Transportation Research Record: Journal of the Transportation Research Board*, 2069(Journal Article), 55-64.

[5] Wang, Y., and Ioannou, P. A. (2011). "New Model for Variable Speed Limits." *Transportation Research Record*, 2249(2249), 38-43.

[6] P. Strömgren and G. Lind, "Harmonization with Variable Speed Limits on Motorways," Transportation Research Procedia, vol. 15, pp. 664-675, 2016.

[7] M. Abdel-Aty, N. Uddin, and A. Pande, "Improving Safety and Security by Developing a Traffic Accident Prevention System," in First International Conference on Safety and Security Engineering Proceedings, Rome, Italy, 2005.

[8] C. Lee, B. Hellinga, and F. Saccomanno, "Assessing Safety Benefits of Variable Speed Limits," Transportation Research Record: Journal of the Transportation Research Board, vol. 1897, pp. 183-190, 2004.

[9] M. Papageorgiou, E. Kosmatopoulos, and I. Papamichail, "Effects of Variable Speed Limits on Motorway Traffic Flow," Transportation Research Record: Journal of the Transportation Research Board, vol. 2047, pp. 37-48, 2008.

[10] A. Talebpour, H. S. Mahmassani, and S. H. Hamdar, "Speed Harmonization: Evaluation of Effectiveness under Congested Conditions," Transportation Research Record, vol. 2, pp. 69-79, 2013.

[11] A. Hegyi, B. D. Schutter, and J. Hellendoorn, "Optimal coordination of variable speed limits to suppress shock waves," IEEE Transactions on Intelligent Transportation Systems, vol. 6, pp. 102-112, 2005.

[12] A. Hegyi, S. P. Hoogendoorn, M. Schreuder, H. Stoelhorst, and F. Viti, "SPECIALIST: A dynamic speed limit control algorithm based on shock wave theory," in 11th International IEEE Conference on Intelligent Transportation Systems, Beijing, China, 2008, pp. 827-832.

[13] J. Zhang, H. Chang, and P. A. Ioannou, "A simple roadway control system for freeway traffic," in American Control Conference, Minneapolis, Minnesota, USA, 2006, p. 6 pp.

[14] H. Chang, Y. Wang, J. Zhang, and P. A. Ioannou, "An integrated roadway controller and its evaluation by microscopic simulator VISSIM," in European Control Conference, Kos, Greece, 2007, pp. 2436-2441.

[15] R. C. Carlson, I. Papamichail, and M. Papageorgiou, "Local Feedback-Based Mainstream Traffic Flow Control on Motorways Using Variable Speed Limits," IEEE Transactions on Intelligent Transportation Systems, vol. 12, pp. 1261-1276, 2011.

[16] E. Rauh Muller, R. Castelan Carlson, W. Kraus, and M. Papageorgiou, "Microsimulation Analysis of Practical Aspects of Traffic Control With Variable Speed Limits," IEEE Transactions on Intelligent Transportation Systems, vol. 16, pp. 512-523, 2015.

[17] G.-R. Iordanidou, C. Roncoli, I. Papamichail, and M. Papageorgiou, "Feedback-Based Mainstream Traffic Flow Control for Multiple Bottlenecks on Motorways," IEEE Transactions on Intelligent Transportation Systems, vol. 16, pp. 610-621, 2015.

CHAPTER 3: PREDICTING DRIVER BEHAVIOR UNDER VARIABLE SPEED LIMITS

Based on C. Conran and M. Abbas, "Predicting Driver Behavior under Variable Speed Limits," Submitted for publication to ASCE Journal of Transportation Engineering Part A.

3.1. Abstract

Based on vehicle trajectory data collected from a driving simulator experiment, this paper aims to quantify and predict driver compliance to variable speed limits (VSL), and to develop a microscopic behavior model that incorporates driver compliance. The study quantifies driver compliance through the development of a model that considers the vehicle's initial and final states, and captures the degree to which compliance occurs at each speed decision. Regression results show that a statistically significant driver compliance model exists ($R^2 = 0.95$) and can be utilized to predict the degree to which drivers will comply with VSL based on the presence / absence of variable message signs, the base speed limit, and the requested speed change of the VSL. Finally, the compliance model is incorporated into a two state microscopic behavior model which considers both car following and speed limit tracking. Several vehicle trajectories obtained from the simulator experiment are fit to the model with low calibration error.

3.2. Introduction

There has been substantial growth in the area of Intelligent Transportation Systems (ITS) over the last twenty years. Largely fueled by the advancement of technology in data collection and communication, ITS applications are designed to improve both the safety and operation of roadways. A subset of ITS is known as Active Traffic Management (ATM). Transportation agencies introduce ATM applications in order to influence an otherwise passive system – road infrastructure and capacity. One primary ATM application is Variable Speed Limits (VSL) (Qiu et al. 2015). Traffic engineers implement VSL systems to add dynamic control to an ordinary static system – speed limits. In traditional scenarios, speed limits are predetermined static values formulated in offline engineering studies. However, traffic conditions are dynamic by nature with constant changes in flow and speed characteristics over both the spatial and temporal dimensions (Nissan and Koutsopoulosb 2011). VSL systems responsively regulate speed in light of the current traffic and weather conditions, often measured with system detectors (Talebpour et al. 2013). There are a variety of prevailing VSL objectives including the handling of congestion, incidents, or construction, as well as minimizing safety risk or delaying breakdown formation.

Variable speed limits are displayed on the freeway via electronic message screens. In many European applications they are mandatory just like the normal static speed limits. However, in the United States there are barriers to the implementation of automated speed enforcement; therefore in most situations the posted speed limit is only advisory (Hellinga and Mandelzys 2011). This fact emphasizes the importance of driver compliance and behavior in regards to VSL systems in the United States, particularly in regards to VSL effectiveness.

3.3. Objective

A large amount of research has been conducted on a multitude of VSL control algorithms designed to optimize a specified combination of operations and safety. These studies do an excellent job of outlining the proposed control and quantifying impact via measures of performance such as delay, average travel time, shockwave formulation and crash rate. Several of these studies also analyze the broader impact on the macroscopic traffic conditions, notably Cho et al. who conducted a theoretical validation of the congestion reduction capabilities of VSL by examining the induced changes to the fundamental diagram (Cho and Kim 2012). However, much of the control research under-develops the microscopic behavior of vehicles operating under the VSL control. More specifically, there is a lack in research focused on predicting driver compliance under advisory VSL systems. The study conducted in this paper attempts to fill this research gap by doing the following: a) quantify driver compliance at VSL speed decisions; b) develop a statistically significant driver compliance model and; c) incorporate the driver compliance model into a broader microscopic behavior model. The remainder of this paper is divided into four sections: 1) Relevant Literature Synthesis; 2) Methodology; 3) Analysis; 4) Results and Conclusions.

3.4. Literature Synthesis

Most VSL research studies account for driver compliance by assuming several compliance levels (percentage of drivers who comply), and running their models at each. Several research teams have gone beyond this in developing driver compliance and several more have conducted focused studies on compliance. Yu et al. were one of several research teams to develop speed distributions for various compliance rates (CR) within the microscopic traffic simulation software VISSIM, recognizing that CR would change the speed distribution range. They also observed negligible VSL performance improvement for low CRs, suggesting a minimum CR is requisite for positive VSL impact (Yu and Abdel-Aty 2014). Hellinga et al. also developed speed distributions and observed that VSL safety performance increased non-linearly as CR increased, with the largest performance jump occurring between low and moderate CR. Travel time increased however with every increase in CR. A caveat in this research is that the authors kept the speed coefficient of variation (COV) constant across the four CRs – realistically the COV should change (Hellinga and Mandelzys 2011). Qiu et al. advanced the speed distribution concept a step further – formulating three speed distributions (for three CRs) for each of six speed limits based on field data. As CR increased, decreases in travel time and crash probability and an increase in throughput were observed (Qiu et al. 2015). On a general driver behavior level, Giles was one of several researchers to note that drivers are more likely to comply with high speed limits than low speed limits (Giles 2004).

Lee et al. approached driver VSL compliance from a different perspective by developing a driving simulator experiment for various scenarios containing VSL and variable message signs (VMS). By having participants test a variety of scenarios (gradual/abrupt speed change, congestion/free flow, different VMS text), they were able to run statistical analysis on individual participant's driving behavior. They found strong evidence of smoother speed transitions preceding congestion zones, spatial correlations in driver reaction in regards to VSL and VMS, and an absence of driver reaction in uncongested flow (Lee and Abdel-Aty 2008). However, they did not develop their observations into an applicable driver behavior model that could be utilized in future simulations work. From a microscopic modeling perspective, Wang et al. proposed a two state model to capture the transient effects of dynamic VSL systems. In the proposed model, drivers switch between car following mode and a VSL speed limit tracking mode based on safety constraints – notably the precedence of the car following model (Wang and Ioannou 2011). However, this model assumes a mandatory VSL system and thus does not account for driver compliance less than 100%. There remains a fillable gap in the literature involving developing a behavior model that incorporates the prediction of driver compliance based on the VSL scenario and design.

