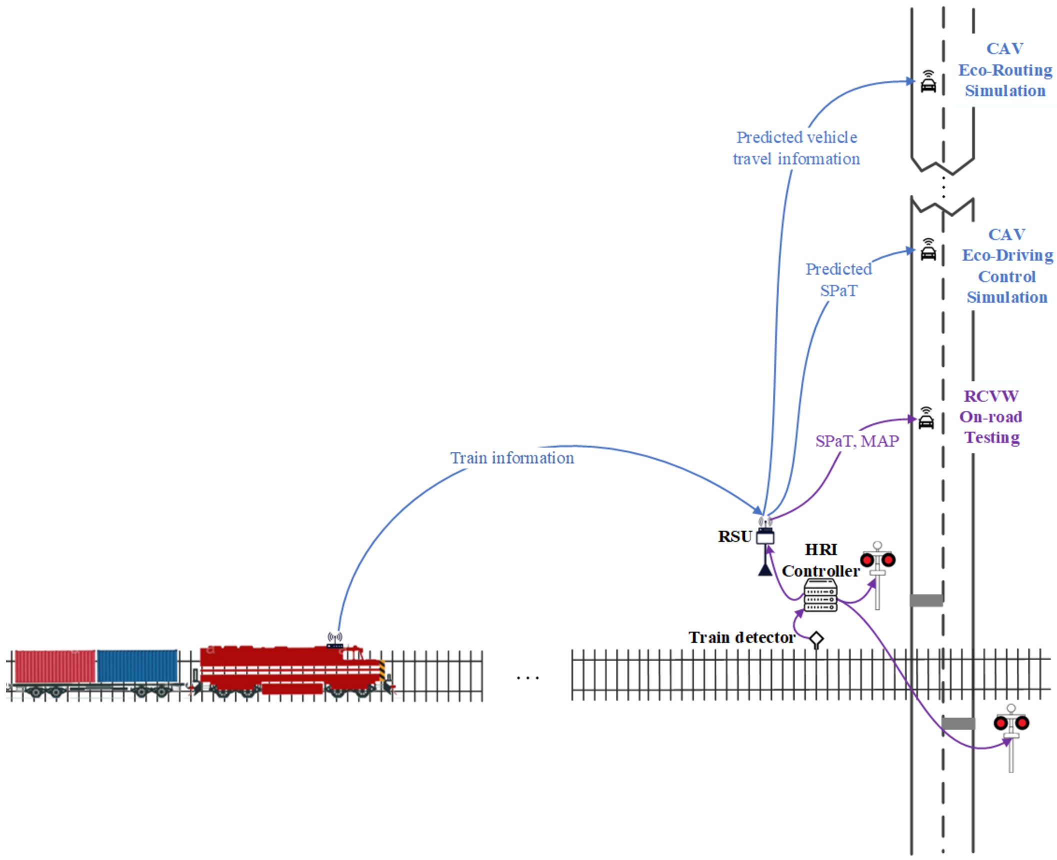
U.S. Department of Transportation
Federal Railroad Administration

Office of Research,
Development and Technology
Washington, DC 20590

Developing Safe and Efficient Driving and Routing Strategies at Railroad Grade Crossings based on Highway-Railway Connectivity



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14. ABSTRACT
This report documents the research involved in developing safe and efficient driving and routing strategies at highway-rail grade crossings (i.e., highway-rail intersections) based on highway-rail connectivity for economic evaluation, driver behavior analysis, and Eco-Driving and Eco-Routing strategies. From September 2019 to December 2022, a research team from Michigan Technological University led this project with a team from the University of Kentucky as an academic partner and Escanaba & Lake Superior (E&LS) Railroad as an industry partner. This project was sponsored by the Federal Railroad Administration through the 2018 Broad Agency Announcement on Intelligent Railroad System Research.

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Grade crossing, highway-rail intersection, HRI, highway-rail connectivity, Connected and Automated Vehicle, CAV, economic assessment, human factor, driver behavior, on-road testing, Rail Crossing Violation Warning, RCVW, Eco-Driving, Eco-Routing, safety, mobility, energy efficiency

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METRIC/ENGLISH CONVERSION FACTORS

ENGLISH TO METRIC

LENGTH (APPROXIMATE)

1 inch (in)	=	2.5 centimeters (cm)
1 foot (ft)	=	30 centimeters (cm)
1 yard (yd)	=	0.9 meter (m)
1 mile (mi)	=	1.6 kilometers (km)

AREA (APPROXIMATE)

1 square inch (sq in, in^2)	=	6.5 square centimeters (cm^2)
1 square foot (sq ft, ft^2)	=	0.09 square meter (m^2)
1 square yard (sq yd, yd^2)	=	0.8 square meter (m^2)
1 square mile (sq mi, mi^2)	=	2.6 square kilometers (km^2)
1 acre = 0.4 hectare (he)	=	4,000 square meters (m^2)

MASS - WEIGHT (APPROXIMATE)

1 ounce (oz)	=	28 grams (gm)
1 pound (lb)	=	0.45 kilogram (kg)
1 short ton = 2,000 pounds (lb)	=	0.9 tonne (t)

VOLUME (APPROXIMATE)

1 teaspoon (tsp)	=	5 milliliters (ml)
1 tablespoon (tbsp)	=	15 milliliters (ml)
1 fluid ounce (fl oz)	=	30 milliliters (ml)
1 cup (c)	=	0.24 liter (l)
1 pint (pt)	=	0.47 liter (l)
1 quart (qt)	=	0.96 liter (l)
1 gallon (gal)	=	3.8 liters (l)
1 cubic foot (cu ft, ft^3)	=	0.03 cubic meter (m^3)
1 cubic yard (cu yd, yd^3)	=	0.76 cubic meter (m^3)

TEMPERATURE (EXACT)

[(x-32)(5/9)] °F = y °C

METRIC TO ENGLISH

LENGTH (APPROXIMATE)

1 millimeter (mm)	=	0.04 inch (in)
1 centimeter (cm)	=	0.4 inch (in)
1 meter (m)	=	3.3 feet (ft)
1 meter (m)	=	1.1 yards (yd)
1 kilometer (km)	=	0.6 mile (mi)

AREA (APPROXIMATE)

1 square centimeter (cm^2)	=	0.16 square inch (sq in, in^2)
1 square meter (m^2)	=	1.2 square yards (sq yd, yd^2)
1 square kilometer (km^2)	=	0.4 square mile (sq mi, mi^2)
10,000 square meters (m^2)	=	1 hectare (ha) = 2.5 acres

MASS - WEIGHT (APPROXIMATE)

1 gram (gm)	=	0.036 ounce (oz)
1 kilogram (kg)	=	2.2 pounds (lb)
1 tonne (t)	=	1,000 kilograms (kg)
	=	1.1 short tons

VOLUME (APPROXIMATE)

1 milliliter (ml)	=	0.03 fluid ounce (fl oz)
1 liter (l)	=	2.1 pints (pt)
1 liter (l)	=	1.06 quarts (qt)
1 liter (l)	=	0.26 gallon (gal)
1 cubic meter (m^3)	=	36 cubic feet (cu ft, ft^3)
1 cubic meter (m^3)	=	1.3 cubic yards (cu yd, yd^3)

TEMPERATURE (EXACT)

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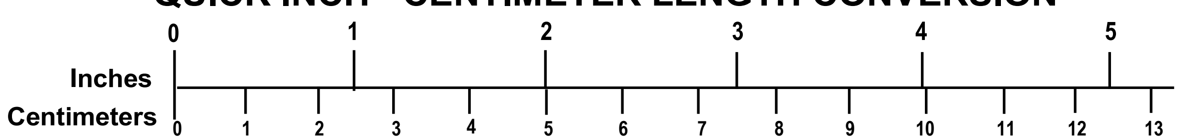
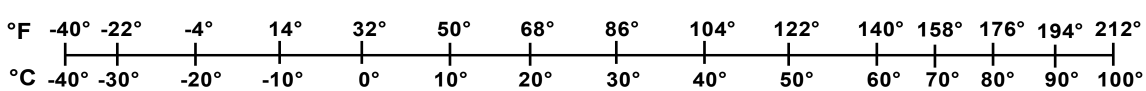
QUICK INCH - CENTIMETER LENGTH CONVERSION



QUICK FAHRENHEIT - CELSIUS TEMPERATURE CONVERSIO



For more exact and or other conversion factors, see NIST Miscellaneous Publication 286, Units of Weights and Measures. Price $2.50 SD Catalog No. C13 10286

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Executive Summary

The highway-rail grade crossings (i.e., highway-rail intersections (HRIs)) in North America create potential conflict between highway and train traffic, creating safety and efficiency implications. Connected and Automated Vehicle (CAV) technologies have the potential to reduce the frequency and severity of HRI safety-related incidents. Safety and efficiency have been the main motivators for the US Department of Transportation (USDOT) to explore using CAV technologies for highway transportation, and there exist opportunities to use CAV applications at HRIs. This project was designed to enhance the safety, mobility, and energy efficiency of CAVs around HRIs by conducting economic analysis, analyzing driver behavior, optimizing automated driving control, and providing alternative routes based on insights gained from CAV technologies.

Researchers conducted an economic assessment to improve understanding of the potential impacts of emerging CAV technologies on grade crossing safety and economics. Although many studies have examined the safety benefits of CAV technologies in general, no method or tool has been available to calculate the benefits of their application, specifically at HRIs at a local, regional, state, or national level. The project team developed such a tool to estimate the shift in benefits from conventional countermeasures to CAV technologies for HRI safety under mixed traffic (i.e., CAVs and non-CAVs). The team then tested the tool in a case study to estimate the benefits of deploying future Rail Crossing Violation Warning (RCVW) applications in Kentucky and Michigan. Based on the analysis, the team determined that predicted benefits for Kentucky range from $207 to $350 million for active crossings and $66 to $112 million for passive crossings. The predicted benefits for Michigan range from $253 to $428 million for active crossings and $131 to $222 million for passive crossings. Nationwide, the predicted benefits range from $8.70 to $14.7 billion for active crossings and $6.84 to $11.6 billion for passive crossings.

Since the advent of connectivity technologies raises concerns about how drivers would react to the presence of CAV safety applications at HRIs, the project team performed a field study and road test of the RCVW system at HRIs and completed a driver behavior analysis. Fifteen drivers participated in the initial field test to examine driver behavior during HRI approaches and traversals. Drivers provided usability ratings and were interviewed about their perceptions of the RCVW system. Drivers reported that the RCVW system was easy to learn and use, and provided helpful information about their experience. The team performed driver behavior analysis that indicated speed and gaze behavior response to the RCVW alerts and warnings was consistent and as expected.

