Emergency Vehicle-to-Vehicle Communication

CONNECTED VEHICLE/INFRASTRUCTURE UNIVERSITY TRANSPORTATION CENTER (CVI-UTC)

Emergency Vehicle-to-Vehicle Communication

Prepared for the Research and Innovative Technology Administration (RITA);
U.S. Department of Transportation (US DOT)

Grant Project Title:
Advanced Operations Focused on Connected Vehicles/Infrastructure (CVI-UTC)

Consortium Members:
Virginia Tech Transportation Institute (VTTI),
University of Virginia (UVA) Center for Transportation Studies,
and Morgan State University (MSU).

Program Director:

Dr. Thomas Dingus
Program Director, Connected Vehicle/Infrastructure University Transportation Center
Director, Virginia Tech Transportation Institute
Professor, Department of Biomedical Engineering and Mechanics at Virginia Tech
tdingus@vtti.vt.edu
(540) 231–1501

Report Authors:

Pamela Murray-Tuite
Associate Professor,
Civil and Environmental Engineering,
Virginia Tech
murraytu@vt.edu
(703) 538-3764

Aphisit Phoowarawutthipanich
Graduate Research Assistant,
Civil and Environmental Engineering,
Virginia Tech

Rauful Islam
Graduate Research Assistant,
Civil and Environmental Engineering,
Virginia Tech

Naser Hdieb
Graduate Research Assistant,
Civil and Environmental Engineering,
Virginia Tech

DUNS: 0031370150000 EIN: 54-6001805

Grant Funding Period: January 2012 – September 2016
Final Research Reports

August 15, 2016

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Connected Vehicle/Infrastructure UTC

The mission statement of the Connected Vehicle/Infrastructure University Transportation Center (CVI-UTC) is to conduct research that will advance surface transportation through the application of innovative research and using connected-vehicle and infrastructure technologies to improve safety, state of good repair, economic competitiveness, livable communities, and environmental sustainability.

The goals of the Connected Vehicle/Infrastructure University Transportation Center (CVI-UTC) are:

- Increased understanding and awareness of transportation issues
- Improved body of knowledge
- Improved processes, techniques and skills in addressing transportation issues
- Enlarged pool of trained transportation professionals
- Greater adoption of new technology

Abstract

Emergency response vehicles (ERVs) frequently navigate congested traffic conditions to reach their destinations as quickly as possible. In this report, several efforts performed by the research group are described, including micro-simulation, field-testing, and optimization, to determine mechanisms for facilitating safe and efficient ERV travel.

Micro-simulation of a network based on the Northern Virginia Connected Vehicle Test Bed examined the effect of a variety of factors on ERV travel time, including the presence of vehicle-to-vehicle (V2V) communication, traffic volumes, cycle length, ERV speed distributions, non-ERV speed distributions, and traffic signal preemption. The results indicated that V2V communication could reduce travel time for an ERV in congested traffic conditions.

The research group developed a V2V communication prototype to alert non-ERVs of an approaching ERV by triggering a flash of the infotainment system, followed by audible instructions to move to the left, move to the right, or stay put. Twelve drivers, aged 25 to 50, tested the V2V prototype on the Northern Virginia Connected Vehicle Test Bed during off-peak periods. Data from this field test and associated questionnaires were used to investigate reaction time to the instructions. The estimated reaction times using the developed model varied from 1.4 to 5.8 seconds.

A mixed-integer nonlinear program (MINLP) optimization model was formulated to maximize the forward progress of ERVs by sending information to ERVs and non-ERVs within a given road segment. A single set of instructions was sent to each non-ERV, assigning them to a location out of the ERVs path. Numerical case analysis for a small, uniform section of roadway with a limited number of non-ERVs revealed the model is capable of optimizing the behavior of non-ERVs to maximize the speed of the ERV.

Acknowledgements

The authors would like to thank the Connected Vehicle/Infrastructure University Transportation Center for funding this project. We would also like to thank Roma Bhatkoti for her assistance in conducting the driving experiments and the VTTI staff who helped develop the communication prototype and process the data.

Table of Contents

List of Figures

List of Tables

Chapter 1. Introduction

Emergency response vehicles (ERVs) frequently navigate a variety of traffic conditions during an emergency response. ERVs may face traffic conditions that slow response time, such as heavy congestion and limited maneuverability. Additionally, ERV drivers must safely handle other high-risk scenarios such as moving against oncoming traffic, driving on shoulders, and proceeding through red lights. Non-emergency response vehicles (non-ERVs) on the road are supposed to yield the right of way to ERVs; however, some drivers may not be aware of an approaching ERV. Vehicle-to-vehicle (V2V) communication can help alert non-ERVs to the presence of an ERV, the ERV's desired maneuvers, and how to accommodate the ERV. This cooperative behavior could make ERV travel safer and faster.

Connected and automated vehicle technology is expected to improve driving conditions through constant V2V and vehicle-to-infrastructure (V2I) communication. This technology is capable of providing real-time information about traffic conditions on the roadway as well as guidance from the traffic management center and other eligible sources. Constant exchange of information is expected to improve driver awareness, response, efficiency, and comfort while simultaneously improving mobility and safety [1-4]. Connected vehicle technology also has the potential to improve the safety and efficiency of emergency response. Communication from an ERV to other vehicles on the road can provide non-ERV drivers with guiding information that is expected to reduce confusion and direct drivers to a complete stop until the ERV has moved past.

The National Highway Traffic Safety Administration (NHTSA) reported that 368,946 ERVs were involved in crashes from 2001 to 2010 [5]. Motor vehicle crashes were the second leading cause of death for on-duty firefighters, with almost 30,000 fire apparatus related crashes per year [6]. The United States Fire Administration reported almost 100 firefighter deaths each year, with 20%–25% of firefighter on-duty deaths attributed to vehicle crashes [6]. Current Federal Motor Carrier standards exempt emergency workers from the requirement to wear seatbelts when responding to an emergency [6], making them more susceptible to injuries in a crash.

Nearly twice the number of ambulance crashes occurred during emergency operations compared to routine operations. For fire trucks, the ratio was about 1.6 to 1 for emergency to routine operations, while for police cars, the ratio was only slightly over 1. Police car crashes occurring during routine operations are attributed to greater exposure, as police cars are on the road much more than other types of ERVs [7]. In fact, transportation related incidents are the leading cause of death among police officers, with nearly 36% of on-duty police officer deaths caused by vehicle crashes and an additional 10% due to being hit by a vehicle [8]. Between 2004 and 2013, the average number of traffic incident related deaths among on-duty police officers was almost 68 per year. In the case of ambulance related crashes, the numbers are also striking. NHTSA reported that, between 1992 and 2011, an annual mean of 4,500 motor vehicle crashes involved an ambulance, resulting in 33 fatalities and 1,500 injuries per year. Almost 58% of these injuries and fatalities happened during emergency use [9].

ERV related crashes pose an even bigger threat to the occupants of the non-ERV involved in the crash. Due to the size of the fire trucks and ambulances, other vehicles involved in a crash are at higher risk of damage. Ninety percent of fire truck occupants involved in all fire truck crashes escaped with no injuries [6]. However, 75% of fatalities involving fire trucks happened to the occupants of the non-ERVs involved [6]. In the case of ambulance related crashes, 63% of deaths and 54% of injuries between 1992 and 2011 happened to the occupants of other vehicles [9].

Most research associated with ERV-related crashes has focused on the ERV driver, the environment, and the health related outcome [10-12]. Research related to crash factors for the non-ERV driver is limited. However, the few available studies on non-ERV driver factors indicate that visually detecting, or not detecting, the ERV in different driving conditions is one of the primary factors contributing to crashes [5].

The current method of driver warning adopted by fire trucks has seen many iterations throughout the last century. Warning systems have evolved from small fire trucks with hand cranked sirens to much larger and louder trucks with a plethora of flashing, blinking, wobbling lights and sound systems [12]. When an ERV approaches with lights and sirens, drivers of non-ERVs are supposed to slow down and pull over on the right side of the road to facilitate the ERV's progress; however, information delivery by siren may cause driver confusion due to the non-directional nature of sound. Previous research has found sirens to be an extremely limited-information warning system [13], based on sound only without information on the approach direction, the ERV's intended path, or instructions on actions to take. This kind of warning system becomes more problematic in heavily populated areas, where it is more difficult to determine which direction the siren is coming from due to lower visual range and more closely-spaced roads, and more difficult to decide on the appropriate action to take in congested situations. These difficulties in information delivery (loud sound only), reception (hearing the siren), interpretation, and determining the best action limit the effectiveness of sirens and light based warning systems compared to more advanced communication systems.

In many jurisdictions, ERVs can take advantage of signal preemptions, and in some jurisdictions, ERV drivers are allowed to proceed through a stop sign or violate red lights at intersections. However, the literature on the actual impact of this kind of signal preemption on ERV service time is contradictory [5]. The ERV driver may also be held responsible for collisions caused by red light or stop sign violations [14]. This costs local agencies millions of dollars in insurance settlements and vehicle repairs [15]. Therefore, there is also an economic incentive for developing advanced warning systems.

Based on the information presented above, a strong argument can be made for the development of advanced and effective warning systems for approaching ERVs. Such a system, using V2V communication, can help alert drivers to the presence of an ERV, its desired maneuvers, and the best way to get out its path. Advanced warning systems have the potential to initiate cooperative behavior among vehicles and may make ERV travel safer and faster.

Goals and Objectives

The goal of this study was to facilitate faster and safer ERV travel time. This requires addressing multiple aspects of the problem, including variables related to ERVs, non-ERVs, and signal control. Accordingly, this study seeks to accomplish the following objectives:

1. Determine the potential for emergency V2V communication to improve the ERV's travel.
2. Determine the conditions under which V2V communication is most beneficial.
3. Determine the best behavior for non-ERVs in order to facilitate the ERV's movement.
4. Determine the ERV's safest and most efficient path through traffic.
5. Develop a message prototype for the non-ERVs.
6. Test the prototype.

The first and second objectives were addressed through micro-simulation of a network based on the Northern Virginia Connected Vehicle Test Bed. A variety of factors were considered, including the presence of V2V communication, traffic volumes, cycle length, ERV speed distributions, non-ERV speed distributions, and whether signal preemption was available. This study is described and the results are discussed in Chapter 2. Simulation of Emergency Response Vehicle-to-Vehicle Communication.

The third and fourth objectives were addressed through an optimization model developed for this study. Inputs to the model included the current position of the vehicles in the road segment, vehicle characteristics, and travel barriers (e.g., roadway edges). In this initial study, non-ERV "behavior" was simplified to moving right, moving left, and staying put. The outputs of the model were instructions for each non-ERV in the segment of interest, as well as instructions for the ERV's local navigation through traffic. In this study, it was assumed that all vehicles had the necessary communication technology. The model is described and the results are discussed in Chapter 3. Drivers' Reaction Times to Vehicle-to-Vehicle Movement Instructions for Emergency Response Vehicle Travel Facilitation.

In order to address the fifth and sixth objectives, the research group worked with Virginia Tech Transportation Institute (VTTI) to develop a V2V communication prototype. In this initial study, the prototype was designed for V2V communication between an ERV and non-ERVs. This prototype involved a flash of the infotainment system in the non-ERV participants' vehicles, followed by instructions to move to the left, move to the right, or stay put. The research group tested the prototype with 12 drivers, aged 25–50, on the Northern Virginia Connected Vehicle Test Bed during off-peak periods. Data from this field test were used to investigate reaction time to the messages. The communication prototype is described and the results are discussed in Chapter 4. Facilitating Emergency Response Vehicle Movement through a Transportation Network Link.

Organization of the Report

This report has four main chapters following the introduction: two related to studies conducted, one presenting an optimization model and test case, and, finally a concluding summary. Chapter 2 presents a simulation study that investigated the potential impact of signal preemption and emergency V2V communication on the ERV's travel time. Chapter 3 presents a field study that used a prototype V2V communication system to send messages directing real drivers to "move to the left," "move to the right," or "stay where you are," and includes a model of reaction time to those messages. Chapter 4 presents an optimization model to provide more specific directions to non-ERVs to further facilitate ERV movement. Finally, Chapter 5 summarizes the conclusions of the individual components and the study as a whole.

Chapter 2. Simulation of Emergency Response Vehicle-to-Vehicle Communication

Introduction and Overview

V2V communication technology is based on the use of short-range wireless (e.g. dedicated short range communications [DSRC] or Wi-Fi) technology to transmit messages among vehicles in a network. V2V systems consist of an application component that observes traffic conditions, triggers the dissemination of information, and suggests consequences to the driving behavior; and a communication system component that represents a mobile network of vehicles equipped with communication devices and sensors needed to measure road conditions [16]. The components of a V2V communication system can be modeled as a mobility block and a communication block. The mobility block represents changes in traffic, and the communication block models the communication system. The interaction between the application component and the mobility and communication blocks represent the overall V2V communication system, and can be used to model traffic scenarios with whatever factors are involved in the scenario [16].

A micro-simulation tool was used to test the proposed V2V communication system developed for this study. The system was modeled in VISSIM with the Car2x (C2X) API library extension. The C2X API allowed a script to access data from simulated connected vehicles; the script also simulated sending messages and vehicle reactions to the messages [17]. An application module communicated with the VISSIM network (a mobility component that observes any changes in traffic), and then transmitted messages through the C2X communication module, allowing the ERV to communicate with non-ERVs in the vicinity.

The V2V communication system was tested on a simulated network based on a small portion of the Northern Virginia Connected Vehicle Test Bed. Simulation experiments investigated the effects of V2V communication, as well as traffic volumes, cycle lengths, non-ERV speed distributions, ERV speed distributions, and signal preemption on the ERV’s travel time. Twenty-three total experiments were conducted, varying these factors.

The remainder of this chapter is divided into five subsections. The literature review provides a brief overview of selected connected vehicle studies. The next two subsections outline the simulation methodology and describe the simulation experiments and how the factors varied. The final two subsections present the results of the experiments and provide conclusions and future directions of study.

Literature Review

The research group reviewed a number of publications related to the impact of V2V communication on traffic flow and traffic safety [16, 18-26]. Although most of these publications focused on traffic flow, some related traffic flow to traffic safety, and a few related traffic flow to ERVs.

Chen et al. [19] and Van Arem et al. [27] discussed how V2V technology could be used to reduce traffic using Vehicular Ad Hoc networks (VANET) and computer grids. Van Arem et al.'s application was in Cooperative Adaptive Cruise Control (CACC) and its impact on traffic flow characteristics [27]. Dao et al. focused on utilizing road capacity by optimizing lane assignment using V2V communication [21]. Knorr and Schreckenberg [22] discussed the influence of V2V communication on peak hour traffic flow. Buchenscheit et al. [18], Bhosale et al. [25], and Cetin and Jordan [26] discussed emergency V2V communication and how such communication could improve response time and safety.

Other publications focused mainly on general effects or impacts of V2V on traffic flow, but also discussed traffic safety through simulation. For example, Yeo et al. [23] discussed and presented microscopic traffic simulation of V2V hazard alerts on a freeway. Mei et al. [24] presented a simulation module for studying the impact of V2V on traffic network operations. Finally, Kerner et al. [20] created a test bed for wireless vehicle communication in the context of three-phase traffic theory.

Chen et al. [19] proposed a vehicular-based ad hoc networking and computing grid (VGrid), an ad hoc networking and computer grid formed by leveraging V2V wireless communication. The VGrid used accident alert messages and calculated variable speed limits based on the local density of vehicles. The simulation results showed that VGrid reduced speed variance, corresponding to more homogenous vehicle behavior in free flow and obstructed-lane scenarios. This allowed drivers to make decisions, such as lane adjustments and speed control, at safer ranges and with greater precision than possible with human perception alone [19].

Recognizing that most traffic management systems do not consider vehicle lane organization and only regulate traffic flow by controlling traffic signals or ramp meters, Dao et al. [21] developed an algorithm for optimization of lane assignments using V2V communication to increase traffic throughput and decrease vehicle traffic time. This method was applied in the present study's simulation, where lane assignments based on the ERV's location within the network were used. (Lane assignment messages were disseminated to non-ERVs to assign them to appropriate lanes when an ERV approached.)

While some connected vehicle applications related to safety and traffic flow are close to market, emergency V2V communication applications are still being studied. Buchenscheit et al. [18] outlined a comprehensive design for an ERV warning system. The system made full use of V2V communication technologies. Simulation in this study showed that an ERV communication system could increase safety and reduce ERV travel time.