3.5. Methodology

In order to analyze driver compliance, the authors needed to obtain real microscopic vehicle data from a VSL controlled roadway. Microsimulation software can be designed to replicate human behavior, but cannot be used to initially generate realistic human behavior data that a model could be built from. Due to the lack of availability of such a real world dataset, the authors decided to conduct a driving simulator experiment utilizing the Drive-Safety DS-250 model (Figure 1) located on the campus of Virginia Tech. Based on the conducted literature synthesis, the authors settled on three control variables for the experiment – presence/absence of

Variable Message Signs (VMS), value of base speed limit, and value of change in speed requested by the VSL sign. The literature suggests that all three of these variables have a statistically significant impact on VSL compliance. The experiment runs shown in Table 1 were obtained from the Design of Experiment functionality within the SAS-JMP Pro statistical analysis software (JMP 2016). The experiment design indicated that thirteen scenarios were needed. All thirteen experiment runs were implemented in one of two driving simulator models (one with VMS, the other without).

Figure 1: Drive-Safety DS-250 Driving Simulator

Table 1: Driving Simulator Experiment Design

Experiment	VMS	Base SL kph (mph)	Δ VSL kph (mph)
1	Present	88.51 (55)	16.09 (10)
2	Present	112.65 (70)	32.19 (20)
3	Present	112.65 (70)	8.05 (5)
4	Present	104.61 (65)	24.14 (15)
5	Present	96.56 (60)	8.05 (5)
6	Present	88.51 (55)	32.19 (20)
7	Absent	112.65 (70)	32.19 (20)
8	Absent	96.56 (60)	24.14 (15)
9	Absent	88.51 (55)	8.05 (5)
10	Absent	112.65 (70)	8.05 (5)
11	Absent	88.51 (55)	32.19 (20)
12	Absent	96.56 (60)	16.09 (10)
13	Absent	104.61 (65)	16.09 (10)

The simulator models were designed as mixed two and three lane highway sections with the VSL signs located on overhead gantries. The participant vehicle originates in a platoon of various size vehicles that are each individually programmed to assume a speed within +/- 8.05 kph (5 mph) of the speed limit at every speed decision. Speed zones within the simulator switch back and forth between base speed limit controlled and VSL controlled to test the thirteen experiment runs. The variable message signs were placed 400 meters ahead of the VSL signs and consisted of the following message: “Prepare to Reduce Speed.” A total of seventeen participants operated the two driving simulator models (VMS and non-VMS). All of the driving participants were at least eighteen years old and had United States driving licenses. Participants first operated the no VMS scenario which included a dummy section at the beginning for the purpose of acclimating to the simulator controls. Data analysis for the study was conducted in Microsoft Excel and JMP, and followed the research path portrayed in the flowchart in Figure 2. As described above, the driving simulator study was designed and conducted to obtain the research data. The data was then analyzed to produce three models: an application of microscopic car-

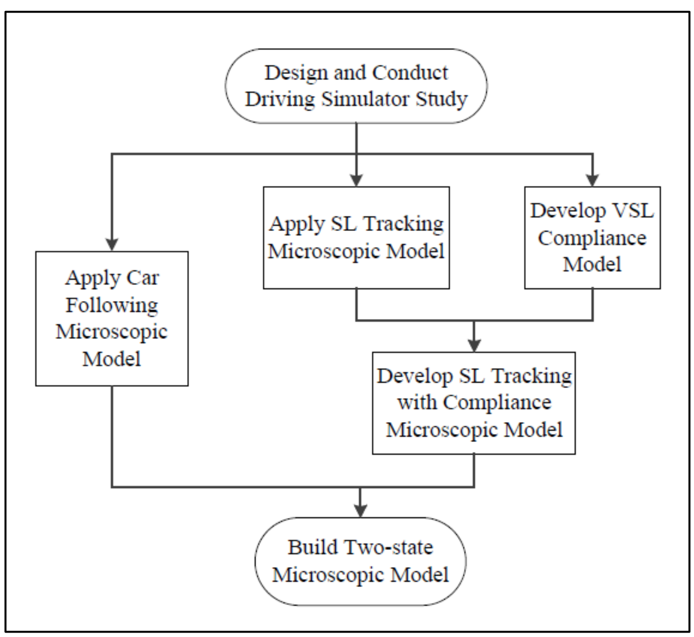

Figure 2: Research Flowchart

following, an application of microscopic speed limit tracking, and a VSL compliance model. The latter two models were then combined to formulate a microscopic speed limit compliance tracking model. Finally, a two-state microscopic model for VSL was built utilizing the car-following and compliance tracking models.

3.6. Analysis

The average speed distributions for the participants are shown in Figure 3. Visual observation indicates that drivers begin to decelerate farther ahead of the VSL signs when a VMS sign is present, thus indicating a positive correlation between VMS presence and driver behavior at VSL signs.

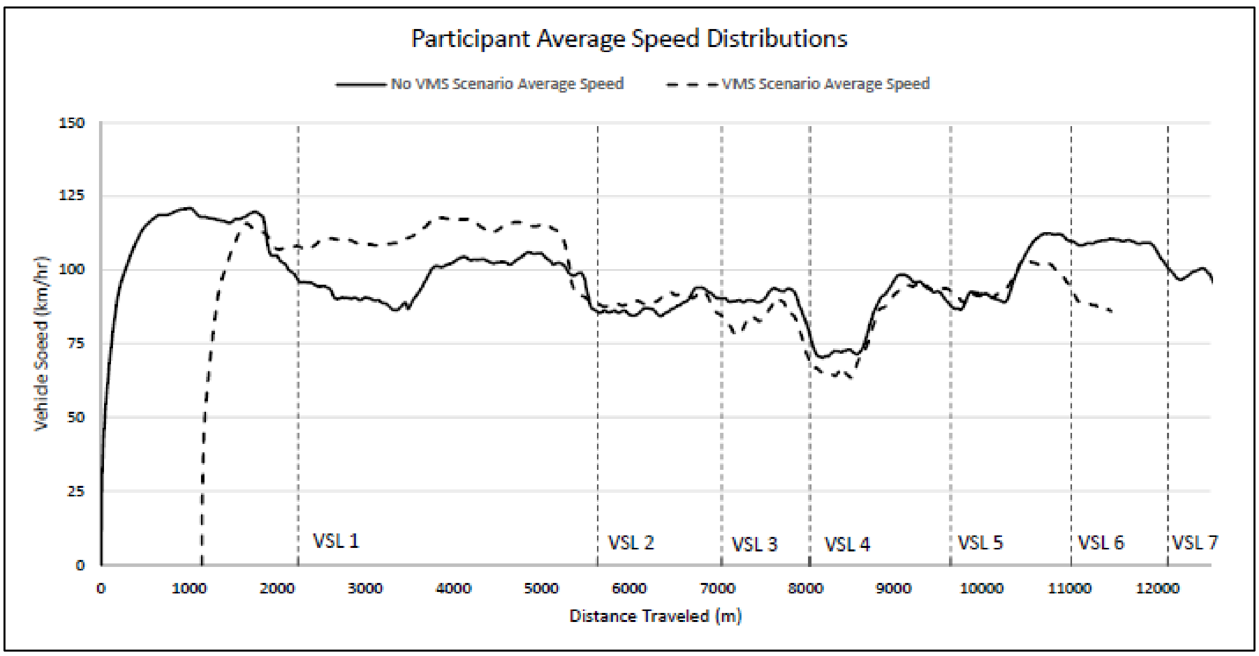

Figure 3: Participant Average Speed Distribution

3.6.1. Quantifying Driver Degree of Compliance at Speed Decisions

The first analysis step in this study was developing an equation to quantify individual driver compliance at each speed decision. The following assumptions were made in the development of this equation (Equation 1):

- Driver target speed is the posted VSL
- Driver speeds should be measured at certain distances down and upstream of VSL sign
- All changes in driver speed should be captured

$$DC = \frac{actual\ speed\ change}{desired\ speed\ change} = \frac{v_{car,upsteam} - v_{car,downstream}}{v_{car,upstream} - VSL} \quad (1)$$

$Where,$

$DC = Degree\ of\ Compliance: degree\ that\ drivers\ comply\ with\ VSL\ speed\ change$

$V_{car,upstream} = velocity\ of\ car\ at\ distance\ upstream\ of\ VSL\ sign\ (km/hr)$

$V_{car,downstream} = velocity\ of\ car\ at\ distance\ downstream\ of\ VSL\ sign\ (km/hr)$

$VSL = posted\ speed\ limit\ on\ VSL\ sign\ (km/hr)$

A DC value equal to one represents 100% compliance, or the driver matching the car's speed perfectly to the VSL. DC values over one represent speed changes (acceleration or deceleration) greater than the requisite amount to meet the VSL; for example a driver decelerated from 90 kph to 80 kph under a VSL of 85 kph. Conversely, values between zero and one represent speed change less than required to meet the VSL. Finally, a DC value less than zero indicates the driver's speed actually changed in the wrong direction; i.e. the vehicle accelerated when it needed to decelerate to meet the VSL or vice versa. Given this equation, it was necessary to address the second assumption mentioned above – at what distances up and downstream should the vehicle's speed be taken? Lee et al. addressed this question by grouping speed change into three categories: acceleration (> 8.05 kph increase), deceleration (< 8.05 kph decrease), and no change (between an 8.05 kph decrease and increase). They then compared the size of these three categories when using speeds taken at 100m, 200m, and 300m up and downstream of the VSL sign, ultimately concluding that speeds taken at 200m showed the highest VSL speed response (Lee and Abdel-Aty 2008).