Finally, researchers simulated CAV Eco-Driving and Eco-Routing strategies at HRIs and analyzed congestion and energy benfits. The team determined that the proposed CAV Eco-Driving strategy offered energy benefits while ensuring safety at HRIs equipped with connectivity technologies. The average energy savings of impacted vehicles under the 100 percent CAV Market Penetration Rate (MPR) was 11.6 percent compared to human-driven vehicles (HDV) not equipped with CAV technologies. The team also found that simulated CAV Eco-Routing strategy could improve mobility and energy efficiency at HRIs compared with vehicles without Eco-Routing services (i.e., non-CAVs). Likewise, the team found that simulated

CAV Eco-Routing strategy could achieve 10 percent travel time savings and 3.96 percent energy savings as compared to non-CAVs.

1. Introduction

This report documents the research involved in developing safe and efficient driving and routing strategies at highway-rail grade crossings (i.e., highway-rail intersections (HRIs)) based on highway-rail connectivity for economic evaluation, driver behavior analysis, and Eco-Driving and Eco-Routing strategies. From September 2019 to December 2022, a research team from Michigan Technological University led this project with a team from the University of Kentucky as an academic partner and Escanaba & Lake Superior (E&LS) Railroad as an industry partner. This project was sponsored by the Federal Railroad Administration (FRA) through the 2018 Broad Agency Announcement (BAA) on Intelligent Railroad System Research.

1.1 Background

The HRIs in North America are critical locations of highway and train traffic with safety and efficiency implications. Connected and automated vehicle (CAV) technologies have the potential to reduce the frequency and severity of HRI safety-related incidents. Human-driven vehicles (HDV) (which are not equipped with CAV technologies) approaching HRIs can generate energy consumption and potential time delays, which motivates both railroad and highway users to search for improvements in Eco-Driving and Eco-Routing strategy efficiencies.

Safety funds compete against other needs, therefore it is essential to correctly calculate cost-benefit estimations. The effectiveness of HRI safety countermeasures is typically considered to remain constant over time. For example, according to the Crash Reduction Factor Clearinghouse, the installation of lights and gates is assumed to reduce crashes by 45 percent. When conducting economic analysis, this reduction is further assumed to apply over the life of the countermeasure, which can be 10 to 20 years or longer. The effectiveness models also assume vehicle fleets, drivers, and in-vehicle safety technologies will remain static. The advent of CAV technologies may violate these assumptions and invalidate the benefits assigned to the countermeasures unless the systems are well-designed. Thus, a well-designed system using CAV technologies will enhance safety by providing complementary and redundant information allowing advance alerts and warnings for drivers. For example, if half of all vehicles used CAV and the applications could warn (or even stop) drivers with the same effectiveness as lights and gates, only half of the benefits (i.e., 22.5%) should be allocated to the actual lights and gates, with the other half justifiably assigned to the CAV systems. This is important in cost-benefit analysis, as the benefits of two different improvements (i.e., lights and gates and CAV applications) should not be double counted. The net effect of CAV technologies, while substantially improving the safety of the HRI, is to reduce the benefits of traditional countermeasures. As non-CAV vehicles are likely to remain in the vehicle fleet, conventional countermeasures will still be required for many years to come. However, returns on safety investments may be significantly overestimated if economic benefits are summed across all future vehicles that travel through an HRI. Therefore, there is a need to estimate the shift in benefits from conventional countermeasures to CAV technologies for HRI safety under mixed traffic of CAVs and non-CAVs.

The use of CAV technologies at HRIs also raises questions about how drivers respond to the use of CAV applications, and whether the CAV application achieves the expected outcomes in terms of usability, driver perceptions, and experiences. Therefore, it is important to collect data and analyze drivers' behavior during HRI approaches and traversals using sensors, cameras, and interview data from participants in road testing.

Safety and efficiency have motivated the US Department of Transportation (USDOT) to explore using CAV technologies at different levels of automation. For example, Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) systems developed for highway vehicles are being combined with communication technologies to support cooperative driving automation (CDA) (Zhao & Zhang, 2020) (Hung & Zhang, 2022) (Tan & Zhang, 2022). These systems react to the surrounding conditions and traffic to control a single vehicle or platoon for safe highway driving with improved mobility and fuel efficiency. With a focus on improving fuel efficiency and reducing congestion, Eco-Driving systems are studied to improve safety and reduce unnecessary acceleration, deceleration, and idle time by optimizing vehicle speed profiles on a freeway or approaching a signalized intersection using connectivity technologies such as Vehicle-to-Infrastructure (V2I) communications (Zhao & Zhang, 2021).

Similarly, USDOT has started to evaluate CAV technologies at HRIs to improve safety. For example, the Rail Crossing Violation Warning (RCVW) from a project on Prototype Rail Crossing Violation Warning Application (Neumeister, Zink, & Sanchez-Badillo, 2017) can provide real-time warning of an imminent HRI violation to drivers based on V2I communications. The current RCVW system is based on track-circuit train detection, and currently does not provide predicted timing information for train arrivals and departures at HRIs. Similarly, for areas where train traffic may cause highway congestion, warning messages without predicted timing information cannot support enhanced efficient driving and routing strategies. Moreover, without a route planner for vehicles approaching the HRIs, it may not be possible to improve traffic throughput, and it is challenging to reduce roadway vehicles' idle time.

1.2 Objectives

The project was designed to enhance safety, mobility, and energy efficiency of CAVs around HRIs by conducting economic analysis, understanding driver behavior, optimizing automated driving control, and providing alternative routes based on insights gained from CAV technologies. The outcome of this research can potentially increase safety, efficiency, and highway capacity at HRIs through highway-rail connectivity. The enhanced efficient driving and routing strategies can help meet FRA's mission to enable the safe, reliable, and efficient movement of people and goods for a strong America, now and in the future (Alexy, 2020). They can also help reduce highway vehicles' energy consumption and idle time at HRIs. More importantly, these technologies have the potential to alleviate driver frustrations due to blocked HRIs. This research may also allow industry practitioners to make more informed decisions regarding the potential safety, mobility, energy efficiency benefits, and economic implications of highway-rail connectivity.

1.3 Overall Approach

To develop enhanced efficient driving and routing strategies at HRIs based on highway-rail connectivity, the project team worked on the following five major tasks.

The first task was to prepare a literature review of the current standards, knowledge, and development of highway-rail connectivity technologies. The project team reviewed the published literature and technical reports of previous research and demonstration projects funded by federal and other agencies. The project team also attempted to gain insights on HRI safety applications and highway-rail communications from published materials and industry presentations.

The second task was to perform an economic evaluation of using CAV applications for HRI safety. A data-driven economic evaluation tool was developed to assess the effectiveness of HRI safety countermeasures in mixed traffic (i.e., CAVs and non-CAVs). The tool is used to estimate the shift in benefits from conventional countermeasures to CAV technologies. The project team also developed a framework for economic analysis to evaluate the benefits of CAV applications at HRIs. The team developed a case study to estimate the benefits of deploying RCVW-type applications using data from Kentucky and Michigan.

The third task was to conduct a driver behavior analysis using data from on-road testing of the RCVW system. The project team deployed the RCVW system at real-world HRIs in Escanaba-Wells-Gladstone, MI, and collected data from vehicles instrumented with RCVW. The project team used sensors, videos, and interview information from drivers participating in the testing of this project to characterize driver behavior during crossing approaches and traversals with the presence of RCVW.

The fourth task was to conduct a simulation analysis of a safe and efficient CAV Eco-Driving Control strategy to reduce the number of full stops and idle time and smooth acceleration and deceleration maneuvers while approaching an HRI. The project team simulated an active HRI in Escanaba-Wells-Gladstone, MI. The simulation analysis evaluated the energy benefits of CAV Eco-Driving Control in different scenarios in various highway and train traffic conditions using crossing timing information via highway-rail connectivity.

The fifth task was to simulate an efficient CAV Eco-Routing strategy at HRIs to improve traffic mobility and energy efficiency for highway vehicles that subcribe to eco-routing services. CAV Eco-Routing can choose an efficient route considering predicted travel time and energy consumption from a predefined route set between the vehicle's origin and destination. The project team simulated the Eco-Routing strategy in a simplified transportation network of Escanaba-Wells-Gladstone, MI, which includes an HRI and four signalized intersections. The numerical analysis showed mobility and energy benefits for different train information provision scenarios via highway-rail connectivity.

1.4 Scope

The literature review focused on the technology aspect of highway-rail connectivity. Its scope was limited to communication technologies to build connectivity, the communication platform to support message exchange, and existing research and projects to improve HRI safety via different levels of highway-rail connectivity. The economic evaluation was performed using a forecasting tool to calculate state-level benefits using data from Kentucky and Michigan. The national-level benefits were estimated by extrapolating the state-level benefits derived by the tool. This approach can be extended to data from other states.

The on-road testing of the RCVW system for human factor analysis was subject to the actual road geometry, traffic rules, speed limit, highway traffic conditions, and train traffic conditions in Escanaba-Wells-Gladstone, MI. Due to the constraints of the real-world environment, there were limited options for routes and crossings, and crossing environments were not identical. As a result, the project team was unable to control all extraneous factors and a real “control group” for the study was not possible.

CAV Eco-Driving Control and CAV Eco-Routing strategies were evaluated through simulations. For CAV Eco-Driving Control, the simulated transportation network consisted of a segment of a two-directional highway, a segment of the railroad, and the HRI located at the intersection of the highway segment and railroad segment. The geometry of the HRI was modeled based on an active HRI in Escanaba-Wells-Gladstone, MI. For CAV Eco-Routing, the simulated transportation network was a simplified version of the one in Escanaba-Wells-Gladstone, MI, which contains one active HRI and four signalized intersections. Assuming CAV Eco-Routing was applied to vehicles traveling from a predefined origin to a predefined destination, three available routes were given based on the Escanaba-Wells-Gladstone transportation network.

Figure 1 illustrates different forms of highway-rail connectivity for RCVW on-road testing, CAV Eco-Driving Control simulation, and CAV Eco-Routing simulation. For RCVW, the HRI Controller, most commonly employing railroad track circuits, detects the approach of a train and activates the conventional bells, lights, and gates at the crossing.The RCVW Road Side Unit (RSU) detects the status of the HRI Controller by monitoring the HRI Controller's preemption connection, which is designed for interconnecting with highway signal systems. The RSU constantly sends Signal Phase and Timing (SPaT) messages (i.e., 10 Hz frequency) and Map (MAP) messages (i.e., 1 Hz frequency) to vehicles equipped with RCVW around the HRI. It should be noted that no predictive timing information is included in the SPaT message since the train detector does not provide train speed or train length information. In the on-road testing, the team used human-in-the-loop to activate the RCVW system rather than directly connect the RCVW system with the HRI controller due to regulations. For CAV Eco-Driving Control simulation, the simulated train directly transmitted Head-of-Train (HOT) position, HOT speed, End-of-Train (EOT) position, and EOT speed to the RSU. The RSU leveraged this train information to predict the crossing timing information (i.e., HRI-occupied time). For CAV Eco-Routing simulation, the simulated train sent its information directly to the RSU to predict vehicle travel time and relay it to vehicle subscribers of the CAV Eco-Routing service.