Bhosale et al. [25], similar to Buchenscheit et al. [18], utilized VANET to disseminate detailed information to non-ERVs from an approaching ERV. They introduced an architecture for ERVs to be given a high priority during an approach. The proposed architecture included Road Side Unit (RSU) communication with an ERV as well (i.e., at traffic signals). According to Bhosale et al. [25], correct, timely, and detailed information messages can aid non-ERVs' decision making, thereby saving valuable time and lives.

Cetin and Jordan [26] discussed methods to make way for ERVs at oversaturated traffic signals using V2V communication. Their approach involved communicating control messages to vehicles to change their behavior so that an ERV can maneuver through congested intersections as quickly as possible. The authors' proposed method made use of the shockwave theory to determine a critical point where a vehicular queue could be split in one traffic lane so the ERV can proceed. This method was simulated and the results showed that the travel time for the ERV was shortened significantly.

In many of the studies, the motivational questions were how many accidents could be avoided, which information increased the traffic flow, and to what extent it was increased. It is hard to determine the exact impact of V2V communication on traffic and safety since the impacts depend on an infinite number of possible traffic situations [16]. This is why it is necessary to assess the impacts by utilizing modeling tools to study different traffic situations. Once a model is built, the effect of adding V2V technology can be assessed. Such an approach is utilized in the present study as discussed in the next section.

Methodology

In this study, micro-simulation was used to determine whether V2V communication could improve the efficiency (i.e., reduce travel time) of an ERV response during different traffic flow conditions. The selected simulation tool was VISSIM. The simulated ERV communicated with other vehicles on its path and sent messages that influenced non-ERV drivers' behaviors. The non-ERV drivers received messages that directed their movements when an ERV was approaching. For example, the ERV sent messages such as, "move to the right lane" or, "move to the left lane."

VISSIM Network Description

The simulated network was based on a portion of the Northern Virginia Connected Vehicle Test Bed, particularly the area covering parts of Highway 29 (Lee Highway) and Gallows Road (Figure 1).

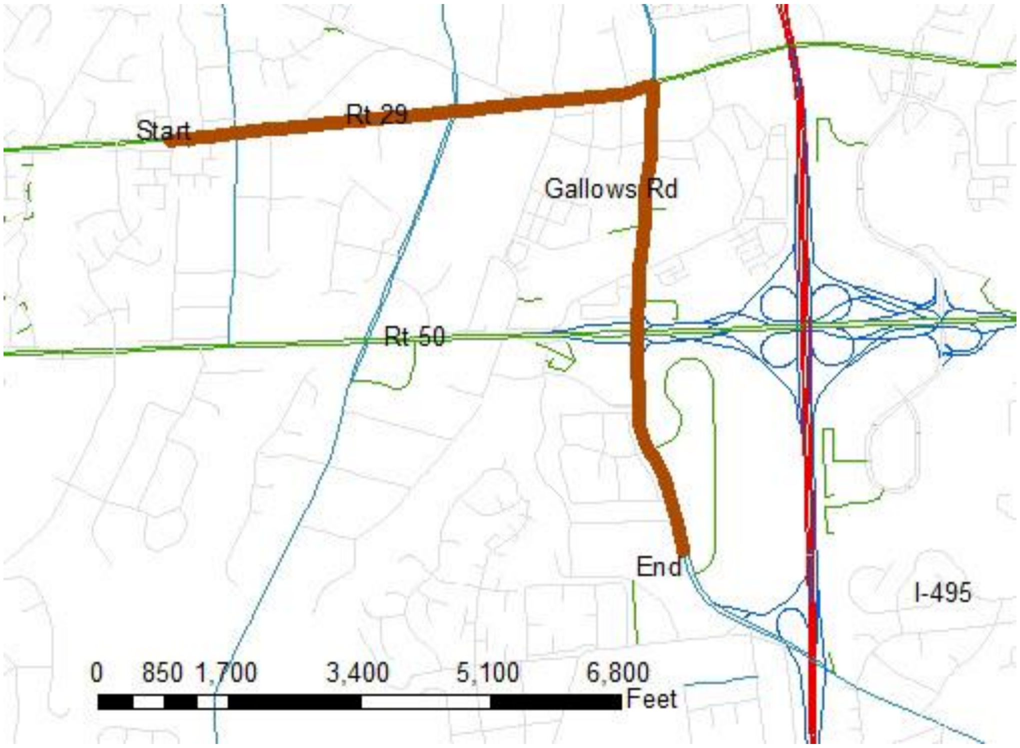

Figure 1. Simulated network based on the Northern Virginia Connected Vehicle Test Bed.

The network consisted of 390 links and connectors. For each intersection of links, traffic volumes were split among routes by a pre-specified percentage. (See Figure 2 as an example.)

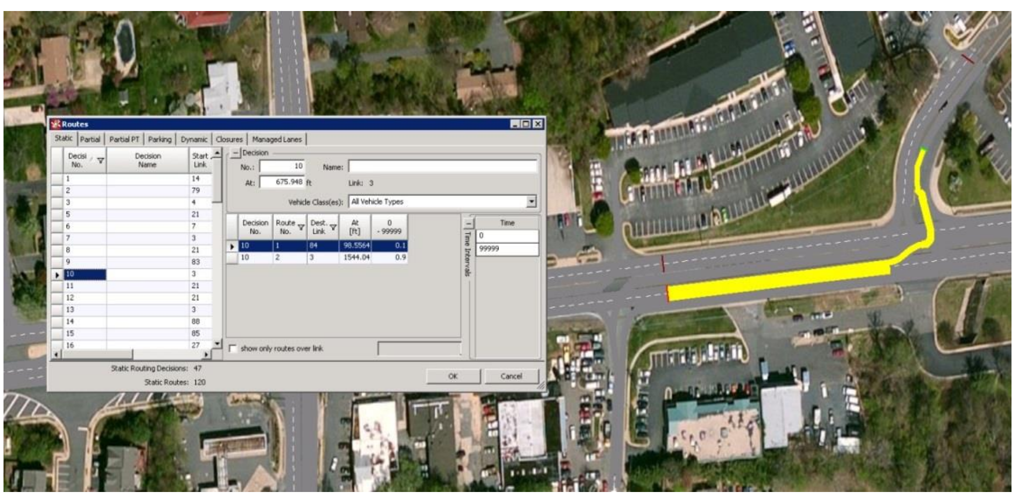

Figure 2. Decision routes modeled in VISSIM.

At appropriate intersections, ring barrier signal controllers were simulated with an ERV signal preemption option. Prior to the signalized intersections, detectors were placed to recognize the presence of an ERV. Once detected, all signal heads at the intersection changed to red except for the ERV's.

As Figure 1 illustrates, there were two major roads: Lee Highway (east and west bound) and Gallows Road (north and south bound). On Lee Highway, the speed limit was 40 mph, and on Gallows Road, the speed limit was 35 mph. Each of these roads was modeled with its vehicle speed distribution. Vehicles entering the network on Lee Highway started at a distribution with minimum and maximum values of 36 and 42 mph, respectively. After entering Gallows Road, the speed distribution was reduced to minimum and maximum values of 32 and 38 mph. In the simulation, however, different scenarios were considered to investigate the effect the vehicle speed distribution had on travel time.

Two parking lots were also modeled. One parking lot was used when the ERV left a location (point A), and a second when it arrived at its destination (point B: the hospital). A static route was created between these two parking lots to ensure the ERV reached its destination. Finally, priority conflict zones were modeled at intersections to avoid collisions.

For the V2V communication, VISSIM's API library extension was used. An ERV_V2V application class object was constructed to represent a V2V equipped ERV application class. This class was derived from VISSIM's base application class (c2x.ApplicationBase). Once the ERV_V2V object was created, it had to be coded to run as a server. After running the application object, VISSIM established a connection with this application server once every time step, and a function named processTimeStep() was called from the computer code. ProcessTimeStep contained the algorithms of the C2X application. When a time step was completed, control was given back to VISSIM and the process was repeated in the next time step. In the processTimeStep() function, messages were disseminated to C2X equipped vehicles.

Experimentation with Simulations

After modeling the network described in the previous section, the research group conducted several simulation experiments to observe the variations in travel times based on a particular determining factor, such as traffic volume, speed distribution, ERV signal preemption, and traffic signal cycle length. Two groups of experiments were conducted: (1) baseline conditions (no V2V communication) and (2) the addition of V2V communication. The experimental factors and associated assumptions are discussed below.

Traffic Volumes

The volume of the network traffic ranged from 6,199–14,696 vehicles per hour. Accurate volume counts were not available at all intersections; hence, values were added by a trial and error technique. Once an acceptable distribution was achieved, the values for all vehicle input from different sources were adjusted by a factor to achieve congestion on the roads.

Traffic volume in VISSIM (vehicle input) was defined for each link in a time interval in vehicles per hour. Usually, vehicles enter a link according to a Poisson distribution. In this simulation study, however, vehicle inputs were assumed to be exact or static, which means the number of vehicles entering the network was fixed within the specified period as opposed to using a

Poisson distribution to facilitate scenario comparison. However, even with static volumes, all vehicles assigned to a link may not have entered the network during a simulation period due to congestion. Hence, the exact number of vehicles that entered a network during a simulation period was written to a file that showed all vehicles in the network and their origination links, lanes, types, time entered, and desired speed. These text files were written for each experiment and investigated in the results.

Due to the nature of randomness of generating vehicle input in VISSIM, a random seed was used. This parameter initialized the random number generator. Simulation ran with identical input and random seeds generated identical results. Using a different random seed changed the profile of the traffic arriving and therefore allowed the results to change. In this way, the stochastic variation of input flow arrival times could be simulated. For meaningful results, VISSIM recommends determining the arithmetic mean based on the results of multiple simulation runs with different random seed settings. For each experiment, the results were generated using five different random seeds, and travel times and vehicle inputs were averaged. As an example, consider an experiment that generates two files: an input vehicle text file as explained above and a travel time file for the ERV from its origin to destination. Using five random seeds (i.e., 12, 24, 30, 42, and 60), 10 files were generated (five files for vehicle input and five for travel times). For the vehicle input files, the total average vehicle input was calculated from the five files, and the same was true for the travel time.

Speed Distributions

VISSIM allows creating a vehicle composition, which is a combination of vehicles entering the network. Each composition consists of different vehicle types. In this study, two vehicle compositions were used. One represented ERVs equipped with V2V communication systems. The other represented non-ERVs on the road, and included cars and trucks that were also equipped with communication systems. Based on the road's speed limit, a speed distribution was selected. For the ERVs, two speed distributions were chosen: 36–42.3 mph and 42.3–48.5 mph. For the non-ERVs, three distributions were chosen, each dependent on which street the vehicle was on: 29.8–36 mph, 36–42.3 mph, and 32–38 mph. The effects of these distributions on travel time were investigated in the experiments.

Intersection Control

The signal controller cycle length varied between 90 and 180 seconds for different experiments. The signal cycle length was varied to adjust for the best traffic scenario, which was dependent on traffic volume at the intersection (i.e., saturation levels).

As mentioned earlier, traffic signal preemption was used for the ERV. When an ERV was detected, signal preemption was applied, giving priority for the ERV to proceed at an intersection.

Experiments

Experiments were conducted based on the assumptions and factors discussed above. For example, the values of inputs, such as the number of non-ERVs in the network, were varied, during a simulation period. These experiments were divided into two groups, one of which determined the variation under base or normal traffic conditions, and a second that determined the variations under V2V conditions. Each experiment was conducted several times with different simulation random seeds as described above, and ERV travel times were calculated as the average of the travel times for each random seed.

Baseline Travel

In the baseline travel condition, all factors were varied in order to observe the behavior of the ERV and non-ERVs. In every experiment, one factor was varied while other factors remained constant, and the research group investigated how each of these factors influenced the ERV's travel time.

The period of simulation varied between 3,600 and 4,200 seconds depending on the traffic volume. If the input volume was large, the simulation period was set to 4,200. The ERV entered the network mid-way through the simulation to allow the generation of enough traffic in the network.

Nineteen experiments were conducted in the baseline condition. Experiments 1 through 11 were used to determine the effect of the cycle length, signal preemption, and traffic volume on the ERV's travel time. Based on the results obtained in these experiments, the VISSIM network model was adjusted to represent a real life traffic scenario. For example, the traffic input was distributed in a way that formed an approximate uniform distribution of traffic across the network. Traffic signal cycles were adjusted to handle this volume. Eleven signal controllers were added to the network. One controller was installed at each intersection. Only the light where the ERV was approaching turned green; all others turned red. Adjustments were made to the routing decision in order to direct traffic toward the path of the ERV so that a congestion condition was reached quickly. Speed distributions and volume variation were investigated to identify the effects on ERV travel time.

Emergency Response Vehicle Travel Time Experimentation

ERV travel time was influenced by a number of factors. The research group expected the addition of V2V communication to improve ERV travel time. The research group conducted four experiments (experiments 20–23) using V2V communication. In the experiments, simple instructions were sent by the ERV to the non-ERVs with instructions to "move to the right," "move to the left," or "stay where you are" (Figure 3). Non-ERV movements in the presence of the ERV were not optimized.

In future experiments, the length of the warning distance or message broadcast range (in experiments 20-23, the warning distance was set to 328 feet [100 meters]) and warning speed should be included in the simulation. The purpose of the V2V communication in the experiments here was to observe the effect of simple messages or commands, as described above, sent via the communication module in VISSIM, on the ERV's travel time without any movement optimization. It is expected that optimizations should further improve travel time.

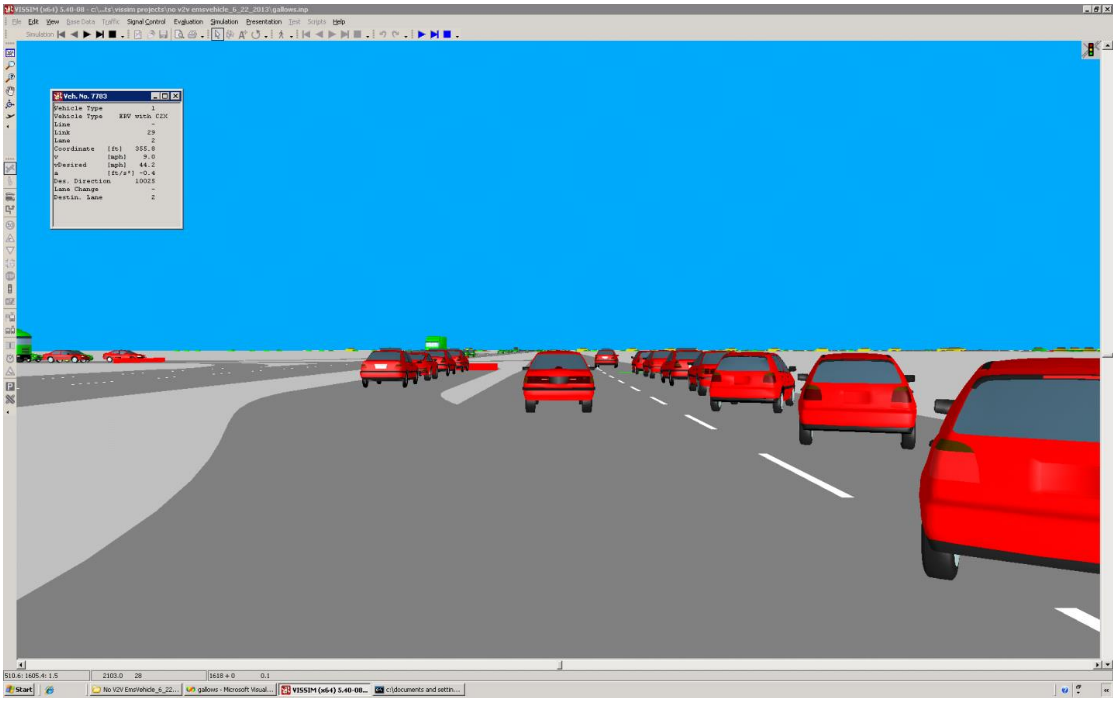

Figure 3. Vehicles moving to the right based on a message received from the ERV.

Results

The set of experiments examined the travel time of an ERV traveling under normal or base conditions and then under the influence of V2V communication. The results of the study revealed that V2V communication has a positive influence on travel efficiency, which was demonstrated through the improved travel time of an ERV in congestion.