Adapting the approach undertaken by Lee et al., the authors analyzed seven vehicle speeds at each VSL sign: 100, 200, and 300 meters up and downstream of the sign and underneath the sign itself. Degree of compliance (Equation 1) was evaluated for fifteen up and downstream distance combinations for every participant at each of the thirteen scenarios. Table 2 reports average participant DC values for different scenario groupings under the fifteen combinations. Several observations can be made from this data regarding VSL design impacts and the selection of optimum speed measurement locations. The effect of VMS is shown in that the highest DC average is measured 100 meters higher upstream in the VMS scenarios compared to the no VMS

Table 2: Average DC Values for Different Speed Measurement Locations

Location Speed Measurement	All 13 Scenarios	Small Delta Scenarios [a]	Large Delta Scenarios [b]	VMS Scenarios	No-VMS Scenarios
300 up to Sign	2.339	4.145	0.231	4.545	0.447
300 up to 100 dn	0.486	**0.598**	0.355	0.634	0.359
300 up to 200 dn	-0.233	-0.603	0.199	-0.662	0.134
300 up to 300 dn	-0.247	-0.686	0.265	-0.656	0.104
200 up to Sign	**0.738**	0.286	1.265	**1.083**	0.442
200 up to 100 dn	0.688	0.413	**1.008**	0.814	0.579
200 up to 200 dn	0.387	0.417	0.351	0.556	0.241
200 up to 300 dn	0.434	0.340	0.544	0.876	0.056
100 up to Sign	-0.263	-0.130	-0.419	-1.271	0.601
100 up to 100 dn	0.147	-0.375	0.757	-0.800	**0.959**
100 up to 200 dn	0.027	-0.979	1.200	-0.526	0.502
100 up to 300 dn	-0.492	-1.061	0.171	-1.297	0.197
Sign to 100 dn	-0.189	0.257	-0.711	-1.071	0.566
Sign to 200 dn	-0.135	0.007	-0.300	-1.578	1.102
Sign to 300 dn	-0.304	-1.001	0.509	-1.469	0.695

Note: Bold faced DC values represent DC closest to one for scenario grouping.
[a] Small delta scenarios are those with VSL change of 8.05 kph or 16.09 kph
[b] Large delta scenarios are those with VSL change of 24.14 kph or 32.19 kph

scenarios, indicating positive correlation between speed reduction and the VMS sign. Additionally, the clustering of peak compliance around the measurements beginning 200 meters upstream indicates this may be the optimal upstream speed measurement location. However in selecting these locations, the primary objective is not optimizing compliance, but rather the predictive power of the compliance model. The decision was thus made to run regression on all fifteen DC data sets and to select the model with the highest predictive capability.

3.6.2. Developing Driver Compliance Model

Visualization of the degree compliance data revealed general linear trends suitable for regression, but also the presence of apparent outliers. Using JMP's "Exploring Outliers" utility, eighty-three data points (from the total data set of 3,232 points) were identified as outliers using the Quantile Range method and were removed from the dataset. This quantitative technique classifies data as an outlier if it is three times the interquartile range past either the lower or upper quantile. Having removed the outliers, the next step in the regression process was data aggregation. Seventeen participants (responses) exist for each of the scenarios (dependent variable combinations) and in order to conduct response surface regression, unique response values are requisite to avoid singularity errors. The participant responses were thus averaged for each scenario and speed measurement location; and an ANOVA test was performed to ensure a statistically significant difference in the mean DC values (Table 3). The F-test reveals that at a confidence level of 95%, the null hypothesis of the means being equal can be rejected, thus confirming that a relationship between the mean DC values exists. Having obtained mean degrees of compliance for each of the thirteen experiment runs under each speed measurement location, JMP's linear model fitting tool was performed on the experimental data with the following conditions:

- Response Surface Model Effects
- Standard Least Squares Regression
- Emphasis on Effect Screening

Regression analysis on the fifteen DC data sets revealed that speeds measured at 200 meters upstream and 300 meters downstream of the VSL sign produced the best predictive model. Initial analysis for this regression fit a model with a high R^2 value of 0.98 and a high overall significance with an F-test P value of 0.0043. However, three of the eight model effects were statistically insignificant with t-test P values greater than 0.05. Improving the model, the authors removed the three insignificant effects from the model. This change resulted in a model with a $R^2 = 0.95$ and an overall F-test P value of 0.0002. The five remaining model effects are all statistically significant with t-test P values less than 0.05. A comparison of the regression results is shown in Table 4.

Table 3: ANOVA Test for Participant Response Averaging

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F
Between Treatments	34.64	12	2.89	2.51
Error (or Residual)	229.89	200	1.15	
Total	264.53	212		

Table 4: Comparison of ANOVA Regression Results

Measure of Performance	Initial Run	Modified Run
R^2	0.98	0.95
RMSE	0.1064	0.1236
F test P value	0.0043	0.0031
Significant Effects	5	5
Insignificant Effects	3	0

Both regression models fit the experimental data very well, but the combined increase of statistical significance and limited reduction in fit found in the modified model lead it to be the preferred choice. The final model fit to the data is shown in Figure 4. As shown in the regression prediction equation below (Equation 2), the statistically significant effects for the driver compliance model are the presence/absence of VMS, the VSL requested speed change, the base speed limit, the product of VSL requested speed change with base speed limit, and the VSL requested speed change squared. The constants 'a' to 'f' are variable coefficients.

$$DC = a + b[VMS] + c[\Delta\, VSL\ (kph)] + d[Base\ SL\ (kph) - 100.27]^2 + e[Base\ SL\ (kph) - 100.27] * [\Delta\, VSL\ (kph) - 19.81] + f[\Delta\, VSL\ (kph) - 19.81]^2 \quad (2)$$

Where,

DC = episode based degree of compliance

Nominal nature of VMS variable → VMS present = 1; VMS absent = -1

a = 0.8108; b = 0.3100; c = -0.0093; d = -0.0040; e = -0.0013; f = 0.0029

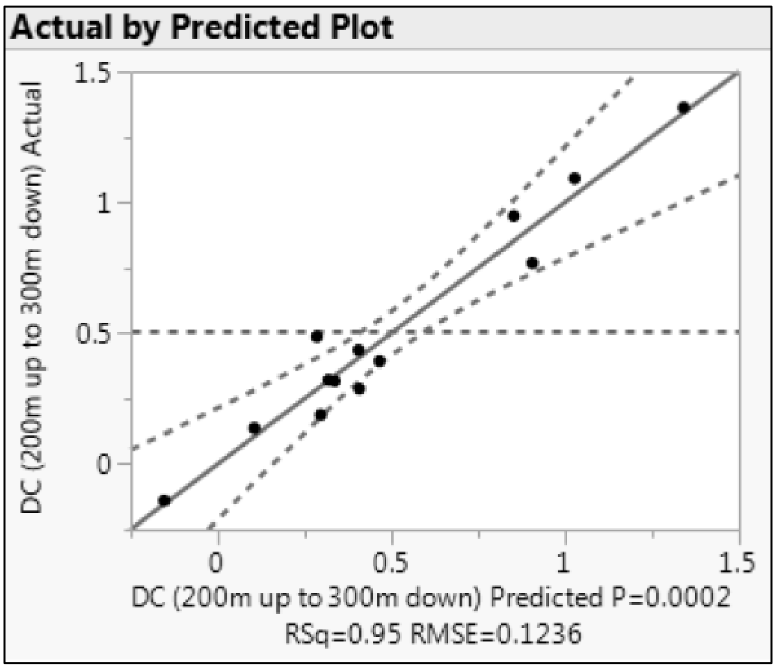

Figure 4: Final Model Fit to Experiment Data

3.6.3. Incorporating Compliance into Microscopic Model

The final objective of this study was to incorporate the developed driver compliance model into a microscopic behavior model that predicts vehicle acceleration. The authors calibrated the two-state model in Equations 3-6 to selected vehicle trajectories obtained from the driving simulator. This model was partially developed based on the work done by Wang and Ioannou (2011).

The first state of the model is car following, what the authors will call the “follow” state, where the acceleration of the following car is directly influenced by the spatial relationship with a leading vehicle. The traditional Gazis-Herman-Rothery (GHR) model shown in Equation 3 is implemented in this paper (Gazis et al. 1961). The units in all the following equations are distance [m], velocity [m/s], and acceleration [m/s^2].

$$a_n(t)_{follow} = c * v_n(t)^m * \frac{\Delta v(t-T)}{\Delta x^l(t-T)} \qquad (3)$$

The model's second state, which the authors will call "SL tracking," is the speed limit tracking model proposed by Wang and Ioannou (2011). Vehicle acceleration is a function of the difference between the driver's speed target and the vehicle's velocity. The constant 'a' is a calibrated parameter while 'T' is the same calibrated driver perception-reaction time parameter from the GHR equation.

$$a_n(t)_{SL} = a * [SL(t-T) - v_n(t)] \qquad (4)$$

The VSL degree of compliance calculated in Equation 2 is next incorporated into the results of Equation 4 to calculate acceleration due to speed limit tracking considering compliance (Equation 5), where the DC is applied as a factor to the acceleration.

$$a_n(t)_{SL,C} = DC * a_n(t)_{SL} \qquad (5)$$

The acceleration selection (Equation 6) between the two states is dependent on several conditions. The vehicle will adhere to car following if car following requires deceleration, if car following requires a greater deceleration than speed limit tracking, and if the headway between the leading and following vehicles (Δx) is less than a calibrated minimum headway (h_{min}). The minimum headway concept is adapted from the psycho-physical microscopic models such as the Wiedemann model (Wiedemann 1974). If these three conditions are not met, the vehicle will follow the speed limit tracking state.