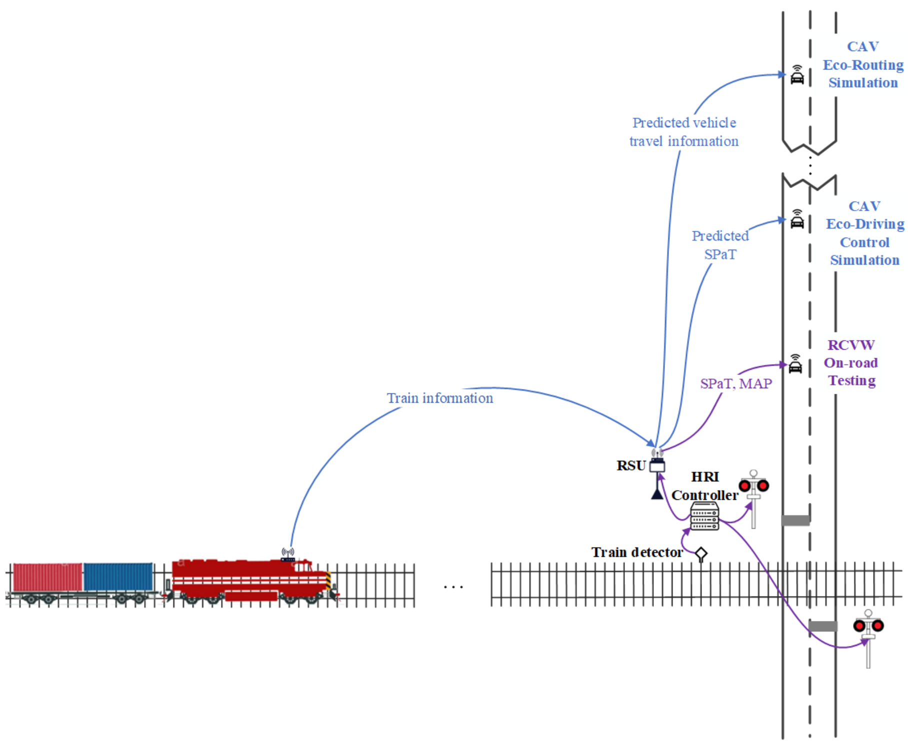

Figure 1. Highway-Rail Connectivity for On-Road Testing and Simulation

1.5 Organization of the Report

This report includes seven sections. Section 1 introduces the project background, objectives, overall approach, scope, and the organization of the report. Section 2 provides a literature review of highway-rail connectivity technologies. Section 3 presents the economic evaluation of deploying highway-rail connectivity technology at HRI using a Data-Driven Rail Safety Assessment for Connected and Autonomous Transportation (ddRailCAT) tool. Section 4 provides the driver behavior analysis of deploying the RCVW system at real-world HRIs through on-road testing. Section 5 simulates the CAV Eco-Driving Control strategy for vehicles approaching an HRI to improve safety and energy efficiency. Section 6 simulates the CAV Eco-Routing strategy that provides pre-trip route choice service for mobility and energy efficiency. Section 7 presents the conclusions and discusses future works.

2. Literature Review

This section presents the results of a literature review of highway-rail connectivity technologies. The idea of highway-rail connectivity is to enable communications among the train, HRI, and highway vehicles. The team performed reviews of communication technologies, the communication platform, and existing studies to improve HRI safety.

2.1 Communication Technologies for Highway-Rail Connectivity

2.1.1 DSRC

Dedicated Short-Range Communications (DSRC) is a wireless communication technology that supports Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructures (V2I) communications. Without relying on base station infrastructures, any vehicle that carries a DSRC unit can directly communicate with surrounding infrastructure or vehicles that are also equipped with DSRC units.

DSRC is based on a collection of cooperative standards that guarantee the interoperability between DSRC units produced by different manufacturers. The Institute of Electrical and Electronics Engineers (IEEE) 802.11p standard (IEEE, 2010) defines operations and protocols at the Physical (PHY) layer and Medium Access Control (MAC) layer. This protocol is an amendment to the IEEE 802.11 standard that aims to reduce the connection setup overhead in the vehicular environment. IEEE also defines other protocols to standardize Wireless Access in Vehicular Environments (WAVE) services. The IEEE 1609.2 standard (IEEE, 2016) defines security services for WAVE management messages and application messages to meet the need for communication safety. The IEEE 1609.3 standard (IEEE, 2020) defines networking services and specifies operations and management of the communications stack. The IEEE 1609.4 standard (IEEE, 2016) provides frequency band coordination and management within the MAC layer and supports multi-channel wireless connectivity.

The Society of Automotive Engineers (SAE) J2735 Message Set Dictionary standard (SAE, 2020) specifies a set of message formats that support a variety of vehicle-based applications using DSRC. The message set defines Basic Safety Messages (BSMs) for vehicle data sharing. Location, speed, acceleration, and heading of the vehicle can be broadcast. MAP Messages contain the geometric layout information of intersections. SPaT messages describe the current state of the traffic control signal system at intersections. Radio Technical Commission for Maritime Services (RTCM) messages are broadcast from infrastructure to vehicles to provide differential corrections for Global Navigation Satellite System (GNSS) or Global Positioning System (GPS) units on the vehicle. By broadcasting and receiving SAE J2735 messages, vehicles and infrastructure can be connected.

DSRC has been tested in real-world deployment projects including Ann Arbor Safety Pilot, Tampa Connected Vehicle (CV) Pilot, New York City DOT CV Pilot, etc. DSRC formerly worked exclusively on the 75 megahertz (MHz) spectrum at the 5.9 gigahertz (GHz) band allocated by the Federal Communications Commission (FCC) for Intelligent Transportation System (ITS). However, by July 2022, FCC had ceased all DSRC operations in the lower 45 MHz of the ITS band, while the upper 30 MHz spectrum had been reserved for another emerging technology (i.e., Cellular Vehicle-to-Everything (C-V2X)).

2.1.2 C-V2X

C-V2X is another wireless communication technology for V2X communications. It is based on Fourth Generation (4G) Long-Term Evolution (LTE) or the Fifth Generation (5G) mobile communication technologies. C-V2X supports not only direct communications over the PC5 (i.e., peer-to-peer) interface but also wide-area communications over the Uu (i.e., network) interface. These two communication modes complement each other and greatly enhance the V2X communication range.

C-V2X uses the Third Generation Partnership Project (3GPP) standardized MAC layer and PHY layer technologies instead of the IEEE 802.11p. 3GPP Release 14 (3GPP, 2015) adopted LTE to enable low-latency and highly reliable V2X communications. 3GPP Release 14 also introduced a wide range of V2X use cases and specified service requirements. However, it was found that not all enhanced V2X use cases (i.e., vehicle platooning, advanced driving, extended sensors, and remote driving) satisfed their communication requirements (e.g., latency and reliability) by using LTE as the only underlying radio access technology for C-V2X. Therefore, 3GPP began to study the potential use of 5G New Radio (NR) for vehicular communications. Release 16 (3GPP, 2020) which specified the 5G system architecture and adopted 5G NR as another radio access technology for C-V2X, is able to address the requirements of enhanced V2X use cases in terms of latency, reliability, and data rate.

C-V2X is preferable in terms of large-scale deployment thanks to the existing comprehensive coverage of cellular network infrastructure. In 2020, the FCC announced a decision to transition from DSRC to C-V2X with a deadline of July 2022. In this time, the FCC has ceased all DSRC operations in the lower 45 MHz of the ITS band, leaving the upper 30 MHz spectrum exclusively for C-V2X. The development and deployment of C-V2X will follow the designed roadmap with support from the telecom and automotive industries. It is anticipated that C-V2X communications will play an important role in enhancing road safety and mobility.

2.2 V2I-Hub/V2X-Hub Communication Platforms for Highway-Rail Connectivity

A communication platform is used to exchange data between the CAV host system and wireless communication devices such as On-Board Units (OBUs) and Road Side Units (RSUs). The platform can generate messages that comply with the standard message format and send them to the communication device. Meanwhile, it is responsible for receiving and decoding messages from the communication device.

V2I-Hub is a communication platform developed by USDOT. It has been upgraded and renamed as V2X-Hub (Balse, Greenwood, Rayamajhi, Iyengar, & Nallamothu, 2021). It employs open-source software that consists of a V2X core and multiple V2X plugins and interfaces with ITS infrastructure, vehicles, and road users. It can translate raw information into SAE J2735 standard messages. For example, vehicle sensing data, including location, speed, acceleration, heading, and braking condition, can be integrated into the SAE J2735 BSM message using V2X-Hub. Other vehicles or infrastructures that receive these BSMs are able to decode and recognize the content using V2X-Hub. A set of safety applications have been developed for V2X-Hub, including Curve-Speed Warning (CSW), Forward Collision Warning (FCW), Red Light Violation Warning (RLVW), Rail Crossing Violation Warning (RCVW), etc.

2.3 Existing Studies to Improve HRI Safety

The study of providing in-vehicle safety warnings to drivers at HRIs dates back to 1995 when FRA developed and investigated prototypes of the Vehicle Proximity Alert System (VPAS) for priority vehicles (i.e., emergency vehicles, school buses, vehicles carrying hazardous cargo, and large trucks) at passive HRIs (Carroll, Passera, & Tingos, 2001). Three prototypes were tested at FRA's Transportation Technology Center (TTC):

1) The SmartStop prototype was a three-point system that consisted of a locomotive transceiver, a transceiver at the HRI, and an in-vehicle receiver that communicated via the 151.6 MHz radio frequency.
2) The Early Alert Response System (EARS) prototype was a standalone in-vehicle system that does not rely on any other devices on locomotives or at HRIs. It detected approaching trains by receiving and analyzing the frequency of the audio signals from the locomotive horn. However, its low accuracy in acoustic recognition during testing made it fail to provide proper warning to drivers.
3) The Dynamic Vehicle Safety Systems (DVSS) prototype was also a standalone, in-vehicle receiver that receives radio signals from the existing Front-to-Rear-End Device (FRED) of the freight train information system in the locomotive. However, it generated numerous nuisance alerts even when the vehicle was not approaching an HRI during the test.

Researchers found that the three-point design (i.e., the SmartStop prototype) using radio frequency wireless communications is the most reliable design, which provides a reference for future studies.