Table 1 presents the results of experiments 1–11, showing that signal preemption decreased the ERV's travel time, and that increased traffic volume increased travel time. Adjusting the cycle length of a traffic controller in accordance with traffic volumes in all directions of travel improved travel time. For this network, a cycle length of 120 seconds was determined to be the best for non-preemptive cases, reducing ERV travel time, as illustrated in Table 1.

Table 1. Results of Experiments 1–11

Experiment	Simulation Period (sec)	Vehicle Speed Distribution (mph)	ERV Speed Distribution (mph)	Volume (veh/hr)	Pre-Empt.	Cycle Length (sec)	Travel Time (sec)	Preemption's Travel time improvement (sec)
1	3600	29.8–36	36–42.3	6199	No	180	819.1	
2	3600	29.8–36	36–42.3	6199	Yes	180	517.2	301.9 (37%)
3	3600	29.8–36	36–42.3	8233	No	180	1192.2	
4	3600	29.8–36	36–42.3	8233	Yes	180	888.0	304.3 (26%)
5	4200	29.8–36	36–42.3	10722	No	180	1340.9	
6	4200	29.8–36	36–42.3	10722	Yes	180	1116.4	224.5 (17%)
7	3600	29.8–36	36–42.3	8233	No	150	842.8	
8	3600	29.8–36	36–42.3	8233	Yes	150	752.1	90.7 (11%)
9	3600	29.8–36	36–42.3	8233	No	120	710.6	
10	3600	29.8–36	36–42.3	8233	Yes	120	590.7	119.9 (17%)
11	4200	29.8–36	36–42.3	10722	Yes	120	792.1	

Table 2 shows the results of experiments 12–19. As experiments 12–14 demonstrate, increasing the traffic volume increases the ERV's travel time. Changing the cycle length to 90 seconds increased the travel time as well, as seen in experiment 15. A 120 second cycle was again found to be the most efficient for this network and demand.

In all of the previous experiments, the speed distribution of all non-ERVs in the network was set with minimum and maximum values of 29.8 and 36.0 mph, and the ERV's speed distribution had minimum and maximum values of 36.0 and 42.3 mph. As noted above, the speed limit on Lee Highway was 40 mph and on Gallows Road it was 35 mph. In experiment 16, the distribution was increased for all non-ERVs on Lee Highway to minimum and maximum values of 36.0 and 42.3 mph, the same as that of the ERV, and on Gallows Road the speed of all non-ERVs was set to minimum and maximum values of 32 and 38 mph. On Gallows Road, the ERV continued with the same speed distribution set at the beginning of the experiments: 36.0–42.3 mph. Compared to experiment 14, which showed an ERV travel time of 1,141.06 seconds, adjusting the speed distribution as in experiment 16 decreased this travel time to 1,074.14 seconds. Repeating experiment 16 (in experiment 17) on a less congested network further decreased the travel time. Compared to experiment 13, travel time in experiment 17 was decreased from 787.75 to 621.2 seconds, which was expected due to the increased speed.

Experiment 17 was repeated (in experiment 18) with an increase in the ERV's speed distribution from (36.0–42.3 mph) to (42.3–48.5 mph). The travel time was lower, which was, again, expected due to the increased speed. An increase in the ERV's speed was more effective when the network was not congested. As illustrated in experiment 18, the travel time decreased slightly, from 621.2 to 590.26 seconds.

Repeating experiment 16 (in experiment 19), with a higher ERV speed distribution, the ERV's travel time was not expected to increase as in experiment 18, due to the fact that the ERV had to follow slow non-ERVs in congested conditions. As expected, the travel time decrease was not considerable, changing only from 1,074.14 (in experiment 16) to 1,071.64 (in experiment 19), with an increase in the ERV's speed distribution.

Table 2. Results of Experiments 12–19

Experiment	Simulation Period (sec)	Non-ERV Speed Distribution (mph)	ERV Speed Distribution (mph)	Volume (veh/hr)	Pre-Emption	Cycle Length (sec)	Travel Time (sec)	Speed Distribution's Improvement on ERV Travel Time (sec)
12	3600	29.8–36	36–42.3	11222	Yes	120	504.7	
13	3600	29.8–36	36–42.3	13233	Yes	120	787.8	
14	3600	29.8–36	36–42.3	14696	Yes	120	1141.1	
15	3600	29.8–36	36–42.3	13265.4	Yes	90	>1700	
16	3600	36–42.3, 32–38	36–42.3	14696	Yes	120	1074.1	66.9 (6%) Compared to 14
17	3600	36–42.3, 32–38	36–42.3	13233	Yes	120	621.2	166.6 (21%) Compared to 13
18	3600	36–42.3, 32–38	42.3–8.5	13233	Yes	120	590.3	30.9 (5%) Compared to 17
19	3600	36–42.3, 32-38	42.3–8.5	14696	Yes	120	1071.6	2.5 (0.2%) Compared to 16

The addition of V2V communications into the network reduced the ERV's travel time. Table 3 shows the results of experiments 20–23, which demonstrate a reduction in travel time compared to experiments 11, 13, 18, and 19. In experiments without V2V communication, the travel times were 792.1, 787.8, 590.3, and 1,071.6 seconds respectively. With V2V communication, the travel times in experiments 20, 21, 22, and 23 were reduced to 544.6, 533.0, 472.2, and 859.9 seconds respectively.

Table 3. Results of Experiments 20–23

Experiment	Simulation Period (sec)	Non-ERV Speed Distribution (mph)	ERV Speed Distribution (mph)	Volume (veh/hr)	Pre-Emption	Cycle Length (sec)	Travel Time (sec)	V2V's Improvement on ERV Travel Time (sec)
20	4200	29.8–36	36–42.3	10722	Yes	120	544.6	247.5 (31%) Compared to 11
21	3600	29.8–36	36–42.3	13233	Yes	120	533.0	254.8 (32%) Compared to 13
22	3600	36–42.3; 32–38	42.3–48.5	13233	Yes	120	472.2	118.0 (20%) Compared to 18
23	3600	36–42.3; 32–38	42.3–48.5	14696	Yes	120	859.9	211.8 (20%) Compared to 19

Conclusions

The research group used micro-simulation experiments based on the Northern Virginia Connected Vehicle Test Bed to investigate the impact of V2V communication on ERV travel time. The experiments examined an ERV's travel time under base conditions (no V2V communication) and under V2V communication conditions. With V2V communication, the ERV was able to disseminate messages to surrounding non-ERVs, which influenced non-ERV drivers' behaviors and shortened ERV travel time.

In addition to V2V communication, the experiments investigated the effects of traffic volumes, cycle lengths, speed distributions, and signal preemption on ERV travel time. As expected, higher traffic volumes increased travel time. Since the ERV's speed was limited by other vehicles on the road in a congested network, increasing the speed of the ERV in a congested network was found to have negligible effects on ERV travel time. Traffic signal preemption decreased the ERV's travel time, allowing it to maneuver faster through intersections. For this relatively small network, signal preemption (without V2V communication) improved the ERV's travel time by approximately 1.5–5.0 minutes (11%–37% improvement), depending on traffic volumes and cycle lengths. Appropriate signal cycle lengths improved traffic movement and mitigated congestion.

The results of the study revealed that V2V communication could have a positive influence on travel time for an ERV in congested traffic conditions. For the simulation network and specified conditions, the benefits were a 20%–32% improvement in the ERV's travel time over scenarios with signal preemption alone. The benefits achieved here should be confirmed in the future with additional networks and traffic conditions. In future experiments, the impacts of the message broadcast distance, length of the warning distance, and warning speed should be investigated in the simulation. In addition, the messages provided in this study were simple. More detailed messages may offer additional benefits and should be considered in future studies.

Chapter 3. Drivers' Reaction Times to Vehicle-to-Vehicle Movement Instructions for Emergency Response Vehicle Travel Facilitation

Introduction and Background

To investigate the potential for V2V communications to effectively guide non-ERVs out of the path of an ERV in a timely manner, the research group developed a set of messages that could be transmitted from a laptop in a following vehicle (simulating the ERV) to a preceding vehicle (simulating the non-ERV). This system was tested with 12 participants on highways and arterials in Northern Virginia on the Northern Virginia Connected Vehicle Test Bed (data was missing for one of these participants, resulting in 11 valid sets of observations). This data was used to explore three specific research questions regarding the relationship between reaction times to prototype instructions from ERVs, driving behavior, and speed considerations. Drivers react differently to unexpected and expected situations, so variation in drivers' reaction times can be explained in terms of different ranges of reaction times depending on various driving factors and conditions. Reaction time in this study was the *time from the beginning of the audio messages to the first brake application.* A stable traffic pattern occurring in light traffic conditions was used in this study to negate the effect that different traffic patterns might have had on reaction time delays [28].

The research questions addressed in this study are as follows:

1. Do kinematic attributes have a statistically significant association with reaction times?

Vehicle operation variables, such as acceleration and speed, have been incorporated in predictive equations of reaction times [29]. In addition, previous studies of reaction times have treated a large group of kinematic and non-kinematic variables as independent variables (contributors), as outlined in Muttart [30]. From Muttart's list of 19 factors, three factors were considered—age, gender, and average speed—for each model.

Throttle position in a three-axis system and acceleration were also considered, as the in-vehicle data acquisition system (DAS) in the non-ERVs used in this study gathered data on various kinematic aspects, and these are not included in most response time prediction literature. Accordingly, one contribution of this study is an investigation of the extent to which different variables affect reaction times for drivers of non-ERVs operating in a connected vehicle infrastructure (CVI) environment.

2. Can reaction times to ERV messages be predicted as in the case of perceiving invisible objects (i.e., audio messages as audible stimuli)?

According to the American Association of State Highway and Transportation Officials (AASHTO) [31], the reaction time for safe stopping distance can be classified into six categories with respect to drivers' perception of the object and stimuli. The six categories are (1) illuminated objects and audible stimuli; (2) path intrusions; (3) pedestrians, bicycles and obstacles (in the road); (4) car-following situations; (5) traffic controls; and (6) overall reaction time. Reaction time-prediction generally focuses on visible objects ahead, such as barriers or pedestrians. The situation for this study is response to audible information. In addition, it appears from the literature review (below) that specific studies of the reaction time to ERVs are limited.

3. Is the reaction time to ERV messages equivalent to 2.7 seconds?

Much of the literature on reaction time prediction [32], [33], [34] has demonstrated that reaction times typically fall in the range between 0.75 and 2.7 seconds depending on the conditions in which the experiments have been conducted. Since connected vehicles represent a new driving environment, reaction time values could be different from those found in traditional reaction time experiments. Accordingly, the hypothesis that the reaction time to the ERV message equals 2.7 seconds should be tested.

The remainder of this chapter is divided into six sections. First, an overview of literature related to driver reaction times and the potential use of V2V or V2I communication for ERV travel facilitation is provided. Then, a description of the study and data collection is provided, followed by an overview of the data and testing of whether reaction time to audible stimuli in a CVI environment is significantly different than the reaction time of 2.7 seconds traditionally recommended by AASHTO. Then, an overview of linear regression and the modeling results is presented. The final section provides conclusions and future directions of study.

Literature Review

Researchers from various fields, such as psychology and transportation, have studied brake reaction times in a number of different contexts. For example, Strayer et al. [35] concluded that drivers who engage in complex multitasking have an increased reaction time and crash risk. Brake reaction time is typically defined as the time between the moment the driver perceives an obstacle in the roadway to the moment the driver responds to the obstacle by applying the brakes [31]. Table 4 presents the range of reaction times found in previous studies and the context in which they were determined.

Table 4. Reaction Times from Previous Studies

Study	Reaction Time(s)	Situation and Stimulus	Reaction Time Definition (if provided)
American Association of State Highway and Transportation Officials (AASHTO) [31]	2.7	A simple, unexpected decision and action	"The interval from the instant that the driver recognizes the existence of an obstacle on the roadway ahead that necessitates braking to the instant the driver actually applies the brakes"
Olson [36], Dewar and Olson [37]	1.5 (85% to 95% of participants)	Lead vehicles after the first appearance of the object or condition of concern	"The time from the first sighting of an obstacle until the driver applies the brakes"
Olson and Sivak [38]	0.75 to 1.5 (85% to 95% of participants)	Leading vehicles	"The time from the first sighting of an obstacle until the driver applies the brakes"
Sivak et al. [39]	0.75 to 1.5 (85% to 95% of participants)	A leading vehicle's anticipated brake light	"The time elapsed from the onset of the lead car's brake signal to the time of the first detectable onset of the brake lights of the subject's car"
Sivak et al. [40]	0.75 to 1.5 (85% to 95% of participants)	A yellow foam rubber object was placed to the left of the vehicle's path after the subject crested a hill	"The time from the first appearance of the object or condition of concern to the first vehicle movement in response"
Green [41]	1.5	Surprising and sudden stimulus in on-road vehicle intrusions (a barrier that springs up from a slot)	"The time it takes for the responder to perceive that a signal has occurred and to decide on a response"
Green [41]	1.25	Unexpected stimulus, brake lights, traffic signals and car following	"The time it takes for the responder to perceive that a signal has occurred and to decide on a response."
Hooper and McGee [42]	2.3 (50th percentile)	Stopping-sight distance, lateral clearance to sight obstructions on horizontal curves, intersection sight distance, and vehicle change interval	"The interval between release of the accelerator and contact with the brake pedal."
Sivak [43]	0.75	Car-following situation	"The time of the first detectable onset of the brake lights of the subject's car"

Study	Reaction Time(s)	Situation and Stimulus	Reaction Time Definition (if provided)
Johansson and Rumar [34]	Median 0.9; 25% with > 1.2	A brief brake application after hearing a horn at the side of the highway	"Time from sounding a horn to applying the brakes"
Lerner et al. [44]	1.31	Unexpected stimulus for braking	"The interval between release of the accelerator and contact with the brake pedal"
Lerner et al. [44]	0.54	The driver is aware that the signal to brake will occur	"The interval between release of the accelerator and contact with the brake pedal"
Gundy [45], Moberly and Langham [46], Muttart [47]	More than 10	"Gradual or delayed onset" (the object is not immediately recognized)	"The time period from when the detection threshold is reached to first vehicle movement in response"

As seen in Table 4, in general, the reaction times fell in the range of 0.75 to 2.7 seconds. However, none of these studies were in the context of reactions to emergency messages or directions from an ERV and few (e.g., [34]) were related to audio stimuli. This research focuses only on V2V audio messages. Partially-related studies address the impact of V2V communication on traffic flow and safety.

ERV applications are being developed to solve real world problems in the areas of safety and traffic flow, and emergency V2V communication applications are still being studied. Buchenscheit et al. [18] outlined an ERV warning system that uses V2V communication technologies. The study shows that an ERV communication system can increase safety and reduce the ERV's travel time. Talebpour and Mahmassani [48] included the simulated reaction times in the stability analysis for traffic flow and used acceleration models to account for the car-following behavior of the connected vehicles. The reaction times were generated based on the assumption that the reaction time of connected vehicles is 50% less than that of regular vehicles [49]. Instead of depending on assumptions, this study involves a field study to collect data to estimate reaction times.

Smith et al. [50] estimated connected vehicle drivers' reaction time to an advisory for making a lane change, where the reaction time was the difference between the timestamp when an advisory was given via infrastructure-to-vehicle (I2V) and V2I communications and the timestamp when the driver completed the task under three different advisories: variable speed limit, lane changing, and merging control for evaluating the freeway merge assistance systems. The average response time to the variable speed limit advisory was 8.68 seconds (s = 1.86 sec).

Participant drivers reacted faster to the lane changing advisory and the merging control advisory, with average response times of 8.43 seconds (s = 1.46 sec) and 7.48 seconds (s = 1.67) respectively.

Although ERV reaction times in this study were predicted based on a field test, the work by Smith et al. [50] is different from the current study. The three CVI-instrumented vehicles ran on the Virginia Smart Road, which was equipped with roadside equipment receiving the visual messages via I2V and V2I, whereas this study took place on real-world highways. Moreover, the current study used only V2V communication, and reaction times may differ from those found using I2V and V2I communications as a result. Some skepticism exists about the practical application of CVI-instrumentation because ERV reaction times studied under controlled laboratory conditions could vary significantly from those in real-world situations. However, one finding that can be adopted from Smith et al. [50] is the development of gap sizes in terms of mean headways to account for response times in high, medium, and low traffic conditions. This would demonstrate the impact of traffic conditions on drivers' response behavior, which is worth taking into account for predicting reaction times. One more lesson taken from the work is the comparison of reaction times across each of the contributing factors, such as gap sizes, genders, and age groups.