$$a_n(t)_{final} = \begin{cases} a_n(t)_{follow} \; if \; a_n(t)_{follow} < 0, a_n(t)_{follow} < a_n(t)_{SL,C}, and \; \Delta x < h_{min} \\ a_n(t)_{SL,C} \; if \; otherwise \end{cases} \qquad (6)$$

Only selected vehicle trajectories were calibrated to the model due to limitations in the simulator data. The simulator does not record the lead vehicle velocity, a standard input to the GHR and many other car following models; instead the simulator records the headway between the participant vehicle and the lead vehicle. Data is recorded at tenth of a second intervals, so an estimate for lead vehicle velocity can be calculated from the change in headway and the distance traveled by the participant vehicle (Equation 7). This proxy estimate fails however at the instant of a lane change – either by the lead vehicle or the participant vehicle. As such, only trajectory data sets between lane changes were fit to the proposed model.

$$v_{lead} = \frac{DistTravled_{follow} - \Delta headway}{time} \qquad (7)$$

The authors additionally observed noise in the trajectory data, where Equation 7 would calculate unrealistic changes in lead vehicle speeds (i.e. several kph in a tenth of a second). In these instances, the data was smoothed to create a realistic lead vehicle trajectory. Two sets of trajectory data (each from a different participant; one from VMS and one from No-VMS scenarios) were fit as examples to the proposed model to visualize the model fit. Optimization fit was conducted utilizing the Evolutionary and GRG non-linear algorithms contained within Microsoft Excel. The optimization objective was the minimization of the root mean square error (RMSE) between the actual and predicted trajectories of the following vehicle. In each trajectory set the following parameters were calibrated: c, m, l, T, a, and $h_{min.}$ Graphical visualization of the two optimized model fits is shown below in Figures 5-6.

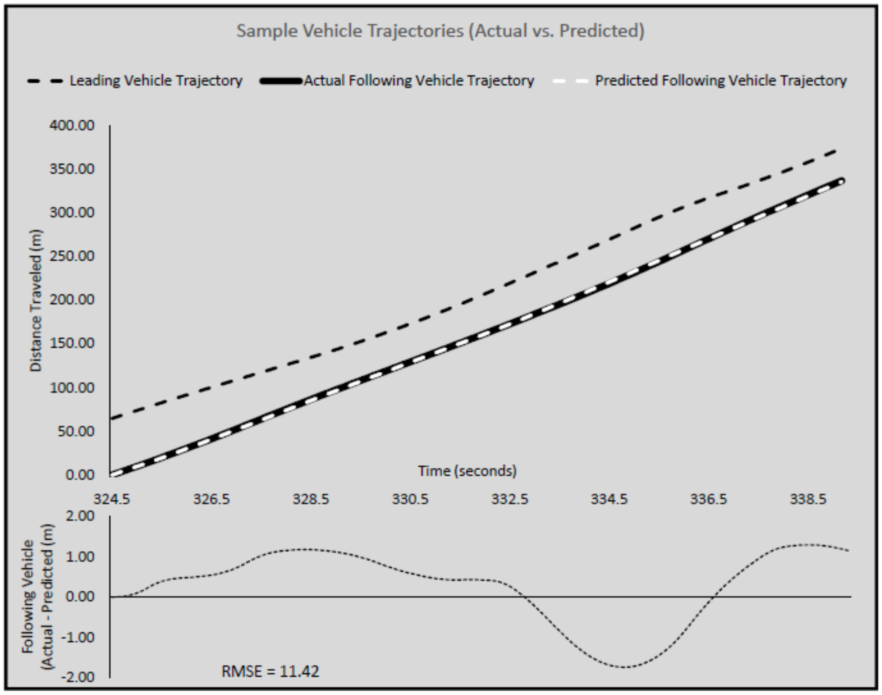

Figure 5: First Optimized Trajectory Fit

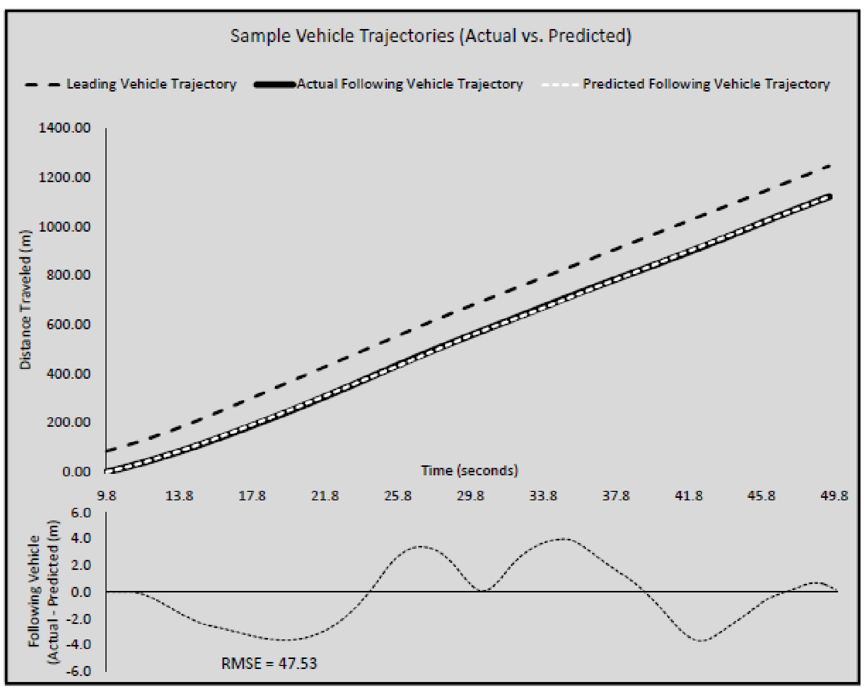

Figure 6: Second Optimized Trajectory Fit

3.7. Results and Conclusions

Several additional conclusions can be drawn from the work conducted in this paper. The compliance prediction profiler from the JMP regression analysis is shown in Figure 7. It clearly indicates the relationship between the three input variables and the degree of compliance. First, variable message signs provide drivers with advance notice of the upcoming speed reduction on the VSL signs thus improving compliance. Secondly, the compliance response to base speed limit appears to be parabolic in nature, with peak compliance around 100 km/hr. One possible explanation for this behavior is that at low speed limits, drivers are less likely to change their behavior solely in response to the VSL. Beyond a certain speed reduction drivers will perhaps only decrease speeds in response to traffic conditions. Conversely, at high speed limits, drivers may be less likely to adjust speed. Further study would need to be conducted to fully analyze this relationship. Finally, as the speed drop drivers are being requested to make increases, the probability of them fully complying decreases except for a small increase occurring at speed drops greater than 25 km/hr. This increase in compliance may be due to the shock value of such a large speed drop request from the VSL. The profiler also shows that the optimal degree of compliance (DC value closest to 1.0) occurs with VMS present at a base speed of 104.67 kph (65 mph) and a VSL speed request difference of 16.09 kph (10 mph). While the profiler illustrates how the degree of compliance varies based on VSL design, VSL control research has shown that while operational benefits vary with compliance rate, benefits are still seen with less than 100% compliance.

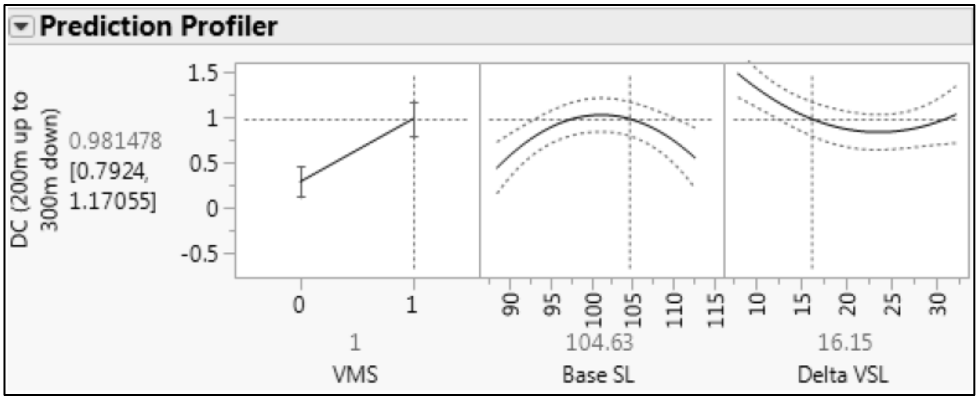

Figure 7: Compliance Model Prediction Profiler

This study has shown a method to quantify driver compliance to variable speed limits at individual speed decision locations as well as an episode based prediction model which incorporates the design conditions of the specific VSL scenario. The compliance model was successfully incorporated into a broader microscopic behavior model that predicts vehicle acceleration due to both car-following and VSL. The work conducted in this paper can help future VSL control research by allowing researchers and engineers to calculate predicted compliance versus the current practice of testing control against several assumed compliance rates. Future work in this subject could improve the research quality by including a wider profile of driving simulation participants – notably a participant population that ranges across the age spectrum to capture the driving habits of young, experienced, and elderly drivers.

3.8. Acknowledgements

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References

Cho, H., and Kim, Y. (2012). "Analysis of traffic flow with Variable Speed Limit on highways." *KSCE Journal of Civil Engineering*, 16(6), 1048-1056.

Gazis, D. C., Herman, R., and Rothery, R. W. (1961). "Nonlinear Follow-the-Leader Models of Traffic Flow." *Operations Research*, 9(4), 545-567.