The Minnesota Department of Transportation project "In-Vehicle Signing for School Buses at Railroad-Highway Grade Crossings" in 1997 developed an in-vehicle signing system to alert drivers of the presence of a train or a vehicle's proximity to an HRI (SRF Consulting Group, Inc., 1998) using existing train detection equipment. The roadside equipment broadcasted train alerts or crossing alerts via a radio signal to vehicles in both visual and audible forms. In their testing, 29 school buses were equipped with an in-vehicle signing system and 5 signalized HRIs were equipped with roadside equipment. Testing results showed the feasibility of the system but surveys revealed drivers' low intention to rely on the system.

The Illinois Department of Transportation project "Pilot Study of Advisory On-Board Vehicle Warning Systems at Railroad Grade Crossings" in 1997 designed an advisory on-board vehicle warning system that provided warnings to drivers via wireless communication on K-Band when there was a train approaching or occupying the HRI (Benekohal, 2004). This system consisted of two major components. The Trackside Transmitter Assembly (TTA), which was connected to the HRI controller, transmitted K-Band warning signals once the train was approaching or occupying the HRI. The In-Vehicle Receiver (IVR), which was installed in the vehicle, received the warning signal from TTA and displayed audible or visual warnings. Field tests were conducted with approximately 300 IVR units installed. Although the system did not meet study expectations and failed to provide reliable warnings for drivers, the project report provided some valuable findings for HRI safety application studies. It was revealed that K-Band was not reliable for wireless highway-rail communications since it produced numerous false alerts. The project report also showed the importance of considering drivers' reactions and acceptance when designing the warning system.

Prototypes in early studies simply warned drivers of a train approaching or occupying an HRI regardless of the vehicle status. The wireless communication technologies used in those prototypes can barely meet requirements. In recent studies, with the development of CAV technologies, HRI safety applications can provide more versatile functions and more reliable services.

The FRA project "Vehicle-to-Infrastructure Rail Crossing Violation Warning" in 2016 developed a Rail Crossing Violation Warning (RCVW) system that provided not only train approaching warnings but also dynamic vehicle violation warnings based on vehicle status (Neumeister, Zink, & Sanchez-Badillo, 2017). It leveraged the existing V2I-Hub system to support message exchange, wireless communication, GNSS positioning, and driver-vehicle interface. The RCVW system consists of a Roadside-based Subsystem (RBS) which was integrated with the roadside infrastructure at the HRI and a Vehicle-based Subsystem (VBS) which was installed in the vehicle. The standardized 5.9 GHz DSRC was used to provide low latency and reliable wireless communications between the two subsystems. Phase I testing results proved the feasibility of leveraging DSRC to achieve the requirements. Phase II of this project further improved the performance and reliability of the RCVW system.

Other studies of HRI safety applications also proposed advanced designs based on CAV technologies. A framework that integrated a Positive Train Control (PTC) system and a Vehicular Ad-Hoc Network (VANET) system was proposed in 2007 (Hartong, Goel, Farkas, & Wijesekera, 2007). This architecture used DSRC communications to achieve two-way communications between the two systems. Both drivers in vehicles and train operators in locomotives can be informed of the HRI approaching to enhance safety. Another novel active warning system for HRI safety based on a crossing risk assessment model was developed in 2019 to provide more intelligent service to road users (Wang, Li, Zhang, & Qiu, 2019). This system used On-Board Equipment (OBE) on the train and the vehicle. Roadside Equipment (RSE) was used to bridge the communications between the train and the vehicle. It was able to estimate collision risk and waiting time for road users based on real-time train and vehicle information.

While researchers focus on exploring new technologies and frameworks for HRI safety applications, analyzing the drivers' behavior, evaluating the economic benefit, and improving the feasibility of large-scale deployment in the real world are still challenging aspects that require more consideration.

3. Economic Evaluation of Highway-Rail Connectivity

3.1 Introduction

Many presume that the introduction of CAV technologies will reduce highway crashes. Given that 94 percent of crashes are due to human errors, this is a reasonable expectation (U.S. Department of Transportation, 2015). The total number of highway crashes eliminated will depend on many factors (e.g., risk compensation, software and hardware reliability, distraction, and improper use). It is estimated that CAV technologies may only prevent up to one-quarter of all crashes (Najm, Koopmann, Smith, & Brewer, 2010). A later study indicates the maximum effectiveness may extend to fifty percent (Yue, Abdel-Aty, Wu, & Wang, 2018). Further, the interaction of CAVs with HDVs could increase some types of crashes. Although there are many studies that have examined the safety benefits of CAV technologies in general, no method or tool is available to calculate the benefits specifically at the HRI at a local, regional, state, or national level. The objective of this study was to provide such a method/tool.

This section serves as a user's guide for the forecasting tool *Data-Driven Rail Safety Assessment for Connected and Autonomous Transportation* (ddRailCAT). ddRailCAT performs benefit analysis of HRI safety treatments/countermeasures such as RCVW. The tool estimates benefits based on the market penetration and effectiveness of railroad crossing hardware and software and in-vehicle components. It can be used to explore the safety and economic implications of CAVs for HRIs and help transportation agencies and other stakeholders make decisions about safety countermeasure investments. The last part of this section uses ddRailCAT to estimate the benefits of deploying RCVW-type technology in two states and a range of benefit estimates at the national level. The structure and main components of ddRailCAT are displayed in Figure 2. Detailed descriptions of each component are discussed in the succeeding sections of this chapter.

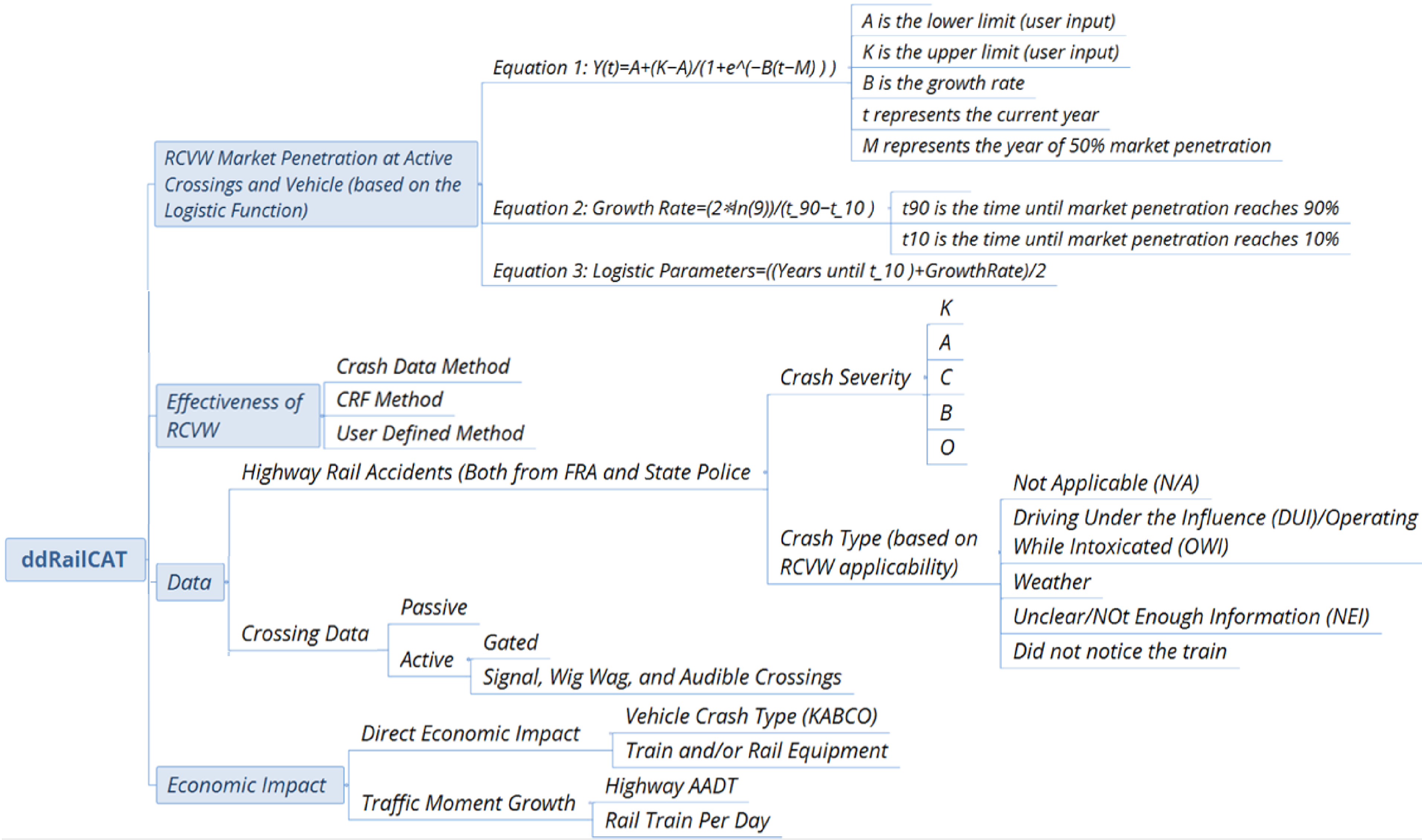

Figure 2. ddRailCAT Topology

3.2 ddRailCAT Tool

The conceptual foundation of ddRailCAT is a previously developed tool – *Data-Driven Safety Assessment for Connected and Autonomous Vehicles* (ddSAFCAT) (Lause III, 2019). ddRailCAT incorporates connected vehicle warning technologies at HRIs and other railroad-related parameters into the ddSAFCAT analytical framework.

ddRailCAT adopts three methods to estimate the safety benefits of RCVW: (1) a method based on historical crash data; (2) a Crash Reduction Factor (CRF) method; and (3) a user-defined method. The tool estimates benefits as a function of several key variables including:

- Market penetration (i.e., deployment rates)
- Effectiveness based on crash data method
- Effectiveness based on the CRF method
- Effectiveness based on a user-defined method
- HRI crash data
- HRI data

Benefit computations Different methods rely on disparate combinations of variables. The crash data method leverages information on market penetration, human factors, estimated effectiveness, and rhw reliability and analysis of real-world crash data. The CRF method estimates safety benefits by borrowing from the USDOT Crash Modification Factors (CMFs) Clearinghouse for analogous technologies. And the user-defined method gives users the option to incorporate effectiveness estimates from other research.

In ddRailCAT, market penetration rates and changes in human factors, other factors, and effectiveness over time follow a generalized logistic function S-curve. Users can manually adjust penetration/change rates and changes in these rates can be modified based on historical and projected trends.