Doecke et al. [51] used the reaction times of 0.7 and 1.2 seconds suggested by Green [41] and Mohebbi et al. [52] to investigate how many simulated crashes could be mitigated by the connected vehicle. The scenarios with 0.7 and 1.2 second reaction times for the operation of the connected vehicle were compared to the fully autonomous vehicle in order to investigate the sensitivity of the reaction times. This research pointed out the importance of the reaction times for the connected vehicle and the benefits of the connected vehicle to the real-world crash and impact speed reduction.

Although Jin and Orosz [53] did not predict connected vehicle-related reaction times, their work demonstrated the acceleration-based connected cruise control design in consideration with some human parameters received via V2V communication, such as reaction times, speed, distance, headway, and acceleration. This paper may offer a good example of how the is dataset useful for ERV modeling work, as the relationships between all the data mentioned above, especially accelerations and reaction times, can apply to the connected car following model. Thus, field-testing ERVs' operation would be useful for collecting practical datasets via V2V communication technology. Moreover, the significant effect of acceleration on the driver reaction times could be emphasized by regressing the reaction times with acceleration. Therefore, the datasets used for this research look promising if regression models must be built to predict the reaction times.

Cetin et al. [26] discussed methods of making way for ERVs at oversaturated traffic signals using V2V communication. They proposed an approach involving communicating control messages to vehicles to change their behavior so that an ERV can maneuver through a congested intersection as quickly as possible. The method proposed by the authors made use of shockwave theory to determine a critical point where a vehicular queue was split in one traffic lane so the ERV could proceed. This method was simulated and the results showed that the travel time for the ERV was shortened significantly. The authors did not explicitly consider reaction times in their paper.

A gap in the existing literature on V2V communication in ERVs is the lack of field experiments. Although the simulation based method is the most popular method in vehicle-to-everything (V2X) studies, its practicality may be limited, because in reality, V2V communication is associated with many dimensions of transportation, such as drivers' behavior, traffic characteristics, and network configuration. The use of models run with simulated data might be flawed without the inclusion of reaction times for applications involving humans, and there are few studies that predict reaction times in the presence of ERVs. Field-testing is expected to help fill this gap and pave the way for the further estimation of reaction times.

Data Acquisition

As an initial prototype, the research group developed a set of messages that could be transmitted from a laptop in a following vehicle (simulating the ERV) to a preceding vehicle (simulating the non-ERV). This prototype was tested on highways and arterials on the Northern Virginia Connected Vehicle Test Bed with participants from the Northern Virginia/Washington, D.C. Metropolitan Area.

The vehicles were equipped with on board equipment with antennae, including a vehicle awareness device, an Aftermarket Safety Device, a Modular Communications Platform, a network box, and a Software Development Kit together with a NextGEN DAS forward and face cameras. In addition to video, the DAS also collected vehicle data (e.g. speed, acceleration, braking, yaw).

Due to the location of the test route, participants were recruited from the Washington, D.C. Metropolitan Area through advertisements posted in a Virginia Tech (VT) building located in the Northern Virginia area, via VT news, Craigslist, social media, and by word-of-mouth. Participants were required to be healthy, U.S. licensed drivers between 25 and 50 years old. They had to be U.S. citizens or hold a green card with a social security number and understand spoken and written English. They had to be able to drive a vehicle with an automatic transmission without special equipment and drive at least two times a week with no more than two driving violations or an injurious accident in the past three years.

Potential participants were asked to provide verbal consent for the screening questions. After verbal consent was provided, the researcher administered the eligibility screening over the phone. Those who were eligible were scheduled to come to VT at the Northern Virginia Center. At least two days prior to the scheduled date, participants were emailed an Informed Consent Form. Upon arrival, an experimenter reviewed the form with the participant and answered any questions. A signed copy was retained by the research group, and another copy was given to the participant for his/her records.

Informal hearing and visual tests were performed with participants. To conform to standard use of roadways and parking lots, the experimenters informed the participant that upon hearing the left/right messages, when safe, they should pull to the appropriate side of the road/parking aisle and park in a standard/permissible parking space.

Participants were acclimated to the vehicles and messages in a low use parking lot prior to testing on the roads. An experimenter accompanied the participant in the vehicle at all times. The vehicle with the participant was followed by another vehicle (representing the ERV) carrying two experimenters—one experimenter drove and one sent the messages from a laptop to the participant's vehicle. The three audio messages were: (1) "Emergency vehicle approaching, pull to the left," (2) "Emergency vehicle approaching, pull to the right," and (3) "Emergency vehicle approaching, stay where you are."

Data collection was conducted on the route shown in Figure 1 during weekday off-peak periods (10 a.m. to 3 p.m.) and weekend mornings (7 a.m. to noon). Collecting data during off-peak periods helped promote safety, reducing traffic movement conflicts while the participant vehicle pulled over and made turns before stopping. The participants drove along the study route shown in Figure 1, beginning at the Merrifield Fire Station on Lee Highway and going eastbound until reaching Gallows Road. At Gallows Road, the route headed south (right hand turn at traffic light) until approximately Inova Fairfax Hospital. While traversing the route, the participant driver received an audio message preceded by a flashing screen on the infotainment display on the dashboard.

Data Description and Hypothesis Testing

There were eleven participants (five males and six females) in this study. The average age of all the participants was 37. Each participant received two to three audio messages during testing. The experimenters collected a total of 30 observations from these tests. The average reaction time to the audio messages was 3.39 seconds with a standard deviation of 1.34 seconds.

The variables examined for this project are shown in Table 5. Acceleration was measured by an inertial measurement unit (IMU), which is "a single unit in the electronics module that collects angular velocity and linear acceleration data, which is then sent to the main processor" [54]. Participant characteristics are also included in the table; the data were self-provided based on written questionnaires.

The modeling variables were tailored for the purpose of the study. All variables were defined based on timestamp and brake application prior to maneuvering the vehicle after hearing the audio messages, and are defined in the following sections of this report. An overview of the variables for the regression modeling is given, along with descriptive statistics, in Table 5.

Table 5. Variable Descriptions and Statistics

Variable	Description (Units)	Basic Statistics
Age	Age of Participants (years)	Mean = 37.1 SD = 8.0 Min = 27 Max = 50
Gen	Gender of Participants	Female = 53% Male = 47%
Vio	Moving violation history of participants	Yes = 40% No = 60%
HearVis	Normal hearing and vision abilities of participants	Yes = 100% No = 0%
Autrans	Ability to use an automatic transmission	Yes = 100% No = 0%
Acd	Auto accident history of participants	Yes = 10% No = 90%
Med	Taking Medications	Yes = 0% No = 100%
Freq	Frequency of vehicle use	2-4 times a week = 40% > 4 times a week = 60%
Dist	Participants' average daily travel distances	< 5 miles = 0% 5-10 miles = 20% 10-20 miles = 43% > 20 miles = 37%
Window	Participants' preferred vehicle window position while driving	Up = 37% Down = 63%
Listen	Listening to music/radio while driving	Yes = 100% No = 0%
Loudness	Participants' preference to listen to loud music while driving	Yes = 17% No = 83%
Device	Preference to use in-vehicle devices	Yes = 63% No = 37%
Freqdev	Frequency of in-vehicle and personal device use while in the vehicle	Do not use = 37% < 1 time a week = 10% 1-2 times a week = 20% 3 times or more a week = 33%
Speed	Speed of the participant vehicle when the infotainment system screen flashes (meters/second)	Mean = 14.65 SD = 3.00
Speedon	Speed of the participant vehicle when the brake is first applied (meters/second)	Mean = 14.41 SD = 2.65
Speedoff	Speed of the participant vehicle when the driver's foot is off the accelerator (meters/second)	Mean = 5.67 SD = 3.90
AcclX	IMU acceleration in lateral direction of the participant vehicle when the participant driver receives the message (g)	Mean = -0.0128 SD = 0.0374
AcclY	IMU acceleration in longitudinal direction of the participant vehicle when the participant driver receives the message (g)	Mean = -0.0053 SD = 0.0310
AcclZ	IMU acceleration in vertical direction of the participant vehicle when the participant driver receives the message (g)	Mean = -0.9923 SD = 0.0234
AcclTurnX	IMU acceleration of the participant vehicle in lateral direction versus time when the driver signals to makes a turn (g)	Mean = -0.0419 SD = 0.0465
AcclTurnY	IMU acceleration of the participant vehicle in longitudinal direction vs. time when the participant driver signals to make a turn (g)	Mean = -0.0016 SD = 0.0274
AcclTurnZ	IMU acceleration of the participant vehicle in vertical direction (up or down) vs. time when the driver signals to make a turn(g)	Mean = -0.9881 SD = 0.0243
Thro	Throttle position when the infotainment screen flashes (%)	Mean = 10.35 SD = 8.42
Throturn	Throttle position when applying the brake to make a turn (%)	Mean = 12.52 SD = 4.78
Overtake	Period of time from the moment the audio message is sent to the moment the vehicle comes to a complete stop (seconds)	Mean = 45,826.8 SD = 25,243.2

* SD = Standard Deviation

Preliminary Analysis

A number of studies (see Table 4 for examples) involving reaction times starting from the moment that an object becomes visible have been previously conducted, but this project involved stimuli that were not immediately recognized. For gradual or delayed onset situations, reaction times from the first moment of visibility to vehicle response could be over 10 seconds [45-47]. From the 30 observations collected, the average reaction times and standard deviation were found to be 3.39 and 1.34 seconds, respectively.

To determine if the reaction times were significantly different from 2.7 seconds, the hypotheses to be tested were $H_0 : \mu = 2.7$ seconds versus $H_a : \mu \neq 2.7$. According to results given by Stata software, a two-sided t-test with a mean of 2.7 was rejected at the 5% level with a *p*-value of 0.001. Further hypothesis testing was performed since the reaction time to invisible objects (i.e., audio messages) in the ERV was assumed to be greater than 2.7 seconds. A one-tailed t-test denoting that the mean was 2.7 rather than a larger amount was also rejected at the 5% level with a *p*-value of 0.0005. Thus, reaction times for this study case were shown to have exceeded the commonly used 2.7 seconds.

Modeling

To further explore reaction times, potentially influential factors were investigated through linear regression. Typically, predictive equations are created by multiple stepwise linear regression based on the selection of variables and the accuracy of the resulting regression as a predictor.

Multiple linear regression (MLR) models have been successfully utilized for reaction time forecasting under different model specifications [43, 55-60]. Although many regression models have been developed to select the significant variables for predicting reaction times for scenarios involving pedestrians and objects, lights, intrusions, following, traffic controls, and overall [42], in this case there were so many variables (i.e., 28 variables), that any correlation between them might have affected the final models. Therefore, this research used stepwise regression, where the best variable candidates were first identified before moving on to the next step of the modeling process to help avoid the burden of regression computation. The second-stage of the modeling process was designed to run the models with a set of variables chosen by experts in the field.

During the experiment, each driver received approximately two to three messages requesting that they pull the participant vehicle to a safe spot. The limited dataset with 11 participant drivers was thereby expanded to a total of 30 observations.

Linear Regression Results Models

MLR was implemented with the ordinary least squares method using STATA and R. Because there were 28 explanatory variable candidates, it was computationally impossible to build and evaluate all possible regression models, so the predictive regression models were estimated based on a small number of subset regression models. Backward and forward stepwise regression methods were used to fit the dataset of 28 variables. The use of these methods allowed for evaluation of all the trade-offs in fitting the models to the small dataset with a number of variable candidates.

However, as Montgomery et al. [61] point out, stepwise methods, though they offer a quick and easy implementation, do not necessarily provide the best models. Based on the large number of explanatory variable candidates, the stepwise methods were initially implemented for screening purposes, eliminating some negligible variables, and then the remaining variables were considered based on the problem environment. This methodology was adapted from a two-stage strategy recommended by Montgomery et al. [61].

The two cutoff parameters of the stepwise methods were specified prior to the implementation. Accordingly, "Alpha to enter," which is the probability of a type 1 error related to entering a predictor into a regression model [62], was assigned 0.1 for forward selection and forward stepwise methods for this study, while backward elimination and backward stepwise methods used the value of 0.15 as "alpha to remove" for representing the probability of a type 1 error related to retaining a predictor previously entered into the regression model.

All 28 explanatory variables were run by the stepwise procedures. The backward stepwise method removed the variables with *p*-values greater than 0.15 from the full model (Model 1) in the decreasing order of the *p*-values as illustrated in Table 6.

Table 6. P-values of Removing Variables for Backward Elimination

Variable	p-value
Vio	0.8925
Age	0.7068
AcclTurnY	0.6747
AcclY	0.6288
Speedoff	0.5879
Gender	0.3161
AcclTurnZ	0.1589

The candidate variables were identified using the backward stepwise method, and incorporated into Model 1 (shown in Table 7) with the R-squared value of 0.79. The null hypothesis that all the coefficients are equal to zero was rejected at a 5% level with a *p*-value of 0.01. This implied that at least one coefficient value was not equivalent to zero. Based on Model 1, predicted values of the reaction times varied from 0.9 to 5.7 seconds, and the average reaction time was 3.4 seconds.

Table 7. Results of Model 1 (Generated with Backward Stepwise Regression)

Variable	Coefficient	Std. Err.	t-statistic	P>t	95% Confidence Interval	
					Lower	Upper
Constant	-36497.31	12867.49	-2.84	0.013	-64095.33	-8899.29
Acd	-2560.12	1310.81	-1.95	0.071	-5371.52	251.28
Symp	1415.93	668.16	2.12	0.052	-17.12	2848.99
Freq	4178.08	1382.75	3.02	0.009	1212.37	7143.79
Dist	3833.09	971.78	3.94	0.001	1748.83	5917.35
Window	4882.43	1518.98	3.21	0.006	1624.55	8140.30
Loudness	-5521.81	1706.57	-3.24	0.006	-9182.04	-1861.58
Freqdev	-1390.28	515.98	-2.69	0.017	-2496.95	-283.60
Speed	-443.34	282.02	-1.57	0.138	-1048.214	161.53
Speedon	561.67	334.94	1.68	0.116	-156.71	1280.05
AcclY	15946.46	9593.63	1.66	0.119	-4629.85	36522.76
AcclZ	-16824.52	10428.83	-1.61	0.129	-39192.14	5543.097
AcclTurnX	-15344.4	6919.43	-2.22	0.044	-30185.1	-503.69
Thro	66.20	21.32	3.10	0.008	20.47	111.94
Throturn	-123.73	59.35	-2.08	0.056	-251.03	3.57
Overtake	-0.03	0.00	-3.17	0.007	-0.0444	-0.0085

The forward stepwise method yielded the results shown in Table 8 with the R-squared value of 0.61. The hypothesis $\beta_{Loudness} = \beta_{Speedon} = \beta_{Speedoff} = \beta_{Thro} = 0$ where βs are the set of the coefficients of the regression model (Model 2) was rejected at the 5% level with a p-value of < 0.01. This implied that at least one of the independent variables had some predictive effect.

Table 8. Results of Model 2 (Generated with Forward Stepwise Regression)

Variable	Coefficient	Std. Err.	t-statistic	P>t	95% Confidence Interval	
					Lower	Upper
Constant	1764.84	1083.38	1.63	0.116	-466.42	3996.09
Loudness	-919.98	454.93	-2.02	0.054	-1856.92	16.96
Speedon	133.50	65.36	2.04	0.052	-1.1139	268.12
Speedoff	-146.94	46.20	-3.18	0.004	-242.09	-51.79
Thro	66.47	20.80	3.20	0.004	23.64	109.2991

This model was built by entering each variable that had a p-value less than "Alpha to enter = 0.1" into the regression model. The first variable entered was Speedoff, with the p-value of 0.0014. The variables Thro, Speedon, and Loudness followed. The p-values of the significant variables entered are illustrated in Table 9.