Giles, M. J. (2004). "Driver speed compliance in Western Australia: a multivariate analysis." *Transport Policy*, 11(3), 227-235.

Hellinga, B., and Mandelzys, M. (2011). "Impact of Driver Compliance on the Safety and Operational Impacts of Freeway Variable Speed Limit Systems." *Journal of Transportation Engineering*, 137(4), 260-268.

JMP Pro.In, SAS Institute Inc, Cary, NC, 1989-2016.

Lee, C., and Abdel-Aty, M. (2008). "Testing Effects of Warning Messages and Variable Speed Limits on Driver Behavior Using Driving Simulator." *Transportation Research Record: Journal of the Transportation Research Board*, 2069(Journal Article), 55-64.

Nissan, A., and Koutsopoulosb, H. N. (2011). "Evaluation of the Impact of Advisory Variable Speed Limits on Motorway Capacity and Level of Service." *Procedia - Social and Behavioral Sciences*, 16(Journal Article), 100-109.

Qiu, T. Z., Fang, J., Hadiuzzaman, M., Karim, M. A., and Luo, Y. (2015). "Modeling Driver Compliance to VSL and Quantifying Impacts of Compliance Levels and Control Strategy on Mobility and Safety." *Journal of Transportation Engineering*, 141(12), 4015028.

Talebpour, A., Mahmassani, H. S., and Hamdar, S. H. (2013). "Speed Harmonization: Evaluation of Effectiveness Under Congested Conditions." *Transportation Research Record*, 2(2391), 69-79.

Wang, Y., and Ioannou, P. A. (2011). "New Model for Variable Speed Limits." *Transportation Research Record*, 2249(2249), 38-43.

Wiedemann, R. (1974). *Simulation des Strassenverkehrsflusses*, Schriftenreihe des Instituts fur 275Verkehrswesen der Universitat Karlsruhe, Band 8, Karlsruhe, Germany.

Yu, R., and Abdel-Aty, M. (2014). "An optimal variable speed limits system to ameliorate traffic safety risk." *Transportation Research, Part C*, 46(Journal Article), 235-246.

CHAPTER 4: SAFETY AND MOBILITY TRADE-OFF ASSESSMENT OF A MICROSCOPIC VARIABLE SPEED LIMIT MODEL

Based on C. Conran and M. Abbas, “Safety and Mobility Trade-off Assessment of a Microscopic Variable Speed Limit Model,” Submitted for publication to IEEE 20th International Conference on Intelligent Transportation Systems.

4.1. Abstract

In this paper a three part traffic simulation environment is utilized to quantify the multi-objective optimization frontier of variable speed limit (VSL) control. Specifically the trade-off between safety and mobility performance is quantified for a VSL control algorithm designed to homogenize vehicle speeds within a freeway incident region. A microscopic driver model for VSL traffic previously developed by the authors is implemented in VISSIM’s API module and simulation is controlled via a MATLAB COM interface. The microscopic model is a two-state longitudinal acceleration model developed from a driving-simulation experiment. Simulation results in this paper indicate an inverse relationship between safety and mobility performance, forcing jurisdictions designing VSL systems to either conduct multi-objective optimization or set a dominant policy objective (safety versus mobility). Control algorithm parameters that invoke VSL adjustment more frequently produce greater safety benefits but also greater mobility impairments. Safety benefits emerge in decreased speed variance across freeway traffic lanes while mobility impairment materializes as increased travel time delay. Variation in freeway volume had no significant effect on VSL performance in this study.

Keywords— automated highways; computer simulation

4.2. Introduction

Speed limit control has two functions – traffic homogenization and breakdown prevention. The homogenization approach is designed to reduce the speed differences between vehicles, thereby improving flow stability and safety [1]. Speed differences are a proven indicator of crash hazard – a 1999 study of crash data indicated an increased crash likelihood when large amplitude changes occurred in the slope of average vehicle speeds [2]. Alternatively, speed control can limit the traffic inflow to bottleneck regions thus preventing traffic breakdown and allowing higher flow through the region [1]. The easiest method of speed control, and one that has been implemented in numerous studies and field applications, is variable speed limits (VSL). Variable speed limits replace traditional static speed limits, thereby giving traffic engineers dynamic control over system state in response to traffic and weather conditions [3].

4.3. Objective

In previous work by the authors, a microscopic model was developed to define individual driver behavior under VSL [4]. The developed two-state acceleration model incorporates speed limit following with VSL compliance and traditional car following logic. VSL compliance prediction was developed from a driving simulator experiment and the two-state model was formulated on the principles of speed-limit tracking [5] and the GHR car-following model [6]. In this paper the previously developed microscopic model is implemented in traffic simulation, and a VSL control algorithm is evaluated under this context for a safety-mobility performance analysis. Algorithm design parameters are explored to clearly identify performance trade-offs between design iterations, allowing design selection based on selection of system objective (e.g. maximize safety versus mobility). The remainder of this paper is organized into the following sections: 1) Relevant literature review on VSL control algorithms; 2) Methodology; 3) Analysis; and 4) Conclusions.

4.4. Literature Review

In the literature, several control approaches have been proposed and implemented for both homogenization and breakdown prevention. Control approaches include threshold calibration [3, 7-9], model predictive control [1, 10-12], and feedback control [13-16]. One Swedish study proposed updating an existing threshold flow-based VSL in Stockholm to threshold coefficient of variation of speed (CVS) [7]. CVS, which is defined in (8), was originally proposed as a simplified variable to help predict accidents [17]. Stockholm field data observation indicated an increase in CVS in the five to ten minutes preceding an accident, suggesting that CVS is a strong candidate upon which to base homogenization control [7]. In another safety approach, a regression model for crash likelihood was developed based on variables such as lateral and longitudinal speed variance and volume variance between lanes. VSL was implemented when crash likelihood thresholds were reached, and results indicated a tradeoff between reduced crash potential and an increase in travel time [9]. An occupancy based threshold algorithm shifted critical occupancy to higher values and enabled higher flows at the same occupancy values at overcritical conditions [8]. Implementation of a threshold model (flow, speed, and density values) combined with shockwave prediction resulted in higher maintained flows and a more concentrated flow-density graph [3].

$$CVS = \frac{Standard\ Deviation\ of\ Vehicle\ Speeds}{Mean\ of\ Vehicle\ Speeds} \tag{8}$$

The objective of model predictive control is to accurately predict the future traffic state of the system and implement current control to alleviate predicted future problems. In several approaches, the authors designed algorithms to detect and suppress shockwaves that are the cause of both safety and mobility problems. Results included the resolution of the shockwaves, increase in average flow, and decrease in travel time [1, 11]. VSL control has also been modeled as virtual ramp metering, where the speed control dictates the inflow to the downstream highway section. The speed strategy is obtained from flow rate mapping via the flow-density relationship. Simulation results included a 28% reduction in travel time as well as positive indicators of speed homogenization and shockwave suppression [10, 12].

Feedback VSL control is built upon the Mainstream Traffic Flow Control (MTFC) concept designed to improve traffic flow through bottlenecks. Congestion is moved upstream (via VSL) from the bottleneck to a controlled location in order to avoid the bottleneck capacity drop. Vehicles clear the controlled flow region and accelerate back to critical speed prior to arriving at the bottleneck [13]. Several feedback controllers were designed to accomplish this by selecting the VSL rate which establishes critical density at a single [13, 14] or multiple point bottleneck [15]. The general logic of the controller begins with detectors measuring bottleneck density which is compared to critical density. A macroscopic traffic model (METANET) then determines the optimum flow to achieve critical density. Measurement of current VSL outflow and comparison to optimum flow allows computation of new VSL to achieve critical density. Simulation results indicated reduction in STT (system travel time) between 15-20% for single bottlenecks [13, 14] and an additional 3% reduction for using multiple bottleneck control in applicable situations [15].

Most performance measures in previous VSL studies have been reported for the optimized objective design (e.g. mobility measures for VSL system designed to optimize bottleneck throughput). However, practitioners are faced with a multi-objective optimization problem in balancing VSL safety and mobility performance. This paper quantifies this optimization frontier for a chosen control algorithm. Additionally, drivers are following driving-simulation-based calibrated behavior, as described in the authors' previous work, an expansion over previous studies which have used the default driver behavior within the traffic simulation software of choice.