For ease of use, the tool comes pre-loaded with data (e.g., baseline year train-vehicle crashes, crash classification by severity, and costs). ddRailCAT computes crash reductions and monetary savings (benefits) realized from lower crash numbers. Inputs are coded as user-defined, data input, based on other studies, or computed. Because of ddRailCAT's flexibility, additional data may be included where available to improve the accuracy of forecasted benefits.

The ddRailCAT tool is available by request.

3.2.1 Inputs & Graphs Sheet

Figure 3 illustrates the main page users see once they open ddRailCAT. A color-coded key in the middle portion of the right side defines the four types of data used in the tool:

- Blue: User-defined inputs based on the user's best judgment or other information
- Green: Values from published data (can be altered by users)
- Yellow: Based on data from other studies (can be altered by users)
- Gray: ddRailCAT computed outputs, which are linked to other spreadsheets

ddRailCAT

	Market Penetration: @ Active Crossings	Market Penetration: Vehicle	Crash Data Method – Human Factors: Proper Use	Human Factors: Distraction Factor	Human Factors: Risk Compensation Factor	Other Factors: Non-human Factors	Other Factors: Software and Hardware Reliability	Applicability/Effectiveness: Crash Data-Derived Applicability	Applicability/Effectiveness: Net effectiveness	CRF Method (effectiveness)	User-Defined Method (effectiveness)
baseline	0%	0%	80%	99%	100%	94%	90%	21.7%	14.6%	14.8%	25.0%
ultimate value	95%	90%	100%	100%	90%	94%	99%	22.5%	18.8%	14.8%	25.0%
years until t_{10}	3	3	5	5	3		3	3		3	3
year of t_{10}	2023	2023	2025	2025	2023		2023	2023		2023	2023
t_{90}-t_{10}	5	15	5	5	3		5	5		5	5
year of t_{90}	2028	2038	2030	2030	2026		2028	2028		2028	2028

	Crash Data Method	CRF Method	User-Defined Method
Cumulative Crash Reduction	5,897	4,671	7,890
Benefit ($ billions)	14.5	11.5	19.4

Severity	K (fatality)	A (major injury)	B (minor injury)	C (possible injury)	O (Property damage only)	Total
average cost	$13,914,052	$5,083,219	$771,216	$78,778	$21,006	
baseline	11.5%	15.9%	4.8%	1.5%	66.3%	100%
future	11.5%	15.9%	4.8%	1.5%	66.3%	100%
years until t_{10}	1	1	1	1	1	
year of t_{10}	2021	2021	2021	2021	2021	
t_{90}-t_{10}	60	49	49	49	49	
year of t_{90}	2081	2070	2070	2070	2070	

Crash Data-Derived Applicability (Inputs)

Crash Type Category	Effectiveness	% of crashes (baseline)	% of crashes future
NA	0%	54.3%	55%
DUI/OWI	25%	19.1%	15%
Weather	25%	4.7%	5%
unclear/NEI	50%	12.3%	15%
did not notice	100%	9.6%	10%
	Total:	100%	100%

General Parameters

Baseline train-vehicle crashes per year	1890
Baseline Year	2020
Analysis Period	25

Key:	
Computed	Based on data from other studies
Data input	User-Defined (Judgment)

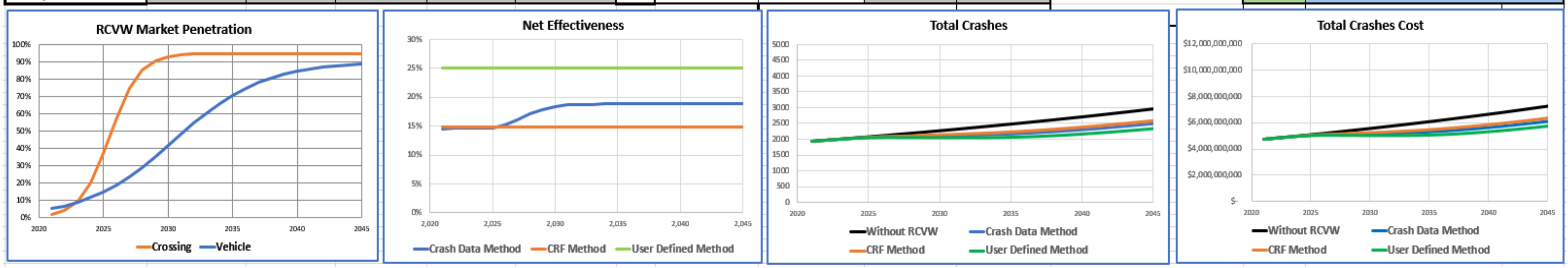

Figure 3. ddRailCAT Inputs and Graphs Page

The four graphs located at the bottom of Figure 3 include forecasted trend lines for RCVW market penetration, net effectiveness, total crashes, and total crash cost. These trends are forecast based on a mixture of input and computed data. Each section of the *Inputs & Graphs* sheet is explained below.

3.2.1.1 Market Penetration Section

Uncertainty remains over the rate at which connected vehicle technologies will be deployed at railroad crossings (assuming all active crossings) and in vehicles. ddRailCAT lets users envision different scenarios. The deployment (i.e., market penetration) for crossings equipped with RCVW-type systems and the deployment of equipped vehicles are allowed to be different (e.g., start later, deploy faster, saturate sooner, etc.). The methodology assumes independence of the deployment rates of the in-vehicle technology and equipment at a railroad crossing. The probability that any vehicle and railroad crossing have both the required in-vehicle and roadside equipment to make RCVW work is the product of the two market penetration rates. Required inputs are the *Baseline* (values from published data but can be altered by users), *Ultimate Value*, *Years Until* t_{10}, and *Penetration Time* (t_{90}-t_{10}). These are considered the "maturity" factors for market penetration as well as other components of ddRailCAT (see Figure 4). For the *Years Until* t_{10} values, users enter the number of years until wayside and in-vehicle connected technology each reach 10 percent deployment. The tool provides default starting points, but users can experiment with different values. Increasing the amount of real data improves results, making them less speculative and more data-driven.

ddRailCAT	Market Penetration	
	@ Active Crossings	Vehicle
baseline	0%	0%
ultimate value	95%	90%
years until t_{10}	3	3
year of t_{10}	2023	2023
t_{90}-t_{10}	5	15
year of t_{90}	2028	2038

Figure 4. Market Penetration Section

3.2.2 Crash Data Method Section

<u>*Human Factors Subsection*</u>

Proper Use of the CAV technology is another important determinant of overall system effectiveness. User-defined inputs are the maturity factors (i.e., *Baseline*, *Ultimate Value*, *Years Until* t_{10}, and *Penetration Time* (t_{90}-t_{10})) and may be developed based on weighted average parameters for various user types (e.g., commercial drivers, driving experience, etc.)

A *Distraction Factor* is included because the connected vehicle technologies themselves may pose a distraction to drivers. Proper HCI design and familiarity can mitigate the distraction, which will presumably lessen over time.

A *Risk Compensation Factor* is provided to account for the human propensity to find their own risk comfort level. For example, anti-lock brakes may encourage some users to drive more closely behind other vehicles, thereby compensating for any safety improvement provided by the enhanced braking technology. It is somewhat likely that drivers would increasingly disregard RCVW informs and alerts over time if they become desensitized to the warnings.

Other Factors Subsection

Non-Human Factors refer to the fact that some crashes result from vehicle failure or other circumstances a driver cannot control. The National Highway Traffic Safety Administration (NHTSA) reports that 6 percent of crashes do not involve human factors. RCVW is not expected to prevent crashes caused by non-human factors; therefore, the baseline (i.e., starting point) for using the crash data method to estimate RCVW is 94 percent, although users can change this number if desired.

Software and Hardware Reliability maturity values can be entered by the user to reflect the initial reliability of the software, hardware, and communications systems to provide the proper warnings.

Net Effectiveness is calculated using inputs from the *Market Penetration* section and other cells in the *Crash Data Method* section. *Cumulative Crash Reduction* is the sum of the estimated number of crashes *reduced* during the analysis period. *Benefit* is based on *Cumulative Crash Reduction*, the assumed severity distribution in the *Severity* section, and the cost of crashes of different severity levels.

Crash Data Method								
	Human Factors			Other Factors		Applicability/Effectiveness	
	Proper Use	Distraction Factor	Risk Compensation Factor	Non-human Factors	Software and Hardware Reliability	Crash Data-Derived Applicability	Net effectiveness
baseline	80%	99%	100%	94%	90%	21.7%	14.6%
ultimate value	100%	100%	90%	94%	99%	22.5%	18.8%
years until t_{10}	5	5	3		3	3	
year of t_{10}	2025	2025	2023		2023	2023	
t_{90}-t_{10}	5	5	3		5	5	
year of t_{90}	2030	2030	2026		2028	2028	
				Cumulative Crash Reduction			5,897
				Benefit ($ billions)			14.5

Figure 5. Crash Data Method Section

Crash Data-Derived Applicability Subsection

For *Crash Data-Derived Applicability*, values are taken from crash data and crash narratives. The value entered as the *Baseline* represents the subjective likelihood (based on a reading of crash narratives) that train-vehicle crashes at both active and passive HRIs would be mitigated by connected vehicle technology. Users specify input for the *future* value. Future work may focus on breaking down this factor by crash severity.

Crash Data-Derived Applicability (Inputs)			
Crash Type Category	Effectiveness	% of crashes (baseline)	% of crashes future
NA	0%	54.3%	55%
DUI/OWI	25%	19.1%	15%
Weather	25%	4.7%	5%
unclear/NEI	50%	12.3%	15%
did not notice	100%	9.6%	10%
	Total:	100%	100%

Figure 6. Crash Data-Derived Applicability

Crashes are classified into six categories according to the expected applicability of RCVW.

- Not Applicable (e.g., suicide, vehicle chasing with train, left the vehicle on track, etc.)
- Driving Under the Influence (DUI)/Operating While Intoxicated (OWI)
- Weather-related
- Unclear/Not Enough Information (NEI)
- Did Not Notice the Train

Effectiveness indicates the potential effectiveness of the RCVW. The research team estimated default values after evaluating seven years of crash narratives from Kentucky and Michigan.

Users may change the names of crash categories and related percentage effectiveness.

Default inputs for the *Percentage of Crashes (Baseline)* are derived from over 700 state police crash report narratives from Kentucky and Michigan covering the 2013-2019 period. Only incidents that took place at HRIs are included in these figures. Also, note that 2019 Kentucky police crash report narratives were not available during this project.

Future values may be input by the user if the percent applicability for each crash category is expected to change.

3.2.3 CRF Method Section

This section is populated with CRF data for analogous countermeasures selected from the USDOT CMF Clearinghouse. The average (i.e., mean) of analogous CRFs of connected vehicle applications at highway intersections are selected. *Cumulative Crash Reduction* is the sum of the estimated number of crashes saved per year. *Benefit* is based on the *Cumulative Crash Reduction* cell, the assumed severity distribution in the *Severity* section, and the cost of crashes of different severity levels.