Table 9. P-values of Entering Variables for Forward Stepwise Methods

Variable	p-value
Speedoff	0.0014
Thro	0.0044
Speedon	0.0999
Loudness	0.0540

Model 2, which was generated by the forward selection and forward stepwise methods, showed some candidate variables for the final model. This is because some models built later from the set of candidate variables as recommended by the backward elimination were statistically less significant than those resulting from forward methods, even though the backward elimination method appeared to be better than forward methods in terms of R-squared values. As the results in Figure 4 show, the forward method provided a better model than Model 1, with average predicted reaction times of 3.4 seconds. Moreover, a no-intercept regression model (Model 3) was fitted for these final variables, providing the R-squared value of 0.94 and the same average reaction time (3.4 seconds). The model and statistics are demonstrated in Table 10.

Table 10. Results of Model 3 (No Intercept; Generated with Forward Selection)

Variable	Coefficient	Std. Err.	t-statistic	P>t	95% Confidence Interval	
					Lower	Upper
Loudness	-902.15	469.04	-1.92	0.065	-1866.27	61.97
Speedon	231.17	26.85	8.61	0.000	175.97	286.37
Speedoff	-110.49	41.68	-2.65	0.013	-196.17	-24.80
Thro	76.84	20.42	3.76	0.001	34.88	118.81

It is relatively easy to misuse the no-intercept model because the relationship is quite different near the origin than it is in the region containing data for the model [61]. However, the interpretation of this model makes sense; the reaction times cannot be predicted with zero values of all significant variables.

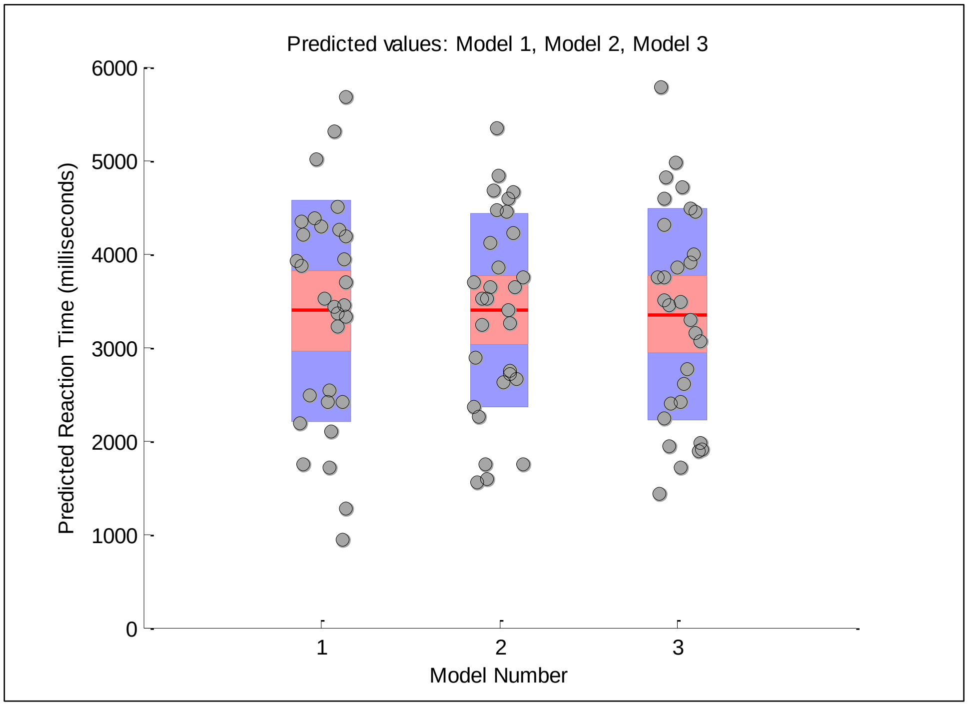

Figure 4. Predicted reaction times for regression models 1–3.

A comparison of the predicted and actual values among the three models previously discussed is shown in the scatter plot in Figure 4. Model 1, which was built using the backward stepwise regression method, resulted in the predicted reaction times falling within the range of 0.9 and 5.7 seconds with a standard deviation of 1.2 seconds. The predicted values were mostly located within two standard deviations from the average reaction times. Model 2, using the forward methods, estimated the reaction times ranging from 1.6 to 5.5 seconds with a standard deviation of 1.04 seconds. Reaction times predicted by Model 3 (no intercept model) varied from 1.4 to 5.8 seconds, with a standard deviation of 1.14 seconds. The average predicted reaction times were relatively the same for all models. The last two models had more predicted reaction times beyond the upper bound, with a + 2 standard deviation value from the first model.

Conclusions

This study investigated drivers' reaction times to a V2V message. Data came from a field study where a participant vehicle was followed by a study vehicle acting as a simulated ERV in off-peak conditions. The "ERV" sent messages to the participant vehicle informing the driver that an ERV was approaching and directing him/her to the left or right. Drivers' reaction times were calculated as the time between when the message began and the time when the driver applied his/her foot to the brake. Since there were multiple messages per driver, the 11 participants generated 30 observations for reaction times.

Linear predictive models were built to estimate reaction times to the ERV's messages based on the field test's dataset. The forward stepwise linear regression resulted in four statistically significant variables: Loudness (preference for listening to loud music while driving), Speedon (speed at the time the brake was applied), Speedoff (speed at the time the drivers took their feet off the accelerator), and Thro (throttle position at the time the message was received). The predicted reaction times to V2V movement instructions developed by the no intercept model (Model 3) fell in the range of 1.4 to 5.8 seconds. The upper bound reaction time was approximately two times greater than the 2.7 second reaction time identified in the previous literature. The reaction time range for the field test was wider than that found in the literature, which makes sense, as this is a new technology to which most drivers are not yet accustomed.

The lower bound of the estimated values for Model 2 (generated with forward stepwise regression and including an intercept) was not close to the average reaction time of 0.75 seconds (0.28 seconds of standard deviation) found by Johansson and Rumar [34] when the brake was applied after hearing a horn at the side of the highway. All four of the explanatory variables for Model 2 were statistically or scientifically significant. It is reasonable that drivers' reaction times to the audio messages (negative coefficient) could be negatively associated with listening to loud music while driving (these drivers have lower reaction times). Drivers accustomed to radio voices may be better attuned to responding to verbal cues. In addition, Speedon and Speedoff variables—the participant vehicle's speed when the brake was applied and the participant vehicle's speed when the foot was removed from the accelerator shortly after hearing the V2V messages—were included in the reaction time prediction model (Model 2). The Speedoff variable had a negative influence, indicating that while traveling at a higher speed, reaction time was lower (faster), perhaps suggesting that drivers more comfortable with higher speeds have faster reaction times. However, the Speedoff term should not be completely treated in isolation, as the other term, Speedon, was also included in Model 2. The time at which the brake was applied was not long after the foot was removed from the accelerator. The Speedon term had a positive effect on reaction time. If the speeds were the same at both instances, the coefficients would partially cancel each other out. Throttle position (%) caused an increased reaction time.

In the future, this study could be expanded for other traffic conditions in different surroundings, such as heavy traffic on arterials and free-flow conditions. Moreover, the simulation could be used in conjunction with the field experiment to predict reaction times. The simulation method may be helpful for more complicated traffic conditions, such as the propagation of V2V communication and car-following scenarios.

Chapter 4. Facilitating Emergency Response Vehicle Movement through a Transportation Network Link

Introduction and Background

In this study, the research group developed a mathematical program and solution approach that leveraged V2V communication to maximize the speed of an ERV through an idealized section of roadway.

Most recent studies on ERV travel facilitation focused on automatic crash notification, dispatching, dynamic routing, and signal preemption through an existing network [63-67]. These studies depended on real-time sensors or crowd-sourced traffic condition data to determine the shortest possible route for minimum service time. They did not consider the impact of the ERV on the non-ERVs on the road. Adaptive traffic signals to facilitate emergency service have also received some research attention. Some studies have also proposed different methods of moving non-ERVs out of the path of the ERV by means of V2V communication [68]. Most of these studies did not optimize the desired behavior of the non-ERV for a required movement of the ERV. In this study, non-ERV behavior was optimized to maximize the forward progress of ERVs. This approach considered initial speed, initial position, size, and deceleration capabilities of the non-ERVs and the geometry of the transportation network downstream.

The rest of this chapter is organized into five sections. First, a brief literature review is provided on the current state of ERV travel facilitation research using CVI. Next, the formulation of the optimization model is presented and the solution approach is described. Then the input data used for the optimization is presented along with the results from the optimization model for a small case study. Finally, limitations of this approach are discussed and some direction to improve ERV facilitation is provided.

Literature Review

Connected and automated vehicle research has gained momentum in recent years. Facilitation of ERV travel is a part of the associated growing body of literature. V2V and V2I communication have been leveraged to provide support during emergency situations. Proposed examples include, but are not limited to, automatic crash notification systems [69-71] and using wireless sensor networks to provide emergency navigation to individuals inside buildings [72-75]. The use of geographic information systems (GIS) has also been explored [76-78]. For example, Kejun et al. designed an emergency accident rescue system for a freeway using a GIS [76].

V2V and V2I systems, along with automation, have also begun to be applied for ERVs. For example, the Federal Highway Administration's Response, Emergency Staging, Communications, Uniform Management, and Evacuation (RESCUME) program [79], aims to provide automatic crash notification, responder staging with dynamic routing, incident zone protection, and evacuation support. Jordan et al. proposed an approach based on kinematic wave theory to split vehicle queues at signalized intersections using V2V communication to facilitate

ERV movement through the intersections [68]. Although not specifically stating the use of V2V or V2I, Moussa [80] used a cellular automata (CA) approach for lane changing to facilitate the movement of ERVs through a two-lane highway.

In terms of incorporating ERVs into automated environments, Dresner and Stone [81-83] considered intersections while Toy et al. [84] worked with links. Toy et al. [84] proposed two objectives: “to ensure rapid ERV transit” within the system and “to promote ERV transit through stopped” traffic. In the latter case, non-ERVs need to move out of the ERV’s way. Their work assumed no dedicated shoulders for ERV use (and did not show how any type of shoulder would be used), focused on highways, and used platoon-based approaches [84]. A limit to the existing work [68, 80, 84] is the lack of consideration of shoulder use.

Finally, the general problem of path clearance for ERVs on arterials using wireless communications has been examined by several researchers, (e.g., [18, 26, 68, 85-90]), primarily through simulation or at the conceptual level. For example, Buchenscheit et al. [18] presented a VANET-based ERV warning system, which informs non-ERVs of approaching ERVs, as well as the ERV’s desired route. While existing works provide information propagation (warnings) to non-ERV drivers, they typically do not optimize non-ERV movement to allow ERVs to quickly reach their destinations.

Optimization Formulation & Heuristic Solution

The proposed formulation for ERV facilitation in a CVI environment maximizes the speed of the ERV through a pre-specified road segment. The current states (speed, location) and physical properties of each vehicle in front of the ERV as well as geometric properties of the transportation network were assumed known for the purposes of this study. These data served as inputs that could be leveraged through information exchange via wireless networks. The model proposed in this study divided the road segment into cells with a fixed length and width, with the number of lateral cells depending on the width of the roadway section under consideration.

The optimization model produced a set of instructions that to be sent to the non-ERVs to stop at certain positions downstream, which they could reach safely and with minimal conflict with other vehicles. Depending on the ERV’s position at the time the instructions were sent and its destination, an intra-link path was selected by assigning the ERV continuous longitudinal cells over the path. The instructions sent to the non-ERVs moved them out of the ERV’s path. The formulation was a Mixed-Integer Non-Linear Program (MINLP) where the objective function and some constraints were non-linear. The objective function maximized the speed of the ERV through the link.

Additional constraints reduced lane-changing conflicts among non-ERVs. The positional assignment took place on a uniform roadway segment with no additional vehicles entering or leaving the section during the ERV’s movement. The problem setup closely resembled the CA system that has been used in traffic simulation (see for example [91–113]). The CA model was also implemented in transportation analysis simulation system (TRANSIMS) software [114]. For the purpose of optimization, a longitudinal cell size of 21 feet was used, which is less than the 7.5 meters used in TRANSIMS. The lateral cell size used was 10 feet. The optimization framework could also handle different cell sizes.

The optimization for this study took place on a homogenous roadway section. The numbers of variables and equations in the optimization model vary with the length and geometry of the roadway section being optimized. The number of integer variables was quite high, even with a short roadway segment, and also varied with the number of non-ERVs on the optimized section. The preliminaries of the problem setup, variable notation, objective function, constraints, and pre-processing involved are explained below.

Preliminaries

The optimization formulation required a specific network setup and vehicle labeling. To convert the regular network and traffic conditions to those needed for the formulation, the following tasks were performed and are illustrated in Figure 5:

- Vehicles downstream of the ERV and in the broadcast range were identified and numbered, with the lowest number being closest to the ERV.
- Link and roadway shoulders forward of the ERV were divided into cells the size of the regular vehicle plus buffers. A link was terminated when the ERV reached its destination or turned at an intersection.

In Figure 5, below, the 'X' direction represents forward motion and the 'Y' direction represents the lateral movement (e.g., for lane change).

- 'X' cells are labeled with 1 being closest to the ERV and numbers increasing with distance.
- 'Y' cells are labeled in ascending order from bottom to top.

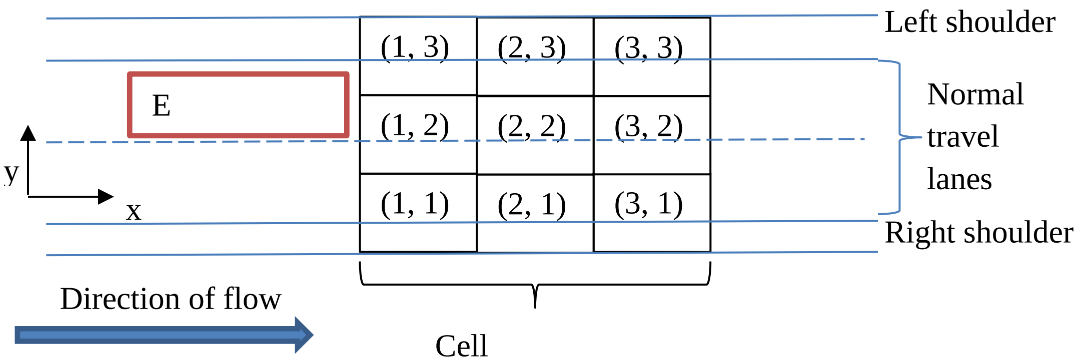

Figure 5. Discretization of roadway network.

The notation used in the formulation is as follows.

Sets:

x	Index of cell number in longitudinal direction from ERV
y	Index of cell number in lateral direction. (Starts from right.)
j	Non-ERV number index from the ERV. (If in same x cell then the left vehicle has lower index.)

Variables:

Variable Notation	Variable Type	Variable Description
w^{xy}	Binary	Variable that takes the value 1 if ERV was assigned to cell (x, y), 0 otherwise. (Cell was part of ERV's path during the time step.)
s^{xy}	Integer	Variable denoting the speed of the ERV at cell (x, y). (Cells per unit time.)
d_k^{xy}	Binary	Variable that takes the value 1 if the ERV was given instruction k at cell (x, y). k = 1 means move right, k=2 means go straight, k=3 means move left.
$V_j^{x,y}$	Binary	Variable that takes the value 1 if vehicle j was assigned to cell (x, y) and 0 otherwise.

Parameters:

Data Notation	Default Value	Data Description
α^{xy}	n/a	Intersection Indicator. α^{xy} =1 if cell (x ,y) was in an intersection, 0 otherwise.
Y^x	n/a	Number of lateral cells at position x.
L	21'	Length of cell in longitudinal direction.
t^r	2.5 sec	Reaction time.
σ_j	36-40 fps	Speed of vehicle j at beginning of time step.

δ_j	5 fps^{-2}	Deceleration of vehicle j. (Constant from time of reaction until full stop.)
S^{free}	3	Max speed of the ERV on the link. (Discrete values – cells per unit time.)
S^{min}	1	Min speed of the ERV on the link. (Discrete values – cells per unit time.)
N	n/a	Number of longitudinal cell required to accommodate the ERV. (Discrete values.)
LL	n/a	Number of longitudinal cells in broadcast range.
x_j'	n/a	Current (before assignment) x index of vehicle j.
x_j''	n/a	Longitudinal x index that the vehicle j needs to reach before coming to a full stop.

Formulation

The nonlinear objective function was the summation of the product of the assignment variable and integer speed variable. The summation was done only on those x indices just in front of the ERV at any moment.

$$\text{Max}\, z = \sum_{y=1}^{Y^x} \sum_{i=1}^{\frac{LL}{N+1}-1} s^{i(N+1),y} w^{i(N+1),y} \tag{1}$$

The objective function was subject to the following constraints.