4.5. Methodology

Project development for this paper occurred in three phases: creation of simulation network, programming a new driver behavior model, and programming simulation and VSL control and data collection. Together, these three phases formed the simulation environment (Fig. 8). VISSIM was chosen as the microscopic traffic simulation tool due to its functionality for implementation of driver behavior models and outside simulation control, as well as the authors' familiarity with the software [18]. External driver behavior models are implemented via VISSIM's API modules. Written in C/C++, the external driver behavior model DLL receives the state and surrounding conditions of each vehicle at every simulation time step. The DLL then computes the vehicle's acceleration and lateral behavior and passes the values back to VISSIM to be set for the next time step [19]. In the work in this paper, only the vehicle's acceleration behavior was modified in the DLL; the default lateral behavior prescribed in VISSIM's internal logic was passed through to vehicles. Acceleration behavior was modified to represent the

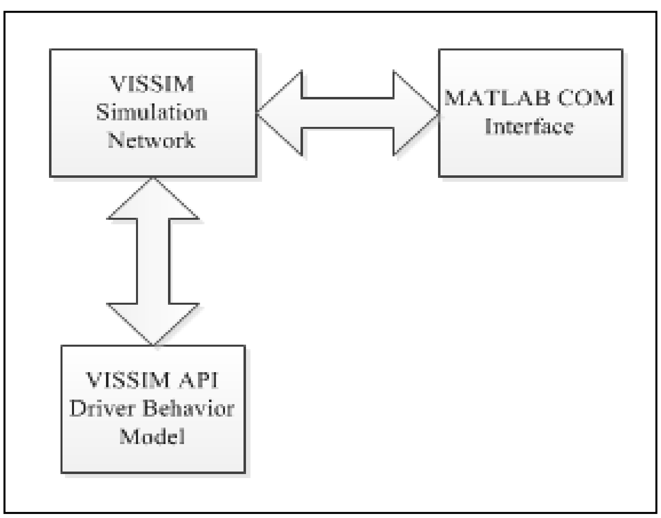

Figure 8: Simulation Environment

microscopic model previously developed by the authors. One modification to the model was implemented in the DLL – instead of tracking to the speed limit, vehicles were programmed to track to their desired speed. Desired speed is a functionality built within VISSIM to create a distribution of vehicle speeds around the speed limit, thus more accurately representing real driver behavior where different drivers will have various target speeds around the speed limit value. Finally, outside simulation control of VISSIM is implemented via the Component Object Model (COM) interface. The COM interface can be used to create new instances of VISSIM (making it a useful tool for multiple scenario control), control simulation runs, and access, read, or change VISSIM object attributes during simulation [20]. With COM not dependent on a certain programming language, the authors chose to implement this interface in MATLAB [21].

The simulation network and VSL control algorithm are shown in Fig. 9. The network consists of a simple, three-lane highway section, with a VSL application zone upstream of an incident zone. The incident is located immediately upstream off an off-ramp and is isolated in the left travel lane. The two hour simulation (following a ten minute network loading time) begins with no incident present, but the incident increases in severity at twenty minute increments

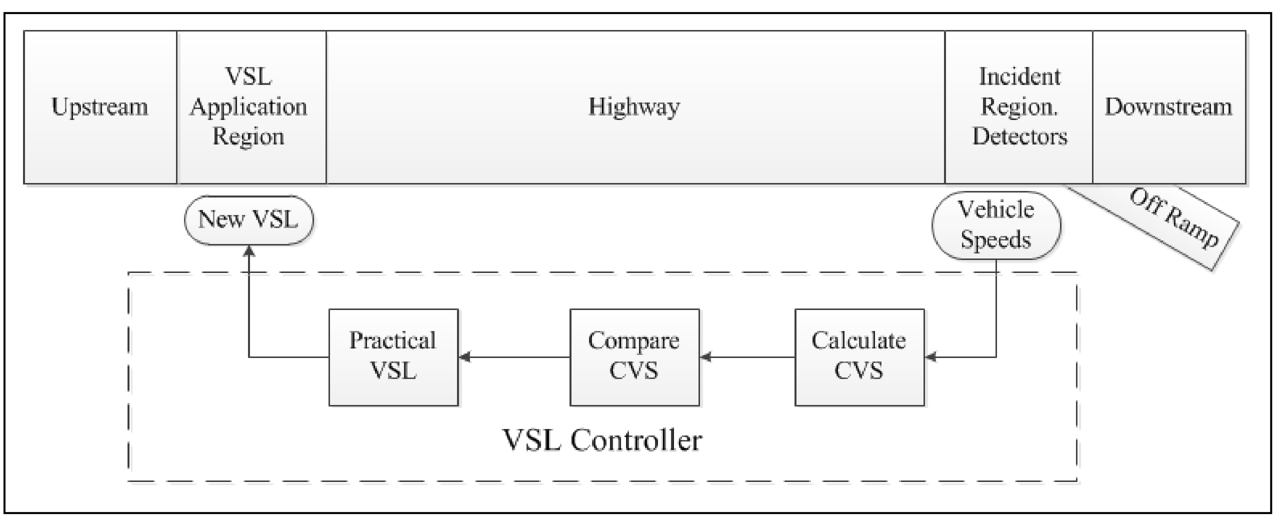

Figure 9: Simulation Network and Control Algorithm

beginning at a time of ten minutes. The incident then decreases in severity, again at twenty minute increments, before traffic returns to base conditions for the final ten simulation minutes. The combination of the incident and traffic diverging caused by the off-ramp produces increased speed variance, a previously indicated measure of safety risk. The chosen VSL control algorithm is a modification of the Coefficient of Variation of Speed (CVS) algorithms discussed in the literature with the primary difference being the presence of both single and double threshold response levels as described below. CVS is calculated in the incident region and compared to CVS threshold values, and this relationship is used to determine the new VSL which will be introduced to the system. VSL design was subject to the following constraints which are similar to those proposed in other VSL studies:

- VSL should only be changed at five minute increments. More frequent change poses safety hazards and prevents flow from stabilizing from prior VSL change.
- VSL should not be raised above base speed of 100 kilometers per hour or lowered below 60 kilometers per hour

Ninety total scenarios consisting of a variety of network volumes and CVS algorithm design parameters were simulated to capture the effects on performance. Research indicates that speed harmonization is only possible in metastable traffic state where flows are greater than free flow but speed is greater than congestion [22]. Because of this, six volume scenarios were analyzed for each of fifteen design scenarios – flows of 1560 and 2300 vehicles/hour/lane (maximum flows for LOS C and E), each with three relative off-ramp flows (5%, 7.5%, and 10%) to capture different volumes of weaving vehicles. The fifteen design scenarios for the CVS algorithm are shown in Tables 5 (Single CVS Threshold) and 6 (Double CVS Threshold). In the single threshold scenarios, the VSL change is implemented when the current CVS rises above or falls below the threshold value. In the double threshold scenarios, the VSL change is implemented similarly but with the following changes:

Table 5: Simulation Control Scenarios 1-8: Single CVS Threshold

Scenario	CVS Threshold Value	VSL Change (km/hr)
1	0.10	10
2	0.15	10
3	0.20	10
4	0.25	10
5	0.10	20
6	0.15	20
7	0.20	20
8	0.25	20

Table 6: Simulation Control Scenarios 9-15: Double CVS Threshold

Scenario	CVS Lower Threshold (VSL Change of 10 km/hr)	CVS Upper Threshold (VSL Change of 20 km/hr)
9	0.10	0.15
10	0.10	0.20
11	0.10	0.25
12	0.15	0.20
13	0.15	0.25
14	0.20	0.25
15	None – Base Scenario	None – Base Scenario

- Lower and upper threshold level with VSL change of 10 and 20 kilometers per hour respectfully
- If CVS drops from above the upper threshold to between the thresholds, on the next time step VSL will not decrease to allow system to fully stabilize before determining if an additional VSL drop is necessary
- VSL only increases when CVS has been below lower threshold for two time steps. This constraint was added following observation of fluctuation between lower and middle regions during testing.

4.6. Analysis

Shown in Fig. 10 are the control results of one of the scenarios compared to the corresponding no control scenario. The upper half of the figures records the change in CVS while the bottom half records the current value of the VSL. The no control figure on the left illustrates the changing impact of the incident as it increases in severity before declining. As the simulation progresses, the VSL control responds in the control scenario in the right figure by adjusting the speed limit – first lowering as CVS increases and then increasing as the incident resolves and CVS values fall below the lower threshold.

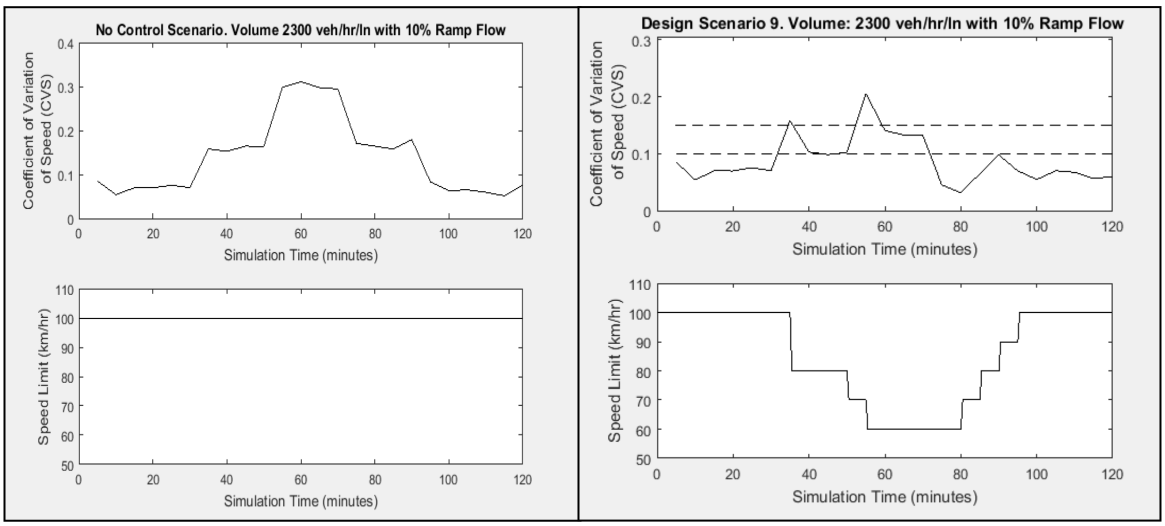

Figure 10: Sample Control Results (No Control vs. Double Threshold at 0.10 and 0.15)