3.2.4 User-Defined Method Section

If a user prefers to input estimates of effectiveness from other research, they enter data in the *User-Defined Method* section. The *Baseline* estimate comes from *Frequency of Target Crashes for IntelliDrive Safety Systems* (Najm, Koopmann, Smith, & Brewer, 2010) as listed on the *Other Studies* sheet. *Cumulative Crash Reduction* is the sum of the estimated number of crashes eliminated per year. *Benefit* is based on *Cumulative Crash Reduction*, the assumed severity distribution in the *Severity* section, and the cost of crashes of different severity levels.

	CRF Method (effectiveness)
baseline	14.8%
ultimate value	14.8%
years until t_{10}	3
year of t_{10}	2023
t_{90}-t_{10}	5
year of t_{90}	2028
Cumulative Crash Reduction	4,671
Benefit ($ billions)	11.5

Figure 7. CRF Method Section

	User-Defined Method (effectiveness)
baseline	25.0%
ultimate value	25.0%
years until t_{10}	3
year of t_{10}	2023
t_{90}-t_{10}	5
year of t_{90}	2028
Cumulative Crash Reduction	7,890
Benefit ($ billions)	19.4

Figure 8. User-Defined Method Section

3.2.5 Severity Section

Data on average crash cost (by crash type – KABCO) are derived from NCHRP report 755 (Brod, 2013) and have been updated to 2020 dollars. Users can also obtain values from local data. User-defined inputs are the *Baseline*, *Future*, *Years Until t_{10}*, and *Penetration Time* (t_{90}-t_{10}). Default *Baseline* percentages for each crash type are taken from FRA's inventory of highway crossing crash data for 2013-2019. *Baseline* percentages are applied to all crashes, while *Future* percentages are applied to the crashes that RCVW cannot mitigate, which theoretically should be more severe. As such, the percentage of fatal crashes in the future could be higher than the baseline value, although the total number of fatal crashes would be lower.

Severity	K (fatality)	A (major injury)	B (minor injury)	C (possible injury)	O (Property damage only)	Total
average cost	$13,914,052	$5,083,219	$771,216	$78,778	$21,006	
baseline	11.5%	15.9%	4.8%	1.5%	66.3%	100%
future	11.5%	15.9%	4.8%	1.5%	66.3%	100%
years until t_{10}	1	1	1	1	1	
year of t_{10}	2021	2021	2021	2021	2021	
t_{90}-t_{10}	60	49	49	49	49	
year of t_{90}	2081	2070	2070	2070	2070	

Figure 9. Severity Section

3.2.6 General Parameters Section

Users-defined inputs are *Baseline Year*, *Baseline Train-Vehicle Crashes Per Year*, and *Analysis Period*. The default *Baseline Year* is 2020. Crash data for a geographic area are used to populate *Baseline Train-Vehicle Crashes Per Year*. The default value of the average number of all train-vehicle crashes at all public HRIs in the United States from 2013 to 2019. Data are sourced from the FRA highway crossing crash database (Federal Railroad Administration, 2020). For *Analysis Period,* any value between 1 and 50 years may be selected.

General Parameters	
Baseline train-vehicle crashes per year	**1890**
Baseline Year	**2020**
Analysis Period	**25**

Figure 10. General Parameters Section

3.2.7 Plots Section

The four plots in this section (see Figure 11) capture trends in (1) percent RCVW market penetration by year, (2) percent net effectiveness by year, (3) total expected crashes by year, and (4) cumulative crash costs over the user-defined analysis period. Plots update automatically when input cell values are modified.

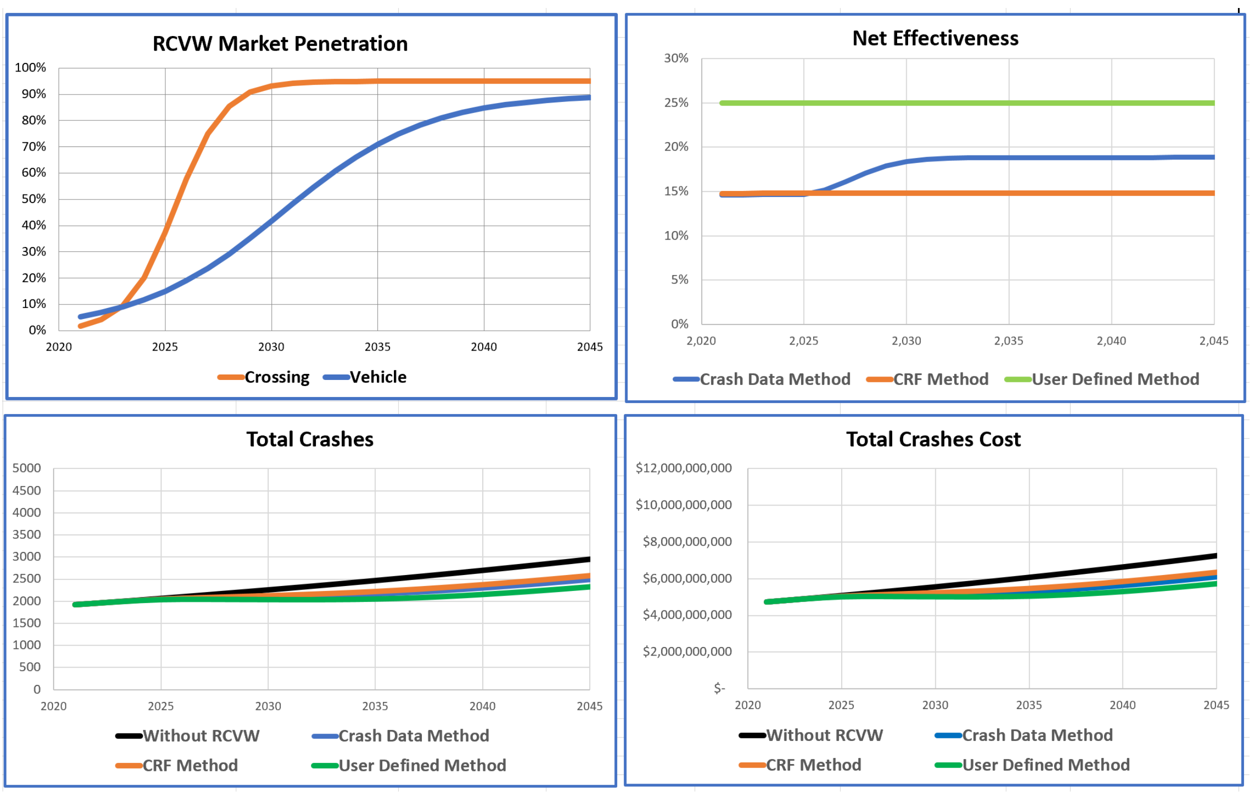

Figure 11. Plots Section

3.2.8 Instruction Sheet

The *Instruction Sheet*, found in the second tab of the Microsoft Excel workbook, provides a quick reference for all sheets and their main components. For user convenience, description cells on this page are hyperlinked to the corresponding locations on subsequent worksheets (i.e., tabs).

3.2.9 Market Penetration Sheet

This sheet details the intermediate calculation used in the *Market Penetration* section of the *Inputs & Graphs* sheet. Calculations are based on the logistic functions (S-shaped curve), which are often adopted to model technology deployment. The generalized logistic function (i.e., Richards' curve) is used because it accepts a variety of inputs, affording flexibility in shaping curves. Richards' curve for the specific case of maximum growth rate at time M is implemented in *Market Penetration* and *Effectiveness*, which lets users enter different values to forecast the future of connected vehicle technology safety.

$$Equation\ 1: Y(t) = A + \frac{K - A}{1 + e^{-B(t-M)}}$$

Where:

A is the lower limit (user input)

K is the upper limit (user input)

B is the growth rate B

t represents the current year

M represents the year of 50 percent market penetration (also the point of maximum growth rate)

$$Equation\ 2: Growth\ Rate = \frac{2 * \ln(9)}{t_{90} - t_{10}}$$

Where:

t_{90} is the time until market penetration reaches 90 percent

t_{10} is the time until market penetration reaches 10 percent

$$Equation\ 3: Logistic\ Parameters = \frac{(Years\ until\ t_{10}) + Growth\ Rate}{2}$$

Data for cells shaded blue come from the *Inputs & Graphs* sheet. Data for cells shaded brown populate Column D on the *Crash Data Method*, *CRF Method*, and *User-Defined Method* sheets.

3.2.10 Severity Sheet

This sheet details the intermediate calculation used in the *Severity* section of the *Inputs & Graphs* sheet. Data for cells shaded blue come from the *Inputs & Graphs* sheet. Data for cells shaded brown populate Column M on the *Crash Data Method*, *CRF Method*, and *User-Defined Method* sheets.

3.2.11 Effectiveness Sheet

This sheet details the intermediate calculations used in computing the effectiveness of each of the analysis methods. Data in cells shaded blue come from the *Inputs & Graphs* sheet. Data in cells shaded brown populate Column E on the *Crash Data Method*, *CRF method*, and *User-Defined Method* sheets.

3.2.12 Crash Data Method Sheet

The intermediate calculation for the crash data method section is in the *Inputs & Graphs* sheet. This spreadsheet calculates the number of crashes on HRIs with RCVW and without RCVW year by year. Data in cells highlighted in blue comes from the *Inputs and Graphs* sheet (columns M, N, and O also get info from the *Severity* sheet). Data in cells highlighted in brown goes to the *Inputs and Graphs* sheet.

3.2.13 CRF Method Sheet

The intermediate calculation for the CRF method section is in the *Inputs & Graphs* sheet. This spreadsheet calculates the number of crashes on HRIs with RCVW and without RCVW year by year. Data in cells highlighted in blue comes from the *Inputs and Graphs* sheet (columns M, N, and O also get info from the *Severity* sheet). Data in cells highlighted in brown goes to the *Inputs and Graphs* sheet.

3.2.14 User-Defined Method Sheet

The intermediate calculation for the User-Defined method section is in the *Inputs & Graphs* sheet. This spreadsheet calculates the number of crashes on HRIs with RCVW and without RCVW year by year. Data in cells highlighted in blue comes from the *Inputs and Graphs* sheet (columns M, N, and O also get info from the *Severity* sheet). Data in cells highlighted in brown goes to the *Inputs and Graphs* sheet.

3.2.15 Traffic Moment Growth Sheet

The *Traffic Moment* sheet is used to calculate the growth factor for traffic and crash prediction. The train and Annual Average Daily Traffic (AADT) by functional class and area type come from FRA’s safety database, which takes account of both the highway vehicle traffic and rail train traffic at the railroad crossing.