Each cell could be occupied by at most one vehicle, as indicated in equation (2).

$$w^{x,y} + \sum_j v_j^{xy} \leq 1\,, \forall (x,y) \tag{2}$$

Vehicle assignment at an intersection was prohibited, as reflected in equation (3).

$$\alpha^{xy} \sum_j v_j^{xy} = 0, \forall (x,y) \tag{3}$$

Constraint (4) ensured a passing lane for the ERV.

$$\sum_{y}\sum_{j} v_j^{xy} < Y^x, \forall x \tag{4}$$

Vehicles could only be assigned to cells they could reach based on vehicle dynamics. For simplicity, constant deceleration was assumed for all vehicles. For fractional longitudinal cell size, the cell requirement was rounded to the nearest larger integer value as indicated in equation (5). This formulation also minimized conflicts between other vehicles. Equation (6) ensured the cells to which the non-ERV was assigned were within three longitudinal cells beyond the minimum requirement calculated in equation (5). The formulation restricted cells available for assignment of non-ERVs and thereby reduced the feasible space. This simplification improved the calculation time by reducing feasible space rather than using all feasible cells. However, the cutoff value of three longitudinal cells was chosen arbitrarily and should change depending on traffic density and speed. Future analysis should test different cutoff values for different traffic conditions.

Pre-processing
$$x_j'' = x_j' + ceil\left(\frac{\left(t^r\sigma_j + 0.5\frac{\sigma_j^2}{\delta_j}\right)}{L}\right), \tag{5}$$

$$\sum_{x=x_j''}^{x_j''+3}\sum_{y=1}^{Y^x} v_j^{xy} \geq 0, \forall j \tag{6}$$

Passing among non-ERVs was limited by equation (7) so that vehicles had minimal potential conflicts.

$$\sum_{y} v_{j'}^{x'y} < \sum_{y} v_j^{xy}, \forall x' < x, j' > j, \forall y \tag{7}$$

Equation (8) ensured continuity of ERV motion.

$$\sum_{y} w^{xy} = 1, \forall x \tag{8}$$

Equation (9) ensured that one set of instructions was provided to the ERV at each x at the completion of the previous maneuver.

$$\sum_{y}\sum_{k=1}^{3} d_k^{xy} = 1, \forall x = N+1, 2(N+1), 3(N+1), \ldots \tag{9}$$

For forward motion, the assumption was that the ERV needed N+1 cells in the same y open if it moved forward. The formulation expressed in equation (10) was non-linear.

$$d_2^{xy} \sum_{i=x+1}^{N+1} \sum_{j} v_j^{iy} = 0 \tag{10}$$

For lane changing, the assumption was that the ERV needed N-1 forward cells in the same y and free cells in the adjacent lane.

$$d_1^{xy} \left(\sum_{i=x+1}^{N-1} \sum_{j} v_j^{iy} + \sum_{i=x+N-1}^{x+N+1} \sum_{j} v_j^{i,y-1} \right) = 0, \forall y > 1 \tag{11}$$

$$d_3^{xy} \left(\sum_{i=x+1}^{N-1} \sum_{j} v_j^{iy} + \sum_{i=x+N-1}^{x+N+1} \sum_{j} v_j^{i,y+1} \right) = 0, \forall y < Y^x \tag{12}$$

The ERV was not permitted to move in a direction if there was no cell lane in that direction. Equation (13) was for the right portion of the roadway and equation (14) was for the left.

$$d_1^{x1} = 0, \forall x \tag{13}$$

$$d_3^{xY^x} = 0, \forall x \tag{14}$$

The ERV's initial entry into the optimization part of the link was based on the assumption that its initial movement involved a forward only motion. The y' was given as input. These values (equations 15 and 16) came from the initial conditions (input):

$$w^{x\prime y'} = 1, \forall x' = 1, \dots, N+1 \tag{15}$$

$$w^{x\prime y} \quad = 0, \forall x' = 1, \dots, N+1, \forall y \neq y' \tag{16}$$

Equations (17-23) guided the ERV's movement beyond the initial movement.

$$w^{x+i,y} = w^{x,y}, \forall x = (N+1), 2(N+1), 3(N+1) \dots;\ \forall i = 1, \dots, N-1;\ \forall y = 1, \dots, Y^x \tag{17}$$

$$d_1^{x,y} \leq \frac{w^{x,y} + w^{x+i,y-1}}{2}, \forall x = (N+1), 2(N+1), 3(N+1) \dots;\ \forall = N-1, N, N+1;\ \forall y = 2, \dots, Y^x \tag{18}$$

$$d_1^{x,y} \geq w^{x,y} + w^{x+i,y-1} - 1, \forall x = (N+1), 2(N+1), 3(N+1) \dots; \forall i = N-1, N, N+1;\ \forall y = 2, \dots, Y^x \tag{19}$$

$$d_2^{x,y} \leq \frac{w^{x,y}+w^{x+i,y}}{2}, \forall x = (N+1), 2(N+1), 3(N+1) \dots; \forall i = N, N+1;\ \forall y = 1, \dots, Y^x \tag{20}$$

$$d_2^{x,y} \geq w^{x,y} + w^{x+i,y} - 1, \forall x = (N+1), 2(N+1), 3(N+1) \dots; \forall i = N, N+1;\ \forall y = 1, \dots, Y^x \tag{21}$$

$$d_3^{x,y} \leq \frac{w^{x,y}+w^{x+i,y+1}}{2}, \forall x = (N+1), 2(N+1), 3(N+1) \dots; \forall i = N-1, N, N+1;\ \forall y = 1, \dots, Y^x - 1 \tag{22}$$

$$d_3^{x,y} \geq w^{x,y} + w^{x+i,y+1} - 1, \forall x = (N+1), 2(N+1), 3(N+1) \dots; \forall i = N-1, N, N+1;\ \forall y = 1, \dots, Y^x - 1 \tag{23}$$

If the ERV was going straight, it could potentially increase its speed. Equation (24) set the maximum speed while equation (25) ensured a minimum speed. Speeds during the execution of a maneuver were constant. Speeds were discrete and in cells per unit time. So, for a 21-foot cell size, the speed varied as an integer multiple of 21 fps.

$$s^{x,y} \leq S^{free}, \forall\ x = 1, (N+1), 2(N+1), \dots; \forall y \tag{24}$$

$$s^{x,y} \geq S^{min}, \forall\ x = 1, (N+1), 2(N+1), \dots; \forall y \tag{25}$$

$$s^{x+(N+1),y} \leq s^{x,y} + d_2^{x,y}, \forall\ x = 1, (N+1), 2(N+1), \dots; \forall y \tag{26}$$

$$s^{x+(N+1),y} \leq s^{x,y} + \left(Y^x - \textstyle\sum_y \sum_j v_j^{x,y} - 2\right), \forall\ x = 1, (N+1), 2(N+1), \dots; \forall y \tag{27}$$

In equation (27), if (Y^x – sum of other vehicles) was 1, then one was subtracted from the current speed. If there was more than one lateral cell, 0 or a value of at least 1 was added, the limit of which was set by other constraints. The minimum speed constraint prevented the speeds from reaching 0 or becoming negative.

Solution Approach

Knowing that scheduling, routing and selection problems are typically NP-Hard/NP-Complete problems, the ERV facilitation problem can also be proven to be NP-Hard/NP-Complete [115]. Moderate or large sized problems are difficult to solve to optimality. In this optimization, if a 1,000-foot broadcast range was used, the number of longitudinal cells was 40, and the number of lateral cells depended on the number of travel lanes and the shoulder width on both sides of the road. If the number of lateral cells was assumed to be three, then the total number of variables for ERV assignment was 40*3=120. The number of variables was the same for ERV speed and the three types of instructions sent to the ERV. The variables required for non-ERV assignment were dependent on the number of vehicles as well as the cells required for them to come to a full stop. If the vehicle that was assumed to be at the end of the broadcast range needed an additional 20 cells in the longitudinal direction, then the number of variables for non-ERVs was (40+20)*3=180 times the number of vehicles in the broadcast zone. This high amount of variables made finding a true optimal solution difficult.

This high number of variables took any general-purpose optimal solution algorithm like enumeration or tree search out of consideration for this problem, as the computational time required was too high. Some special purpose heuristics could have been considered for obtaining the solution. But even those algorithms would have become computationally ineffective after a certain problem size. Another method was to set the search space to a minimum, which would limit the set of feasible solutions. However, this would also decrease the number of feasible solutions, with the risk that no feasible solution would exist in some instances. Therefore, heuristics and meta-heuristics, balancing computational time and the search space, were logical choices for solving the problem to near-optimality. For this study, a genetic algorithm (GA) was chosen as the heuristic algorithm.

GAs, also known as evolutionary computation, were first introduced by John Holland in 1975 [116]. He proposed search methods based on the process of natural evolution. Since its inception, evolutionary computation has gone through four major paradigms: genetic algorithm, genetic programming, evolutionary strategies and evolutionary programming [117]. Non-linearity of the objective function and constraints made GA a suitable solution approach for this MINLP problem. However, for a large-scale difficult problem, GA has exhibited some problems in generating solutions as a result of premature convergence in suboptimal regions [118]. To avoid premature convergence in the solution approach used in this study, a high crossover fraction and low mutation rate were used to ensure a large search space in each iteration.

Numerical Case Analysis

In the setup for this study, non-ERV positions were provided as input data. Other associated parameters like current speed, deceleration capability, and reaction time could also be used as inputs. For the purpose of the optimization model's initial testing, current speeds were randomly generated. The speeds of non-ERVs were varied between 25 and 30 mph. A constant reaction time and deceleration capability were used. As the number of variables increased with the increase of broadcast range, it was necessary to choose a reasonable length for obtaining a near optimal solution within a reasonable time. Initial testing of the model with 45 longitudinal cells, three lateral cells, and 20 non-ERVs yielded unsatisfactory results. The GA converged prematurely and could not find a solution where all the constraints were satisfied. To reduce the number of variables, an idealized very short segment was chosen. For the results illustrated here, six longitudinal cells of ERV assignment were used, and three lateral cells were used.

The number of longitudinal cells for non-ERVs was higher than the ERV's because of the cell requirement for coming to a full stop. It was also assumed that there was no non-ERV downstream of the six cells assigned to the ERV. The location, speed and longitudinal cell requirements are shown in Table 11. Vehicles were moving from left to right. In the table, all the cells on the right (Y=1) are empty as they physically signify the shoulder of the road. Vehicle position was encoded as binary: 1 means there was a vehicle at the corresponding cell. Otherwise, the cell was coded as 0. Vehicle speed was randomly generated with values between 25 and 30 mph. The speed was then converted to feet per second to calculate the number of cells required to come to a full stop (Equation 5).

Table 11. Input Data

		Non-ERV Location					
	X	1	2	3	4	5	6
	3	0	1	0	1	0	0
Y	2	1	0	0	1	0	1
	1	0	0	0	0	0	0
		Non-ERV Speed (FPS)					
	3	0	26	0	28	0	0
Y	2	27	0	0	28	0	29
	1	0	0	0	0	0	0
		Longitudinal Cell Requirement for Stopping					
	3	0	9	0	10	0	0
Y	2	9	0	0	10	0	10
	1	0	0	0	0	0	0

The programming setup was done in MATLAB. MATLAB’s GA solver was designed to solve programs in standard form. In the case of integer variables, MATLAB’s GA solver could not handle non-linear or linear equality. The standard integer model that could be optimized by using MATLAB is shown below:

Objective,	Min, $f(x)$	
Subject to,	$[A]*x \le b$	(Linear inequality constraint)
	$C(x) \le d$	(Linear inequality constraint)
	$LB \le x \le UB$	(Upper and lower bound of variables)

To convert the model to the standard formulation shown above, the following steps were taken:

- A greater than or equal to linear inequality was converted to a less than inequality constraint by multiplying the equation by -1.
- An equality constraint was converted to two sets of inequalities. The [A]*x = b constraint was converted to [A]*x ≤ b + eps, and [A]*x ≥ b – eps, where eps denotes a very small number near the order of 10^{-16}. As all the variables are integer, this conversion ensured enforcement of equality constraints. Then the greater than or equal to constraint was converted to a less than or equal to formulation using the previous methodology.
- Non-linear equality constraints were also converted to inequality constraints as described above.

As the non-ERVs needed to travel some distance to come to a complete stop, the number of cell requirements was larger than the assignment variable for the ERV. In the testing stage, the longitudinal cell number required for the vehicle with the highest index with some buffer was used as the cell number for non-ERVs. Cells with x = 11–12 index were used as an intersection. As the vehicles were restricted from stopping at the intersection, non-ERVs were not assigned to these cells. The ERV size or the N value in the formulation was assumed to be 2. The ERV started at the middle lane. Optimization runtime for the small size problem varied between 45–55 seconds.

Results

Several runs were made for the small, idealized section. Following the characteristics of population heuristics, the output was different for different runs. One of the best solutions is illustrated in this report. The output of the optimization for the variables associated with the ERV is listed in Table 12. There was no condition enforced on the end position of the ERV. As any lane change was penalized with speed reduction, the model kept the ERV in the same lane. As a result, the speed was maximized and only one instruction was sent to the ERV. In the model formulation, a number of variables were declared but not used in either the objective function or the constraints. MATALB's GA algorithm generated an initial solution for all the variables. As some variables were not used in any formulation, these initially generated values were kept in the solution. These variables' outputs were filtered by post processing. Only the relevant output variables in feasible space were kept.

Table 12. ERV Assignment and Instruction

		ERV assignment					
	X	1	2	3	4	5	6
Y	3	0	0	0	0	0	0
	2	1	1	1	1	1	1
	1	0	0	0	0	0	0
		ERV Speed					
Y	3	0	0	0	0	0	0
	2	0	0	3	0	0	3
	1	0	0	0	0	0	0
		Instruction (Move Right)					
Y	3	0	0	0	0	0	0
	2	0	0	0	0	0	0
	1	0	0	0	0	0	0
		Instruction (Go Straight)					
Y	3	0	0	0	0	0	0
	2	0	0	1	0	0	0
	1	0	0	0	0	0	0
		Instruction (Go Left)					
Y	3	0	0	0	0	0	0
	2	0	0	0	0	0	0
	1	0	0	0	0	0	0

Note: Marked cells are the starting cells of the ERV.

The variables for the non-ERV assignment are shown in Table 13. Vehicles were prohibited from stopping at intersections. Accordingly, although the intersections were within the feasible range for the first and second vehicle, they were assigned beyond that point. Conflict between the non-ERVs was also minimized. Vehicles closer to the ERV were assigned to closer downstream locations than vehicles further away from the ERV. This ensured that no overtaking maneuvers occurred among the non-ERVs.

Table 13. Non-ERV Assignment

	First Vehicle																		
	X	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Y	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	Second Vehicle																		
Y	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Third Vehicle																		
Y	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	Fourth Vehicle																		
Y	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Fifth Vehicle																		
Y	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Note: Marked cells are intersection.																			

Conclusion

The recent growth in wireless-enabled traffic networks and subsequent connected and automated vehicle technology offers opportunities for detection and acquisition of high fidelity traffic data that can be leveraged to develop more efficient and safe traffic control strategies. Though significant literature exists about how automated and connected vehicle systems can improve traffic flow, research on facilitation of ERV travel is more limited. Previous studies typically do not optimize the route, speed, and desired behavior of non-ERVs simultaneously. In this study, desired non-ERV behavior was optimized and the full extent of roadway geometry was used. The formulation used in this study was a non-linear mixed integer program containing a large number of variables. To solve the formulation, a GA heuristic with post-processing was employed to remove declared variables that were never used.

Numerical case analysis for a small, uniform section of roadway with a limited number of non-ERVs revealed the capability of the model to optimize the behavior of non-ERVs to maximize the speed of the ERV. Conflicts among non-ERVs were explicitly limited by the constraints. However, to extend the optimization for a real network with a reasonable broadcast range, pre-processing was required to reduce the number of variables. Pre-processing made it possible to generate the minimum number of variables required for optimizing with minimal time requirements. Extending the formulation with pre-processed variable definitions is the subject of future research. Reduced numbers of variables will improve computational time.