In order to conduct a safety versus mobility analysis, the five minute time step CVS and travel time values were averaged within each scenario to obtain a single scenario measurement. The percentage change in value (compared to the No Control Scenarios) was then calculated for each of the control scenarios. Percentage change in average CVS is shown in Table 7 and percentage change in average travel time is shown in Table 8. Results indicate that the control scenarios with the highest frequency of activation (lowest CVS thresholds – Scenarios 1, 5, 9-11) have the largest decrease in CVS and thus the greatest improvement in speed homogenization and safety. Conversely, these same scenarios have the largest increase in travel time, which logically follows as they have the most frequent reduction in VSL value due to the low CVS

Table 7: Percentage Change in Average CVS Compared to No Control Scenario

		Network Volume Scenario						
		1	*2*	*3*	*4*	*5*	*6*	*Average*
CVS Algorithm Design Scenario	*1*	-31%	-31%	-29%	-32%	-32%	-30%	-31%
	2	-22%	-21%	-20%	-17%	-23%	-17%	-20%
	3	-13%	-13%	-13%	-15%	-14%	-7%	-13%
	4	-6%	-4%	-6%	-7%	-7%	-7%	-6%
	5	-32%	-29%	-30%	-34%	-34%	-33%	-32%
	6	-18%	-16%	-16%	-20%	-19%	-21%	-18%
	7	-11%	-11%	-9%	-14%	-13%	-13%	-12%
	8	-11%	-11%	-9%	-8%	-9%	-7%	-9%
	9	-40%	-38%	-37%	-35%	-33%	-37%	-37%
	10	-39%	-38%	-36%	-38%	-38%	-36%	-37%
	11	-39%	-38%	-36%	-38%	-38%	-36%	-37%
	12	-28%	-27%	-26%	-23%	-23%	-22%	-25%
	13	-27%	-27%	-26%	-24%	-23%	-22%	-25%
	14	-15%	-16%	-14%	-17%	-17%	-16%	-16%

Table 8: Percentage Change in Average Travel Time Compared to No Control Scenario

		Network Volume Scenario						
		1	*2*	*3*	*4*	*5*	*6*	*Average*
CVS Algorithm Design Scenario	*1*	10%	10%	10%	10%	10%	9%	10%
	2	6%	6%	6%	4%	7%	5%	6%
	3	4%	4%	4%	4%	5%	2%	4%
	4	1%	2%	2%	0%	1%	2%	1%
	5	23%	22%	23%	17%	17%	17%	20%
	6	5%	5%	5%	6%	6%	7%	6%
	7	4%	4%	4%	4%	5%	5%	4%
	8	4%	4%	4%	2%	2%	2%	3%
	9	15%	15%	15%	11%	11%	12%	13%
	10	15%	15%	15%	13%	13%	12%	14%
	11	15%	15%	15%	13%	13%	12%	14%
	12	9%	9%	9%	6%	6%	6%	8%
	13	9%	9%	9%	7%	7%	7%	8%
	14	4%	4%	4%	5%	5%	5%	5%

thresholds. The other evident observation from these results is that the change in volume scenario had a negligent effect on control scenario output.

Additional evidence of the VSL control algorithm's capacity to homogenize vehicle speeds is shown in Table 9. In this study, the induced freeway incident creates speed variance between the left lane (in which the incident is contained) and the right two lanes. Results demonstrate the algorithm's ability to reduce the average speed variance between these two lane groups. Similar to the reductions in CVS value shown in Table 7, the algorithm designs that respond quicker to traffic disturbances see the largest reduction in speed variance compared to the no control scenario.

Table 9: Percentage Change in Average Speed Difference between Incident and Free Flow Lanes Compared to No Control Scenario

		Network Volume Scenario						
		1	***2***	***3***	***4***	***5***	***6***	***Average***
CVS Algorithm Design Scenario	***1***	-34%	-33%	-32%	-36%	-37%	-34%	-34%
	2	-22%	-20%	-20%	-18%	-27%	-20%	-21%
	3	-14%	-15%	-14%	-17%	-15%	-8%	-14%
	4	-6%	-6%	-6%	-4%	-4%	-8%	-6%
	5	-44%	-45%	-44%	-49%	-50%	-49%	-47%
	6	-18%	-17%	-17%	-24%	-21%	-27%	-21%
	7	-12%	-12%	-11%	-15%	-15%	-16%	-14%
	8	-12%	-12%	-11%	-8%	-6%	-8%	-10%
	9	-46%	-44%	-43%	-40%	-39%	-43%	-42%
	10	-43%	-43%	-42%	-45%	-44%	-42%	-43%
	11	-43%	-43%	-42%	-45%	-44%	-42%	-43%
	12	-30%	-28%	-28%	-25%	-24%	-25%	-27%
	13	-29%	-28%	-27%	-25%	-24%	-25%	-26%
	14	-14%	-15%	-13%	-20%	-18%	-16%	-16%

To better illustrate and quantify the design trade-offs between the safety and mobility impacts in selecting the CVS-based VSL control algorithm parameters, Pareto Fronts were graphed for each of the volume scenarios (Fig. 11). As mentioned previously, an inverse relationship is apparent between safety and mobility. Scenario five appears as an outlier on the

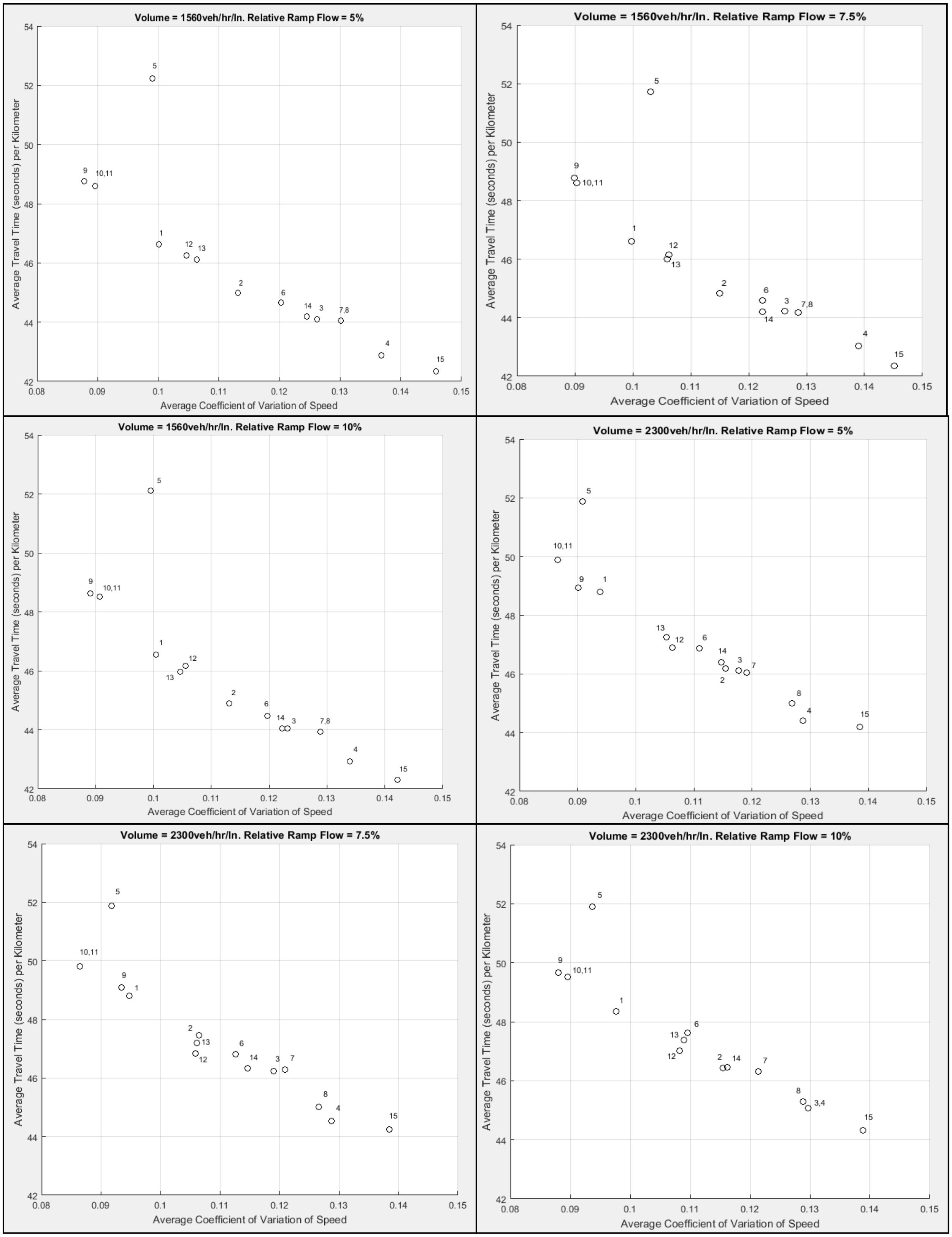

Figure 11: Pareto Fronts for Six Traffic Volume Scenarios. Optimization trade-offs between safety (Coefficient of Variation of Speed) and mobility (Travel Time). Control scenarios labeled.

travel time axis due to the high VSL change (20 kilometers per hour) at the lowest CVS threshold (0.10). When multiple scenarios are represented as sharing the same value on the Pareto Front, it is indicative of identical VSL control response. Given that every scenario is run under the same random seed number, the CVS and travel time values are thus identical.