3.2.16 CRF List Sheet

This sheet includes CRFs of analogous countermeasures used in the tool from the USDOT CMF clearinghouse.

3.2.17 Other Studies Sheet

This sheet is provided for users who may wish to use effectiveness estimates from other research. Default is estimated from *Frequency of Target Crashes for IntelliDrive Safety Systems* (Najm, Koopmann, Smith, & Brewer, 2010).

3.2.18 Crash Cost Sheet

This sheet includes crash average costs by severity derived from the TRB NCHRP report 755 (updated to 2020 dollars using CPI and real income growth). Users also can define these inputs based on local data.

3.2.19 National Extrapolation Sheet

This sheet includes the crash counts from Kentucky and Michigan used in the analysis. These crashes are based on state police crash report databases and the FRA highway-rail crossing crash database. Users also can update these inputs based on local data for their analysis region.

3.3 Benefit Analysis

Cost estimates for RCVW-type systems are likely to be highly dependent on CAV technology. Therefore, this study focused on enumerating the benefits of the RCVW-type system. HRI accident data were obtained from FRA (FORM FRA F6180.57) for Kentucky, Michigan, and the US for the years 2013 to 2019. Kentucky and Michigan State Police crash data were then obtained for all crashes involving railroad equipment for the same period.

For Kentucky, FRA crash data were compared to state agency data. Over the 7-year period, 287 total crossing crashes (i.e., non-suicide) were located in both datasets. Fourteen crashes were found only in the FRA dataset, while 86 were found only in the Kentucky State Police dataset. Figure 12 depicts these findings in a Venn diagram.

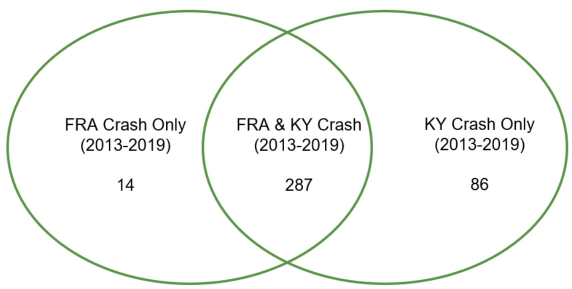

Figure 12. KY Highway Rail Crashes from the FRA vs KY State Police

Similar results were found for Michigan, as presented in Figure 13.

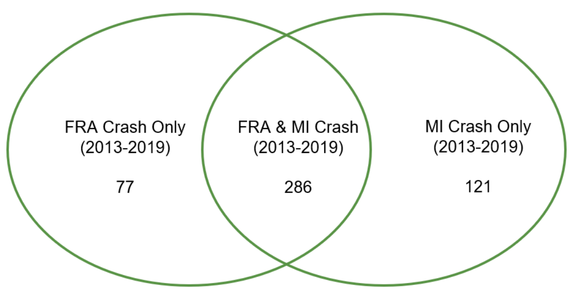

Figure 13. MI Highway Rail Crashes from the FRA vs MI State Police

To determine the reasons the two databases differ, crash narratives were examined for all Kentucky and Michigan records (FRA and State Police). Additional information was obtained by interviewing data stewards from each agency. Reasons for differences include:

- Crashes in the FRA database but not in the state police database
  - The driver did not report the crash to the local police
  - An error of omission
  - Crashes in one database not meeting a "reporting threshold" for the other database (all crossing crashes need to be reported in the FORM FRA F 6180.57)
  - Errors in matching fields (e.g., the one date that was wrong)
    - The incident ID HES423913G in the FRA database was recorded on 2013/08/14, but the MI state police database recorded the crash on 2013/08/15)
  - A police report was later filled in by the desk sergeant (possibly with a different date, e.g., for insurance purposes)
  - No police response (not needed or requested by the driver)
  - Filled out by citizens
  - Not found by the query
  - Crashes not meeting a "reporting threshold" for the state police report database (MI uses $1000 and KY uses $500; both are relatively low compared to other states)
- In the state police database but not in the FRA database
  - The railroad crew may not have known about the crash
  - An error of omission
  - The collision did not involve a train but was near a crossing (e.g., the rear end of a highway traffic queue)
- Other possible reasons
  - FRA and states do not pursue reconciliation of databases
  - A corrupt or incomplete copy of one or more of the databases

It is recommended that state agency crash data be used to supplement and/or validate FRA crash data. The next sections present ddRailCAT benefit analyses for Kentucky and Michigan, which are in turn used to extrapolate to benefits for the nation. A benefit analysis was completed for subcategories of public crossings. For each state, the benefits were calculated using only FRA-identified crashes as a lower bound, and FRA+Police crashes comprised an upper bound. Subcategories include gated, signalized with no gates, all signalized, passive crossings, and all public crossings (see Table 1 and Table 2). Average ratios between the two states were then used to extrapolate the benefits that would accrue to crossings at a national level (see Table 3).

The default number of crashes as well as the analysis time period may both be easily changed using the ddRailCAT tool to provide benefit estimates for other states or national scenarios. The following tables present the results of the default benefit analysis conducted by the ddRailCAT development team. All analyses were conducted for a 25-year period. Benefits for Kentucky range from $207 to $350 million for active crossings and $66 to $112 million for passive crossings. Benefits for Michigan range from $253 to $428 million for active crossings and $131 to $222 million for passive crossings. Nationwide, predicted benefits range from $8.7 to $14.7 billion for active crossings and $6.84 to $11.6 billion for passive crossings.

Table 1. Cumulative Crash Reduction and Benefits for Kentucky Public Crossings

	Avg. Annual Crashes	25-Year Totals for …	Crash Data Method	CRF Method	User-Defined Method
		Gated Crossings			
FRA	11.4	Cumulative Crash Reduction	36	28	48
		Benefit ($ millions)	0.087	0.069	0.117
FRA+Police	17	Cumulative Crash Reduction	53	42	71
		Benefit ($ millions)	130	103	175
		Signal and Audible Crossings			
FRA	14.7	Cumulative Crash Reduction	46	36	61
		Benefit ($ millions)	0.113	0.089	0.151
FRA+Police	17.3	Cumulative Crash Reduction	54	43	72
		Benefit ($ millions)	133	105	178
		Active Crossings			
FRA	26	Cumulative Crash Reduction	81	64	109
		Benefit ($ millions)	199	158	267
FRA+Police	34.1	Cumulative Crash Reduction	106	84	142
		Benefit ($ millions)	262	207	350
		Passive Crossings			
FRA	9	Cumulative Crash Reduction	28	22	38
		Benefit ($ millions)	69	55	92
FRA+Police	10.9	Cumulative Crash Reduction	34	27	46
		Benefit ($ millions)	84	66	12
		All Public Crossings			
FRA	35	Cumulative Crash Reduction	109	86	146
		Benefit ($ millions)	269	213	359
FRA+Police	45	Cumulative Crash Reduction	140	111	188
		Benefit ($ millions)	345	274	462

Table 2. Cumulative Crash Reduction and Benefits for Michigan Public Crossings

	Avg. Annual Crashes	25-Year Totals for …	Crash Data Method	CRF Method	User-Defined Method
		Gated Crossings			
FRA	23.6	Cumulative Crash Reduction	74	58	99
		Benefit ($ millions)	181	143	242
FRA+Police	28	Cumulative Crash Reduction	87	69	117
		Benefit ($ millions)	215	170	287
		Signal and Audible Crossings			
FRA	9.6	Cumulative Crash Reduction	30	24	40
		Benefit ($ millions)	74	58	99
FRA+Police	13.7	Cumulative Crash Reduction	43	34	57
		Benefit ($ millions)	105	83	141
		Active Crossings			
FRA	33.1	Cumulative Crash Reduction	103	82	138
		Benefit ($ millions)	254	201	340
FRA+Police	41.7	Cumulative Crash Reduction	130	103	174
		Benefit ($ millions)	320	253	428
		Passive Crossings			
FRA	13.3	Cumulative Crash Reduction	41	33	56
		Benefit ($ millions)	102	81	137
FRA+Police	21.6	Cumulative Crash Reduction	67	53	90
		Benefit ($ millions)	166	131	222
		All Public Crossings			
FRA	46.4	Cumulative Crash Reduction	145	115	194
		Benefit ($ millions)	356	282	476
FRA+Police	63.3	Cumulative Crash Reduction	197	156	264
		Benefit ($ millions)	486	385	65

Table 3. Cumulative Crash Reduction and Benefits for USA Public Crossings

	Avg. Annual Crashes	25-Year Totals for …	Crash Data Method	CRF Method	User-Defined Method
		Gated Crossings			
FRA	881	Cumulative Crash Reduction	2749	2177	3678
		Benefit ($ billions)	6.76	5.355	9.045
FRA+Police	1133	Cumulative Crash Reduction	3535	2800	4730
		Benefit ($ billions)	8.69	6.89	11.6
		Signal and Audible Crossings			
FRA	236	Cumulative Crash Reduction	736	583	985
		Benefit ($ billions)	1.811	1.434	2.423
FRA+Police	301	Cumulative Crash Reduction	939	744	1257
		Benefit ($ billions)	2.31	1.83	3.09
		Active Crossings			
FRA	1116	Cumulative Crash Reduction	3482	2758	4659
		Benefit ($ billions)	8.56	6.78	11.5
FRA+Police	1431	Cumulative Crash Reduction	4465	3537	5974
		Benefit ($ billions)	11.1	8.70	14.7
		Passive Crossings			
FRA	774	Cumulative Crash Reduction	2415	1913	3231
		Benefit ($ billions)	5.939	4.704	7.947
FRA+Police	1126	Cumulative Crash Reduction	3513	2783	4701
		Benefit ($ billions)	8.64	6.84	11.6
		All Public Crossings			
FRA	1890	Cumulative Crash Reduction	5897	4671	7890
		Benefit ($ billions)	14.502	11.487	19.405
FRA+Police	2513	Cumulative Crash Reduction	7840	6211	10491
		Benefit ($ billions)	19.3	15.3	25.8

4. Driver Behavior Analysis of RCVW On-Road Testing

This section presents RCVW on-road testing at HRIs on surface roads and driver behavior analysis based on the data collected during the testing. RCVW can provide drivers with real-time graphical and audible warning messages of imminent rail crossing violations based on highway-rail connectivity. The section includes a brief introduction to the RCVW system, a description of RCVW deployment, driver recruitment, testing scenario design, and driver behavior analysis.