To be applicable for practical use, data capture, model formulation, optimization and instruction delivery should be done nearly instantaneously. Due to the high number of variables and subsequent computational time, the model in its current format is not applicable for immediate use. Future research should focus on refining the formulation and improving the solution approach or developing a methodology of mining the best instructions and route information from pre-optimized values. To accomplish the latter, a database of optimized values for wide ranging traffic conditions (vehicle position, speed, origin/destination of the ERV etc.) could be developed first so that data mining technology can be used to leverage the values for near instantaneous information delivery. Wireless network infrastructure requirements for this can also be a future research topic.

Chapter 5. Conclusions and Recommendations

The goal of this study was to facilitate ERVs' safe and rapid travel to their destinations. This required addressing multiple facets of the problem, including the ERV, passenger vehicles (non-ERVs), and signal control. The research group pursued the following objectives:

1. Determine the potential for emergency V2V communication to improve the ERV's travel time.
2. Determine the conditions under which the communication is most beneficial.
3. Determine the best behavior for non-ERVs in order to facilitate the ERV's movement.
4. Determine the best path for the ERV through traffic.
5. Develop a message prototype for the non-ERVs.
6. Test the prototype.

The first objective was addressed through micro-simulation of a network based on the Northern Virginia Connected Vehicle Test Bed. A variety of factors were considered, including the presence of V2V communication, traffic volumes, cycle length, ERV speed distributions, non-ERV speed distributions, and whether signal preemption was available. The simulation experiments examined the ERV's travel time under base conditions and under the influence of V2V communication. The ERV was able to communicate with non-ERVs on its path and disseminate messages that influenced other drivers' behaviors.

As expected, higher traffic volumes increased travel time. Traffic signal preemption decreased the ERV's travel time, allowing it to maneuver more quickly through intersections. For this relatively small network, signal preemption (without V2V communication) improved the ERV's travel time by approximately 1.5–5.0 minutes (11–37% improvement), depending on traffic volumes and cycle lengths. Further, appropriate signal cycle lengths improved traffic movement and mitigated congestion. Finally, increasing the desired speed of the ERV had only small effects on its travel time in a congested network. At high levels of congestion, the ERV's speed was limited by other vehicles on the road. The results of the study revealed that V2V communication could have a positive influence on travel time for an ERV in congestion. For the simulation network and specified conditions, the benefits were a 20–32% improvement in the ERV's travel time over scenarios with signal preemption alone.

The third and fourth objectives were addressed through an optimization model developed for this study. Inputs to the model included the current position of the vehicles in the road segment, vehicle characteristics, and travel barriers (e.g., roadway edges). In this initial study, non-ERV "behavior" was simplified to moving right, moving left, and staying put. Since the maneuvering occurred in a small section of the network, the "path" pertained to the path through traffic within the localized section. The outputs of the model were instructions for each non-ERV in the segment of interest as well as for the ERV's local navigation through non-ERV traffic. In this study, it was assumed that all vehicles had the necessary communication technology. The formulation used in this study was a non-linear mixed integer program that contained a large number of variables. To solve the formulation, a GA heuristic with post-processing was employed to remove declared variables that were never used. Numerical case analysis for a small, uniform section of roadway with a limited number of non-ERVs revealed the capability of the model to optimize the behavior of non-ERVs to maximize the speed of the ERV. Conflicts among non-ERVs were explicitly limited by the constraints.

For the fifth and sixth objectives, VTTI employees developed a V2V message prototype based on input and messages provided by the research group. In this initial study, the prototype was designed for communication between an ERV and non-ERVs. This prototype involved a flash of the infotainment system in the participant's vehicle, followed by instructions to move to the left, move to the right, or remain stationary. The research group tested the prototype with 12 real drivers (data was obtained from 11), aged 25–50, on the Northern Virginia Connected Vehicle Test Bed during off-peak periods. Data from this field test were used to investigate reaction time to the messages informing drivers that an ERV was approaching and directing them to the left or right or to remain where they were. Drivers' reaction times were calculated as the time between when the message began and the time when the drivers applied their feet to the brake. There were multiple messages per driver, and the 11 participants with data generated a total of 30 observations for reaction times.

Linear regression models were built to estimate the reaction times to the ERV's messages. The stepwise linear regression models 2 and 3 resulted in four statistically significant variables: Loudness (preference for listening to loud music while driving), Speedon (speed at the time the brake was applied), Speedoff (speed at the time the drivers take their feet off the accelerator), and Thro (throttle position at the time the message was received), and the predicted reaction times to V2V movement instructions fell in the range of 1.4 to 5.7 seconds. The upper bound on reaction time of the ERV field test was approximately two times greater than the 2.7 seconds established in the previous literature. The reaction time range for the field test was also wider than that found in the literature, which stands to reason, as this is a new technology to which most drivers are not yet accustomed.

The lower bound of the estimated values for Model 2 (generated with forward stepwise regression) was not close to the average reaction time of 0.75 seconds (0.28 seconds of standard deviation) found by Johansson et al. [34] when the brake was applied after hearing a horn at the side of the highway—a much simpler communication than the V2V messages used in this study. All four of the explanatory variables for Model 2 are statistically or scientifically significant variables. It is reasonable that drivers' reaction times to the audio messages could be negatively associated (decreased reaction time) with the familiarity of listening to loud music while driving, and drivers accustomed to radio voices may be better attuned to responding to verbal cues. In addition, Speedon and Speedoff variables—the speed of the non-ERV at the time when the brake was applied, and the non-ERV's speed when the foot was removed from the accelerator shortly after hearing the V2V messages—were included in the reaction time predicting model. The Speedoff variable had a negative influence, indicating that while traveling at a higher speed, the reaction time was lower (faster), perhaps suggesting that drivers more comfortable with higher speeds have faster reaction times. However, the Speedoff term should not be treated completely in isolation, as the other term, Speedon, was also included in the model, and the time at which the brake was applied was not long after the foot was removed from the accelerator. The Speedon term had a positive effect on reaction time. The Thro variable, throttle position (%), also increased reaction time; i.e., higher values of Thro were associated with longer reaction times.

Future Directions

Ample opportunities for future work in emergency V2V communication exist. These opportunities involve research directions such as using simulation, refining optimization approaches, developing communication systems, and field tests.

In terms of simulation, the benefits achieved here should be confirmed in the future with additional networks and traffic conditions. In future experiments, the impacts of the length of the warning distance and warning speed should be investigated in the simulation. The messages provided in this study were simple. More detailed messages, such as those developed for the optimization portion of this study, may offer additional benefits and should be considered in future studies.

The mathematical program developed for this study was computationally complex. Due to the high number of variables and subsequent computational time, the model in its current format is not applicable for immediate use. To extend the optimization to a real network with a reasonable broadcast range, pre-processing must be done to reduce the number of variables. Pre-processing would generate only the minimum number of variables required for optimizing with an associated minimal time requirement.

To be applicable for practical use, data capture, model formulation, optimization and instruction delivery should be done nearly instantaneously. Future research could focus on developing a methodology of mining the best instructions and route information from pre-optimized values. To accomplish this, a database of optimized values for wide ranging traffic condition (vehicle position, speed, origin/destination of the ERV, etc.) could be developed first so that data mining technology can be used for leveraging such near instantaneous information delivery. Wireless network infrastructure requirements for this can also be a future research topic.

This study only used one method of message delivery in the field test. Other approaches could be investigated in the future. Cognitive processing and reaction times should be considered and tradeoffs among approaches should be evaluated, including safety impacts. Future field tests should consider a variety of traffic conditions and roadways and larger numbers of participants of all driving ages.

References

1. McMillin, B. and K.L. Sanford. *Automated highway systems.* Potentials, IEEE, 1998. 17(4): pp. 7-11.

2. Fernandes, P. and U. Nunes. Platooning with IVC-enabled autonomous vehicles: Strategies to mitigate communication delays, improve safety and traffic flow. *Intelligent Transportation Systems, IEEE Transactions on*, 2012. 13(1): pp. 91-106.

3. Baskar, L.D. L.Dhevi, B.De Schutter, J. Hellendoorn, and Z. Papp. Traffic control and intelligent vehicle highway systems: a survey. *IET Intelligent Transport Systems*, 2011. 5(1): pp. 38-52.

4. Kim, S.W., G. Gwon, S. Choi, S . Kang, M. Shin, I. Yoo, E. Lee, E. Frazzoli, and S. Seo. Multiple vehicle driving control for traffic flow efficiency, in *Intelligent Vehicles Symposium (IV), 2012 IEEE*. 2012. IEEE.

5. Drucker, C., S. Gerberich, M. Manser, B. Alexander, T. Church, A. Ryan, and E. Becic. Factors associated with civilian drivers involved in crashes with emergency vehicles. *Accident Analysis & Prevention*, 2013. 55: pp. 116-123.

6. Donoughe, K., J. Whitestone, and H.C. Gabler. Analysis of Firetruck Crashes and Associated Firefighter Injuries in the United States. *Annals of Advances in Automotive Medicine / Annual Scientific Conference*, 2012. 56: pp. 69-76.

7. Becker, L.R., E. Zaloshnja, N. Levick, G. Li, G. and T. Miller. Relative risk of injury and death in ambulances and other emergency vehicles. *Accident Analysis and Prevention*, 2003. 35: pp. 941-948.

8. LaTourrette, T. Risk factors for injury in law enforcement officer vehicle crashes. *Policing: An International Journal of Police Strategies & Management*, 2015. 38(3): pp. 478-504.

9. NHTSA. *The National Highway Traffic Safety Administration and Ground Ambulance Crashes*. 2014 [cited 2015 December 10]; Available from: http://www.ems.gov/newsletter/marapr2015/ground-ambulance-safety.html.

10. Kahn, C.A., R.G. Pirrallo, and E.M. Kuhn. Characteristics of Fatal Ambulance Crashes in the United States: An 11-Year Retrospective Analysis. Prehospital emergency care, 2001. 5(3): pp. 261-269.

11. Ray, A.M. and D.F. Kupas. Comparison of Rural andUrban Ambulance Crashes in Pennsylvania. Prehospital emergency care, 2007. 11(4): pp. 416-420.

12. Solomon, S.S. and J.G. King. Fire Truck Visibility: Red may not be the most visible color, considering the rate of accident involvement with fire trucks. *Ergonomics in Design: The Quarterly of Human Factors Applications*, 1997. 5(2): pp. 4-10.

13. De Lorenzo, R.A. and M.A. Eilers. Lights and siren: A review of emergency vehicle warning systems. *Annals of Emergency Medicine*, 1991. 20(12): pp. 1331-1335.

14. Auerbach, P.S., J.A. Morris, J.B. Phillips, S.R. Redlinger, and W.K. Vaughn. *An Analysis of Ambulance Accidents in Tennessee.* Journal of the American Medical Association, 1987. 258(11): pp. 1487-1490.

15. Colwell, C.B., P. Pons, J. Blanchet, and C. Mangino. Claims against a paramedic ambulance service: a ten-year experience. *The Journal of Emergency Medicine*, 1999. 17(6): pp. 999-1002.

16. Killat, M. *The impact of inter-vehicle communication on vehicular traffic*. 2009: KIT Scientific Publishing, 2009.

17. PTV. *VISSIM 5.30-05 User Manual*, 2011: Karlsruhe, Germany.

18. Buchenscheit, A. F. Schaub, F. Kargl and M. Weber. A VANET-based emergency vehicle warning system, in *IEEE Vehicular Networking Conference (VNC),* 2009. IEEE.

19. Chen, A., B. Khorashadi, C. Chuah, D. Ghosal, and M. Zhang. Smoothing vehicular traffic flow using vehicular-based ad hoc networking & computing grid (VGrid*)*, in Proceedings of the *Intelligent Transportation Systems Conference (ITSC'06)*, 2006. IEEE.

20. Kerner, B.S., S.L. Klenov, and A. Brakemeier. *Effect of Ad-Hoc Vehicular Network on Traffic Flow: Simulations in the Context of Three-Phase Traffic Theory.* arXiv preprint arXiv:0910.0381, 2009.

21. Dao, T.-S., C.M. Clark, and J.P. Huissoon. Optimized lane assignment using inter-vehicle communication, in *Intelligent Vehicles Symposium, 2007 IEEE*. 2007. IEEE.

22. Knorr, F. and M. Schreckenberg. Influence of inter-vehicle communication on peak hour traffic flow. *Physica A: Statistical Mechanics and its Applications*, 2012. 391(6): pp. 2225-2231.

23. Yeo, H., S. Shladover, H. Krishnan, and A. Skabardonis, A. Microscopic Traffic Simulation of Vehicle-to-Vehicle Hazard Alerts on Freeway. *Transportation Research Record: Journal of the Transportation Research Board*, 2010(2189): pp. 68-77.

24. Mei, B., H. Hu, N. Rouphail, and J. Lee. Simulation Model for Studying Impact of Vehicle-to-Vehicle Wireless Communications on Traffic Network Operations. *Transportation Research Record: Journal of the Transportation Research Board,* 2010(2189): pp. 107-115.

25. Bhosale, S., N. Dhawas, and A. Burkul. VANET Based Communication for Emergency Vehicles. *International Journal of Advanced Research in Computer Science and Electronics Engineering (IJARCSEE)*, 2013. 2(7): pp. pp: 567-571.

26. Cetin, M. and C. Jordan. Making way for emergency vehicles at oversaturated signals under vehicle-to-vehicle communications, in *Vehicular Electronics and Safety (ICVES), 2012 IEEE International Conference on*. 2012. IEEE.

27. Van Arem, B., C.J. Van Driel, and R. Visser. The impact of cooperative adaptive cruise control on traffic-flow characteristics. *Intelligent Transportation Systems, IEEE Transactions on*, 2006. 7(4): pp. 429-436.

28. Orosz, G. *The role of the reaction-time delay in the dynamics of vehicular traffic*, in *5th European Nonlinear Dynamics Conference*. 2005: Eindhoven University of Technology.

29. McGee, H.W. Reevaluation of Usefulness and Application of Decision Sight Distance. *Transportation Research Record: Journal of the Transportation Research Board*, 1989: pp. 85-89.

30. Muttart, J.W. Development and evaluation of driver response time predictors based upon meta analysis. 2003, SAE Technical Paper no 2003-01-0885.

31. American Association of State Highway and Transportation Officials (AASHTO). *Policy on geometric design of highways and streets*. 2001, 3. Washington, DC: American Association of State Highway and Transportation Officials.

32. Fambro, D. *Determination of Factors Affecting Stopping Sight Distance*. 1994, Working Paper I: Braking Studies (DRAFT) National Cooperative Highway Research Program, Project 3-42.

33. Neuman, T. New approach to design for stopping sight distance. *Transportation Research Record: Journal of the Transportation Research Board*, 1989. 1208: pp. 14-22.

34. Johansson, G. and K. Rumar. Drivers' brake reaction times. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 1971. 13(1): pp. 23-27.

35. Strayer, D.L., J. Cooper, J. Turrill, J. Coleman, N. Medeiros-Ward and F. Biondi. *Measuring cognitive distraction in the automobile*. 2013, AAA Foundation for Traffic Safety.

36. Olson, P. *Forensic Aspects of Driver Perception and Response Time*. 1996, Tucson: Lawyers & Judges Publishing Company, Inc.

37. Dewar, R.E. and P.L. Olson. *Human factors in traffic safety*. 2002, Tuscon, AZ: Lawyers & Judges Publishing Company, Inc.

38. Olson, P.L. and M. Sivak. Perception-response time to unexpected roadway hazards. *Human Factors*, 1986. 28: pp. 91-96.

39. Sivak, M., et al., Automobile rear lights: effects of the number, mounting height, and lateral position on reaction times of following drivers. *Perceptual and Motor Skills,* 1981. 52: pp. 795-802.

40. Sivak, M., D. Post, P. Olson, and R. Donohue. Driver responses to high-mounted brake lights in actual traffic. *Human Factors*, 1981. 23: pp. 231-235.

41. Green, M. How long does it take to stop? Methodological analysis of driver perception-brake times. *Transportation Human Factors*, 2000. 2: pp. 195-216.

42. Hooper, K.G. and H.W. McGee. Driver Perception-Reaction Time: Are Revisions to Current Specifications in Order? *Transportation Research Record: Journal of the Transportation Research Board*, 1983. 904: pp. 21-30.