Policy guidelines can be established from the work conducted in this paper. Specifically, certain design parameters for the CVS threshold-based VSL algorithm should be selected depending on primary VSL objective. As the Pareto Fronts in Fig. 11 show, freeway volume composition has little effect on VSL performance. In each of the six volume scenarios, the same VSL control scenarios held the same performance pattern in favoring either safety or mobility. Table 10 contains these policy recommendations, and Tables 5 and 6 should be referenced to identify the parameters that equate to the different scenarios.

Table 10: Policy Recommendation for VSL Primary Objective

Primary VSL Objective	Scenarios
Safety	1, 5, 9, 10, 11
Mobility	3, 4, 7, 8, 15
Safety-Mobility Mix	2, 6, 12, 13, 14

4.7. Conclusions

In this paper a previously developed microscopic behavior model for drivers under VSL systems was implemented in microscopic simulation of VSL control for an incident region on a freeway. The chosen VSL control was focused on safety improvements by homogenizing vehicle speeds. Performance results matched those in existing literature that indicate that VSL systems designed and optimized for safety produce positive safety benefits but negative mobility impacts. However as quantitatively shown in this paper, engineers face decisions in setting parameters for VSL control algorithms as clear trade-offs exist between safety and mobility performance. This decision may be quantitatively conducted via multi-objective optimization techniques [23, 24] or may be subject to policy considerations. Future work on this subject should include implementing the microscopic driver model on other types of VSL control algorithms, specifically those focused on mobility applications, in order to understand how the Pareto optimization front forms under different control scenarios. Additionally, as mentioned in the API methodology, the default VISSIM lane-changing behavior was passed through to vehicles in the simulation network. Future work could explore VSL lane-changing behavior to determine if a new lane-changing and lateral acceleration model is needed to more accurately model vehicles operating under VSL control.

References

[1] A. Hegyi, B. D. Schutter, and J. Hellendoorn, "Optimal coordination of variable speed limits to suppress shock waves," IEEE Transactions on Intelligent Transportation Systems, vol. 6, pp. 102-112, 2005.

[2] R. G. Hughes, "Variations in average vehicle speeds and the likelihood of peak period crashes," Road & Transport Research, vol. 8, p. 34, 1999.

[3] A. Talebpour, H. S. Mahmassani, and S. H. Hamdar, "Speed Harmonization: Evaluation of Effectiveness under Congested Conditions," Transportation Research Record, vol. 2, pp. 69-79, 2013.

[4] C. Conran and M. Abbas, "Predicting Driver Behavior under Variable Speed Limits," unpublished.

[5] Y. Wang and P. A. Ioannou, "New Model for Variable Speed Limits," Transportation Research Record, vol. 2249, pp. 38-43, 2011.

[6] D. C. Gazis, R. Herman, and R. W. Rothery, "Nonlinear Follow-the-Leader Models of Traffic Flow," Operations Research, vol. 9, pp. 545-567, 1961.

[7] P. Strömgren and G. Lind, "Harmonization with Variable Speed Limits on Motorways," Transportation Research Procedia, vol. 15, pp. 664-675, 2016.

[8] M. Papageorgiou, E. Kosmatopoulos, and I. Papamichail, "Effects of Variable Speed Limits on Motorway Traffic Flow," Transportation Research Record: Journal of the Transportation Research Board, vol. 2047, pp. 37-48, 2008.

[9] C. Lee, B. Hellinga, and F. Saccomanno, "Assessing Safety Benefits of Variable Speed Limits," Transportation Research Record: Journal of the Transportation Research Board, vol. 1897, pp. 183-190, 2004.

[10] J. Zhang, H. Chang, and P. A. Ioannou, "A simple roadway control system for freeway traffic," in American Control Conference, Minneapolis, Minnesota, USA, 2006, p. 6 pp.

[11] A. Hegyi, S. P. Hoogendoorn, M. Schreuder, H. Stoelhorst, and F. Viti, "SPECIALIST: A dynamic speed limit control algorithm based on shock wave theory," in 11th International IEEE Conference on Intelligent Transportation Systems, Beijing, China, 2008, pp. 827-832.

[12] H. Chang, Y. Wang, J. Zhang, and P. A. Ioannou, "An integrated roadway controller and its evaluation by microscopic simulator VISSIM," in European Control Conference, Kos, Greece, 2007, pp. 2436-2441.

[13] R. C. Carlson, I. Papamichail, and M. Papageorgiou, "Local Feedback-Based Mainstream Traffic Flow Control on Motorways Using Variable Speed Limits," IEEE Transactions on Intelligent Transportation Systems, vol. 12, pp. 1261-1276, 2011.

[14] R. C. Carlson, I. Papamichail, and M. Papageorgiou, "Comparison of Local Feedback Controllers for the Mainstream Traffic Flow on Freeways Using Variable Speed Limits," Journal of Intelligent Transportation Systems, vol. 17, p. 268, 2013.

[15] G.-R. Iordanidou, C. Roncoli, I. Papamichail, and M. Papageorgiou, "Feedback-Based Mainstream Traffic Flow Control for Multiple Bottlenecks on Motorways," IEEE Transactions on Intelligent Transportation Systems, vol. 16, pp. 610-621, 2015.

[16] E. Rauh Muller, R. Castelan Carlson, W. Kraus, and M. Papageorgiou, "Microsimulation Analysis of Practical Aspects of Traffic Control With Variable Speed Limits," IEEE Transactions on Intelligent Transportation Systems, vol. 16, pp. 512-523, 2015.

[17] M. Abdel-Aty, N. Uddin, and A. Pande, "Improving Safety and Security by Developing a Traffic Accident Prevention System," in First International Conference on Safety and Security Engineering Proceedings, Rome, Italy, 2005.

[18] "PTV VISSIM," vol. 9.00-06, ed. Germany: PTV Planung Transport Verkerhr AG, 2016.

[19] "PTV Vissim DriverModel DLL - Interface Documentation," L. Kautzsch, Ed., ed. Germany: PTV Planung Transport Verkehr AG, 2016.

[20] "PTV VISSIM - Introduction to the COM API," ed. Germany: PTV Planung Transport Verkehr AG, 2016.

[21] "MATLAB," vol. Release 2016a, ed. Natick, Massachusetts, United States: The MathWorks, Inc.

[22] W. Ackaah, G. Huber, K. Bogenberger, and R. L. Bertini, "Assessing the Harmonization Potential of Variable Speed Limit Systems," Transportation Research Record: Journal of the Transportation Research Board, vol. 2554, pp. 129-138, 2016.

[23] M. M. Abbas, H. A. Rakha, and P. Li, "Multi-objective strategies for timing signal systems under oversaturated conditions," in Proc. of the 18th IASTED International Conference. Montreal, Canada, 2007, pp. 580-585.

[24] M. Abbas and S. Abdelaziz, "Evaluation of Traffic Responsive Control on the Reston Parkway Arterial Network," Virginia Center for Transportation Innovation and Research, 2009.

CHAPTER 5: CONCLUDING REMARKS AND FUTURE RESEARCH POTENTIAL

5.1. Concluding Remarks

This thesis sought to analyze the microscopic behavior of vehicles operating under variable speed limits on freeways. Dynamic, electronically displayed speed limits offer an additional source of input and decision-making to drivers. In the first study contained in this thesis, driving-simulation-based calibrated behavior was developed to capture the effect of this additional element in the driving decision process. The design of the variable speed limit system was determined to be statistically significant as a driver's degree of compliance to the VSL input depends on design parameters such as the base freeway speed limit, the presence of variable message signs, and the value of the VSL speed change. Utilization of a developed VSL microscopic model such as this will create an environment for stronger future macroscopic studies of VSL systems – including studies on performance and control algorithms.

The second study in this thesis implemented the microscopic model inside the microscopic traffic simulation software, VISSIM, thus overriding the default longitudinal acceleration behavior for vehicles. Within this control environment a VSL control algorithm was introduced to an incident region on a freeway. While the primary objective of the chosen control algorithm is safety improvement in the form of speed homogenization, simulation results quantified the existence of a multi-objective optimization frontier between safety and mobility performance. Engineers and policy-setters must thus either perform multi-objective optimization or define a primary performance objective when setting VSL control algorithm parameters. In this study, algorithm parameters that activate VSL in response to small traffic disturbances produce large safety growth but noticeable reduction in mobility performance. Conversely, algorithm parameters that take longer to activate VSL response correlate to lower safety benefits but also decreased mobility costs.

5.2. Future Research Potential

There are several areas of research expansion that could occur within the context of the work conducted in this thesis. The first expansion area is in regards to the developed microscopic VSL model. The model in this thesis was developed from and calibrated to data obtained from a driving simulator experiment. While driving simulators are great research tools and estimators of driving behavior, the accuracy of naturalistic driving data is preeminent. Therefore, if microscopic VSL data became available from a field study, the model could be validated and calibrated to such a dataset. If a driving simulator is utilized, future study should broaden the participant population to capture the driving habits of all driver demographics, notably age. Additionally, the developed model only models longitudinal acceleration behavior; as noted in the second study the default lane-changing behavior was passed through to the simulated vehicles. Further study could explore the lateral acceleration behavior of vehicles under VSL systems to determine if a new model is warranted. Finally, the safety-mobility multi-objective optimization frontier was quantified for only a single VSL control algorithm designed primarily for speed homogenization. Supplementary study should quantify this frontier for other VSL control algorithms, particularly mobility-based algorithms.