43. Sivak, M. Driver reaction times in car-following situations. *Public Health Review*, 1987. 15: pp. 265-274.

44. Lerner, N., R. Huey, H. McGee, and A. Sullivan. *Literature Review: Older Driver Perception-Reaction Time for Intersection Sight Distance and Object Detection*. 1995, Comsis Corp: Washington, DC.

45. Gundy, C. *The influence of the complexity and modality of driver route information on the detection of visual stimuli during a simulated driving task: a critical evaluation and re-analysis.* (NTIS paper No. PB92-202969). 1992, Springfield, VA: National Technical Information Service,.

46. Moberly, N. and M. Langham. *Pedestrian conspicuity at night: a case for biological motion*, in *School of Cognition & Computing Sciences*. 2000, University of Sussex: Falmer, Brighton, UK.

47. Muttart, J.W. Effects of Retroreflective Material upon Pedestrian Recognition at Night. *Accident Reconstruction Journal*, 2000. 11: pp. 51-57.

48. Talebpour, A. and H.S. Mahmassani. Influence of Autonomous and Connected Vehicles on Stability of Traffic Flow, in *Transportation Research Board 94th Annual Meeting*. 2015.

49. Talebpour, A. and H.S. Mahmassani. *Modeling Acceleration Behavior in A Connected Environment*. in *Midyear Meetings and Symposium Celebrating 50 Years of Traffic Flow Theory*. 2014. Portland, OR.

50. Smith, B., H. Park, and T. Hayat. *Connected Vehicle Enabled Freeway Merge Management-Field Test*. 2014, Connected Vehicles/Infrastructure (CVI-UTC).

51. Doecke, S., A. Grant., and R.W.G. Anderson. The Real-World Safety Potential of Connected Vehicle Technology. *Traffic Injury Prevention*, 2015. 16(supl1): pp. S31-S35.

52. Mohebbi, R., R. Gray, and H. Tan. Driver reaction time to tactile and auditory rear-end collision warnings while talking on a cell phone. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 2009. 51: pp. 102-110.

53. Jin, I.G. and G. Orosz. Dynamics of connected vehicle systems with delayed acceleration feedback. *Transportation Research Part C: Emerging Technologies*, 2014. 46: pp. 46-64.

54. University of Maryland Space Systems Laboratory. *Space System Laboratory*. 2013; Available from: http://www.ssl.umd.edu/.

55. Tabachnick, B.G. and L.S. Fidell. *Using multivariate statistics*. 3rd ed. 1996, New York: Harper Collins College Publishing.

56. Brooks, A., A. Lenneman, K.E. George-Maletta, D.R. Hunter, and P.A. Green. *Preliminary examinations of the time to read electronic maps: the effects of text and graphic characteristics* (Technical Report UMTRI-98-36). 1999, Ann Arbor, MI: The University of Michigan Transportation Research Institute.

57. Summala, H. Brake reaction times and driver behavior analysis. *Transportation Human Factors*, 2000. 2(3): pp. 217-226.

58. Marmolin, H. and H.O. Lisper. *Reaction time of night vision ability*. 1973, Department of Psychology, University of Uppsala: Uppsala, Sweden.

59. Lings, S. Assessing driving capability: A method for individual testing The significance of paraparesis inferior studied in a controlled experiment. *Applied Ergonomics*, 1991. 22(2): pp. 75-84.

60. Wierwille, W.W., J.G. Casali, and B.S. Repa. Driver steering reaction time to abrupt-onset crosswinds, as measured in a moving-base driving simulator. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 1983. 25(1): pp. 103-116.

61. Montgomery, D.C., E.A. Peck, and G.G. Vining. *Introduction to linear regression analysis*. 2012, New Jersey: John Wiley & Sons.

62. Alt, F.. *Applied Linear Regression Models.* Class Notes, University of Maryland at College Park, 2012.

63. Huang, Y.-S., J.-Y. Shiue, and J. Luo. A Traffic Signal Control Policy for Emergency Vehicles Preemption Using Timed Petri Nets. *IFAC-Papers On Line*, 2015. 48(3): pp. 2183-2188.

64. Chakraborty, P.S., A. Tiwari, and P.R. Sinha. Adaptive and Optimized Emergency Vehicle Dispatching Algorithm for Intelligent Traffic Management System. *Procedia Computer Science*, 2015. 57: pp. 1384-1393.

65. Musolino, G., A. Polimeni, C. Rindone, and A. Vitetta. Travel time forecasting and dynamic routes design for emergency vehicles. *Procedia-Social and Behavioral Sciences*, 2013. 87: pp. 193-202.

66. Liu, Y., Yuan, Y., Y. Li, and H. Pang, H. A Chance Constrained Programming Model for Reliable Emergency Vehicles Relocation Problem. *Procedia-Social and Behavioral Sciences*, 2013. 96: pp. 671-682.

67. Wang, J., M.Yun, W. Ma, and X. Yang. Travel time estimation model for emergency vehicles under preemption control. *Procedia-Social and Behavioral Sciences*, 2013. 96: pp. 2147-2158.

68. Jordan, C., M. Cetin, and R. Robinson. Path Clearance for Emergency Vehicles Through the Use of Vehicle-to-Vehicle Communication. *Transportation Research Record: Journal of the Transportation Research Board*, 2013(2381): pp. 45-53.

69. Fogue, M., P., Garrido, F. J. Martinez, J.C. Carlos, T. Calafate, and P. Manzoni. Automatic accident detection: Assistance through communication technologies and vehicles. *Vehicular Technology Magazine*, IEEE, 2012. 7(3): pp. 90-100.

70. Fogue, M., P., Garrido, F. J. Martinez, J.C. Carlos, T. Calafate, and P. Manzoni. A system for automatic notification and severity estimation of automotive accidents. *Mobile Computing, IEEE Transactions on*, 2014. 13(5): pp. 948-963.

71. Fogue, M., P., Garrido, F. J. Martinez, J.C. Carlos, T. Calafate, P. Manzoni, and M. Sanchez. *Prototyping an automatic notification scheme for traffic accidents in vehicular networks*, in *IFIP Wireless Days (WD), 2011*. IEEE.

72. Fischer, C. and H. Gellersen. Location and navigation support for emergency responders: A survey. *IEEE Pervasive Computing*, 2010. 9(1): pp. 38-47.

73. Li, S., et al., Efficient Emergency Rescue Navigation with Wireless Sensor Network*s. Journal of Information Science and Engineering*, 2011. 27(1): pp. 51-64.

74. Tseng, Y.C., M.-S. Pan, and Y.Y. Tsai. Wireless sensor networks for emergency navigation. *Computer*, 2006. 39(7): pp. 55-62.

75. Wang, L. and W. Liu. Navigability and reachability index for emergency navigation systems using wireless sensor networks. *Tsinghua Science & Technology*, 2011. 16(6): pp. 657-668.

76. Kejun, L., L. Yong, and L. Xiangwu. Emergency Accident Rescue System in Freeway Based on GIS, in *Intelligent Computation Technology and Automation (ICICTA), 2008 International Conference on*. 2008. IEEE.

77. Kwan, M.P. and J. Lee. Emergency response after 9/11: the potential of real-time 3D GIS for quick emergency response in micro-spatial environments. *Computers, Environment and Urban Systems*, 2005. 29(2): pp. 93-113.

78. Schoenharl, T., G. Madey, G. Szabó, and A. Barabási. WIPER: A multi-agent system for emergency response, in *Proceedings of the 3rd International ISCRAM Conference*. 2006.

79. Battelle, *Response, Emergency Staging, Communications, Uniform Management, and Evacuation (R.E.S.C.U.M.E.) Concept of Operations*. 2012: Washington, DC.

80. Moussa, N., Evacuation Model for Emergency Vehicles in Highways. *International Journal of Modern Physics C*, 2009. 20(01): pp. 59-69.

81. Dresner, K. and P. Stone. Human-usable and emergency vehicle-aware control policies for autonomous intersection management, in *Fourth International Workshop on Agents in Traffic and Transportation (ATT).* 2006: Hakodate, Japan.

82. Dresner, K. and P. Stone. A multiagent approach to autonomous intersection management. *Journal of artificial intelligence research*, 2008. 30: pp. 591-656.

83. Dresner, K. and P. Stone. Traffic intersections of the future. in *Proceedings of the National Conference on Artificial Intelligence*. 2006. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999.

84. Toy, C., K. Leung, L. Alvarez, and R. Horowitz. Emergency vehicle maneuvers and control laws for automated highway systems. *Intelligent Transportation Systems, IEEE Transactions on*, 2002. 3(2): pp. 109-119.

85. Alazawi, Z., S. Altowaijri, R. Mehmood, and M. B. Abdljabar. Intelligent disaster management system based on cloud-enabled vehicular networks. In *ITS Telecommunications (ITST), 2011 11th International Conference on*. 2011. IEEE.

86. Aldunate, R.G., O.A. Herrera, and J.P. Cordero. Early Vehicle Accident Detection and Notification Based on Smartphone Technology. In *Ubiquitous Computing and*

Ambient Intelligence. Context-Awareness and Context-Driven Interaction. 2013, Springer International Publishing. pp. 358-365.

87. Bahora, A.S., T. Collins, S. Davis, S. Goknur, J. Kearns, T. Lieu, T. Nguyen, J. Zeng, B. M. Horowitz, and S. D. Patek. Integrated peer-to-peer applications for advanced emergency response systems. Part II. Technical feasibility. In *Systems and Information Engineering Design Symposium, 2003 IEEE*. 2003. IEEE.

88. Huang, C.M., C.C. Yang, C.Y. Tseng, and C.H. Chou. A centralized traffic control mechanism for evacuation of emergency vehicles using the DSRC protocol. In *Wireless Pervasive Computing, 2009 (ISWPC 2009), 4th International Symposium on*. 2009. IEEE.

89. Rizvi, S.R., S. Olariu, M.C. Weigle, and M.E. Rizvi. A Novel Approach to Reduce Traffic Chaos in Emergency and Evacuation Scenarios. in *Vehicular Technology Conference* (*VTC Fall)*. 2007. IEEE.

90. Yoo, J.B., J. Kim, and C.Y. Park. Road Reservation for Fast and Safe Emergency Vehicle Response Using Ubiquitous Sensor Network. In *Sensor Networks, Ubiquitous, and Trustworthy Computing (SUTC), 2010 IEEE International Conference on*. 2010. IEEE.

91. Barlovic, R., J. Esser, K. Froese, W. Knospe, L. Neubert, M. Schreckenberg, and J. Wahle. Online Traffic Simulation With Cellular Automata. *Traffic and Mobility: Simulation-Economics Environment.* 1999. ppp. 117-134.

92. Barlovic, R., T. Huisinga, A. Schadschneider, and M. Schreckenberg. Open Boundaries in a Cellular Automaton Model for Traffic Flow With Metastable States. *Physical Review E*, 2002. 66(4): pp. 11.

93. Benjaafar, S., K. Dooley, and W. Setyawan. *Cellular Automata for Traffic Flow Modeling*. 1997, University of Minnesota, Minneapolis: Minneapolis. pp. 29.

94. Bham, G.H. and R.F. Benekohal, Illisim. A Fast High Fidelity Traffic Simulation Model Based on Cellular Automata and Car-Following Concepts. National Research Council (U.S.). Transportation Research Board. Meeting (80th : 2001 : Washington, D.C.). Preprint CD-ROM. 2001. 22 pp.

95. Dailey, D.J. and A.N. Taiyab. *A Cellular Automata Model for use With Real Freeway Data for Traffic Prediction*. 2002, Washington State Transportation Center: Olympia.

96. El Dessouki, W.M., Y. Fathi, and N. Rouphail. Meta-Optimization Using Cellular Automata With Application to the Combined Trip Distribution and Assignment System Optimal Problem. *Computer-Aided Civil and Infrastructure Engineering*, 2001. 16(6): pp. 384-398.

97. Emmerich, H. and E. Rank. Investigating Traffic Flow in the Presence of Hindrances by Cellular Automata. *Physica A*, 1995. 216(4): pp. 435-444.

98. Hafstein, S.F., R. Chrobok, A. Pottmeier, M. Schreckenberg, and F.C. Mazur. A High-Resolution Cellular Automata Traffic Simulation Model With Application in a Freeway Traffic Information System. *Computer-Aided Civil and Infrastructure Engineering*, 2004. 19(5): pp. 338-350.

99. Jiang, R. and Q.S. Wu. Cellular Automata Models for Synchronized Traffic Flow. *Journal of Physics A-Mathematical and General*, 2003. 36(2): pp. 381-390.

100. Kerner, B.S., S.L. Klenov, and D.E. Wolf. Cellular Automata Approach to Three-Phase Traffic Theory. *Journal of Physics A: Mathematical and General*, 2002. 35: pp. 9971-10013.

101. Kita, E., T. Tamaki, and H. Shimizu. Cellular Automata Simulation of Traffic Flow. In *Urban Transport XII. Urban Transport and the Environment in the 21st Century*. 2006. Prague: WIT Press.

102. Larraga, M.E., J.A. del Rio, and L. Alvarez-Icaza. Cellular Automata for One-Lane Traffic Flow Modeling. *Transportation Research. Part C: Emerging Technologies*, 2005. 13(1): pp. 63-74.

103. Moussa, N. Car Accidents in Cellular Automata Models for One-Lane Traffic Flow. *Physical Review E*, 2003. 68(3): pp. 036127(1-8).

104. Nagatani, T.. Car Bunching and Traffic Jams in Cellular Automation Models. 1996: Workshop on Traffic and Granular Flow (1995: Julich, Germany).

105. Nagel, K. and M. Schreckenberg. *Traffic Jam Dynamics in Stochastic Cellular Automata*. 1995: Los Alamos National Laboratory.

106. Nagel, K., D.E. Wolf, P. Wagner, and P. Simon. Two-Lane Traffic Rules for Cellular Automata: A Systematic Approach. *Physical Review E*, 1998. 58(2): pp. 1425-1437.

107. Nassab, K.. The behaviour of traffic on a two-lane road in the neighbourhood of two slow vehicles in a cellular automation model. *Recherche - Transports - Sécurité*, 2005. 22(89): pp. 289-304.

108. Olmos, L.E. and J.D. Munoz. A Cellular Automaton Model for the Traffic Flow in Bogota. *International Journal of Modern Physics C*, 2004. 1(2): pp. 1397-1411.

109. Santen, L., J. Esser, L. Neubert, J. Wahle, A. Schadschneider, and M. Schreckenberg. Online Simulation of Urban Traffic Using Cellular Automata, in Mathematics in Transport Planning and Control: *Proceedings of the 3rd IMA International*

Conference on Transport Planning and Control. 1998, Pergamon: New York. pp. 301-309.

110. Schadschneider, A. and M. Schreckenberg. Cellular Automata for Traffic Flow: Analytical Results. Workshop on Traffic and Granular Flow. 1995. Julich, Germany.

111. Schreckenberg, M. and K. Nagel. Physical Modeling of Traffic With Stochastic Cellular Automata, in *International symposium on automotive technology and automation: dedicated conference on mechatronics - efficient computer support for engineering, manufacturing, testing and reliability*. 1995, Los Alamos National Laboratory: Stuttgart, Germany. pp. 10.

112. Wagner, P. Traffic simulations using cellular automata: comparison with reality. In *Workshop on Traffic and Granular Flow*. 1996. Julich, Germany: World Scientific.

113. Wang, Z. and P. Murray-Tuite. Modeling Incident-Related Traffic and Estimating Travel Time with a Cellular Automaton Model. In *Annual Meeting of the Transportation Research Board* 2010, Transportation Research Board: Washington, D.C.

114. Nagel, K., R.J. Beckman, and C.L. Barrett. TRANSIMS for urban planning. In *6th International Conference on Computers in Urban Planning and Urban Management,* Venice, Italy. 1999.

115. Saydam, C., J. Repede, and T. Burwell. Accurate estimation of expected coverage: A comparative study. *Socio-Economic Planning Sciences*, 1994. 28(2): pp. 113-120.

116. Holland, J.. *Adaptation in artificial and natural systems.* Ann Arbor: The University of Michigan Press, 1975.

117. Sivanandam, S. and S. Deepa. *Introduction to genetic algorithms*. 2007, Springer Science & Business Media. pp. 1-14.

118. Nicoară, E.S. Mechanisms to avoid the premature convergence of genetic algorithms. *Petroleum–Gas University of Ploieşti Bulletin, Math.–Info.–Phys. Series*, 2009. 61: pp. 87-96.