4.1 Introduction to RCVW

4.1.1 RCVW System Overview

RCVW is a hardware and software set that provides drivers with real-time visual and audible warnings of imminent rail crossing violations. As Figure 14 shows, RCVW is composed of two subsystems: a Roadside-based Subsystem (RBS) and a Vehicle-based Subsystem (VBS) (Sanchez-Badillo, Baumgardner, Paselsky, & Seitz, 2022). RBS is installed at the HRI to provide real-time crossing status to approaching highway vehicles by broadcasting SPaT, MAP, and RTCM messages. VBS is installed on the vehicle to receive messages (i.e., SPaT, MAP, and RTCM) from the RBS, apply GNSS position corrections, and determine what type of graphical and audible messages should be displayed.

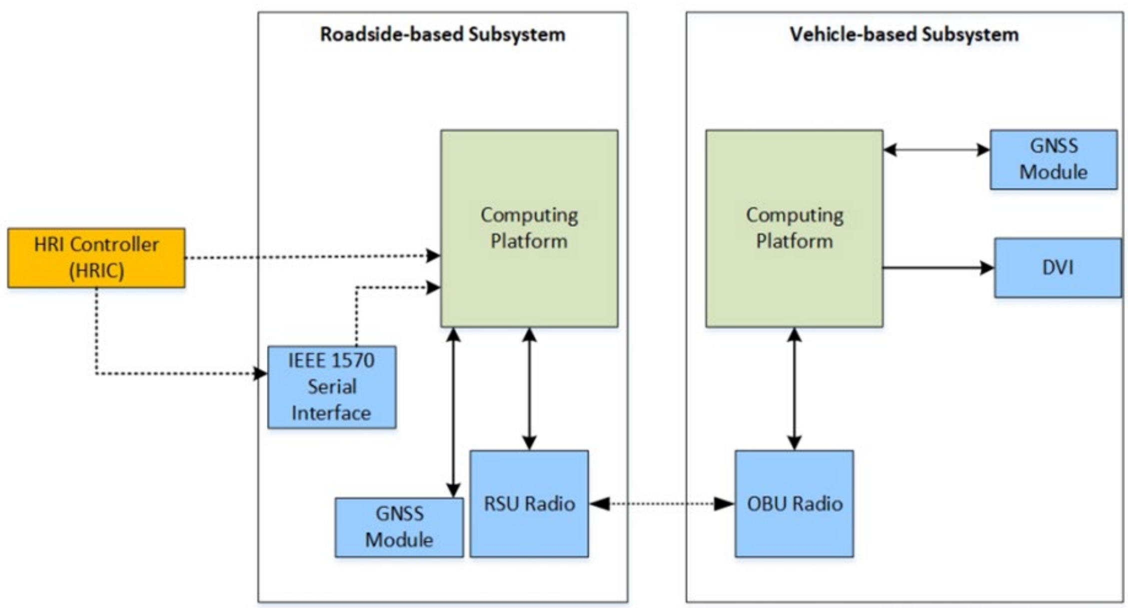

Figure 14. RCVW System Architecture Overview

4.1.2 RBS Components

The Computing Platform (CP) is the core of the RBS system. It receives the preemption signal from the HRI Controller. The preemption signal is generated when the HRI warning devices are activated. Alternatively, it can receive the preemption signal from the IEEE 1570 Serial Interface. The GNSS Module has built-in Real-Time Kinematics (RTK) technology to generate RTCM correction data. Based on the preemption signal, RTCM correction data, and the preconfigured MAP data, the CP generates SAE J2735 standard MAP, SPaT, and RTCM messages. These messages are forwarded from the CP to the Road Side Unit (RSU) Radio, which can be transmitted over DSRC in a predefined message frequency.

4.1.3 VBS Components

The CP in the VBS system receives MAP, SPaT, and RTCM messages from the On-Board Unit (OBU) Radio and forwards RTCM messages to the GNSS Module, where RTCM corrections can be applied. The RTK-level GNSS data then can be sent back to the CP. According to the HRI geometric information from the MAP message, the crossing status from the SPaT message, and the RTK-level GNSS data (including position, speed, acceleration, and heading information) from the GNSS Module, the CP determines if a violation is about to happen and determines which type of RCVW message should be displayed on the Driver-Vehicle Interface (DVI). The DVI is connected to the CP and receives RCVW messages from the CP. It uses a Liquid Crystal Display (LCD) with speakers that displays graphical and audible messages to drivers.

4.1.4 RCVW Messages

Depending on the HRI status and vehicle status, software residing on the VBS CP determines which message should be displayed on the DVI. Below are the six RCVW messages that can be displayed.

4.1.5 Active Crossing Ahead Alert

An Active Crossing Ahead Alert (Figure 15) is issued when the warning devices have been activated at the HRI and the RCVW-equipped vehicle is within the HRI Approach Zone, but no violations are predicted to happen. In such a situation, the Active Crossing Ahead Alert graphic and audio are displayed regardless of the vehicle speed to inform approaching drivers of an activated HRI. This message is also called Inform Message for RCVW Active in the RCVW Phase II project report (Sanchez-Badillo, Baumgardner, Paselsky, & Seitz, 2022).

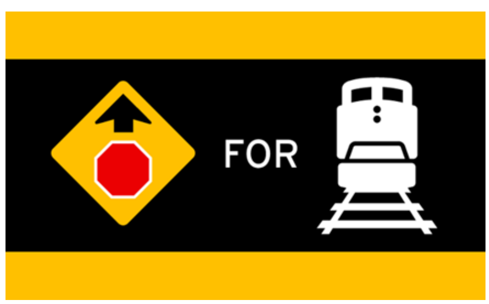

Figure 15. Active Crossing Ahead Alert

4.1.6 Active Crossing Violation Warning

Figure 16 shows the Active Crossing Violation Warning triggered when the HRI is activated and the RCVW system predicts an imminent violation. The Active Crossing Violation Warning and the audible warning advise the driver to take immediate action to avoid an HRI violation. This message is also named Warning Message for RCVW Warning in the RCVW Phase II project report (Sanchez-Badillo, Baumgardner, Paselsky, & Seitz, 2022).

Figure 16. Active Crossing Violation Warning

4.1.7 Vehicle Stopped on Tracks Warning

Figure 17 shows the Vehicle Stopped on Tracks Warning, which is issued when the vehicle stops on the track, regardless of whether the HRI is activated or not. It also comes with an audible warning to urge the driver to exit the track. This message is also named Clear HRI Warning Message in the RCVW Phase II project report (Sanchez-Badillo, Baumgardner, Paselsky, & Seitz, 2022).

Figure 17. Vehicle Stopped on Tracks Warning

4.1.8 RCVW System Unavailable Message

Figure 18 shows the RCVW System Unavailable Message that is displayed when the vehicle is within the HRI zone (i.e., the HRI Hazard Zone or HRI Approach Zone) but is not receiving expected SPaT or MAP messages from the equipped HRI. It is also triggered when the GNSS precision is degraded regardless of the vehicle position. This is also named the System Fault Message in the RCVW Phase II project report (Sanchez-Badillo, Baumgardner, Paselsky, & Seitz, 2022).

Figure 18. RCVW System Unavailable Message

4.1.9 RCVW System Available Message

Figure 19 shows the RCVW System Available Message, which is displayed when the HRI is not activated, the highway vehicle is within the HRI approach zone, no warnings or alerts are triggered, and the system is functioning correctly. It indicates the vehicle is receiving expected SPaT messages and MAP messages from the equipped HRI, and it also indicates the GNSS Module is getting positioning precision within specifications. This is also named the System Available in the RCVW Phase II project report (Sanchez-Badillo, Baumgardner, Paselsky, & Seitz, 2022).

Figure 19. RCVW System Available Message

4.1.10 RCVW System Ready Message

Figure 20 shows the RCVW System Ready Message, which is displayed when a highway vehicle is outside of the HRI zone but the GNSS precision is still within specifications. This is also referred to as System Ready in the RCVW Phase II project report (Sanchez-Badillo, Baumgardner, Paselsky, & Seitz, 2022).

Figure 20. RCVW System Ready Message

4.2 RCVW Deployment at Real-World HRIs and Data Collection

4.2.1 RBS Deployment Location

The project team worked with the E&LS Railroad to deploy two sets of RCVW RBS at two E&LS HRIs with active warning devices. As Figure 21 shows, they are both located along the County 426 M.5 Rd, Wells, MI, and are about 2056 ft (627 m) apart. There are flashing lights and gates at both HRIs.

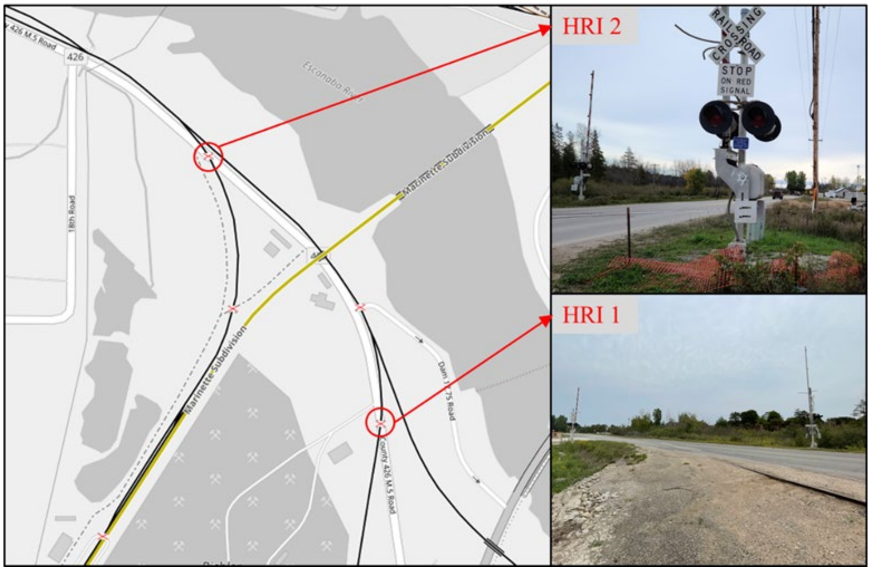

Figure 21. Two E&LS Active HRIs Instrumented with RCVW RBS

4.2.2 RBS Installation

The project team installed an RBS at each HRI. Figure 22 shows the RBS hardware installation at HRI 2. To ensure the wireless communication quality, the RSU Radio was installed on top of a 15 ft pole near the HRI. The pole was held by a heavy-duty tripod and sandbags to protect the RSU from falling. The GNSS Antenna was placed on top of a camera tripod at a surveyed spot. There is an E&LS HRI signal bungalow that houses the HRI equipment (including the HRI Controller) at each HRI. Due to FRA regulations, the project team did not install RBS hardware in the bungalow, but instead installed the hardware in the trunk of a Michigan Tech vehicle parked near the bungalow. The RBS was powered by the 110V AC from the bungalow.

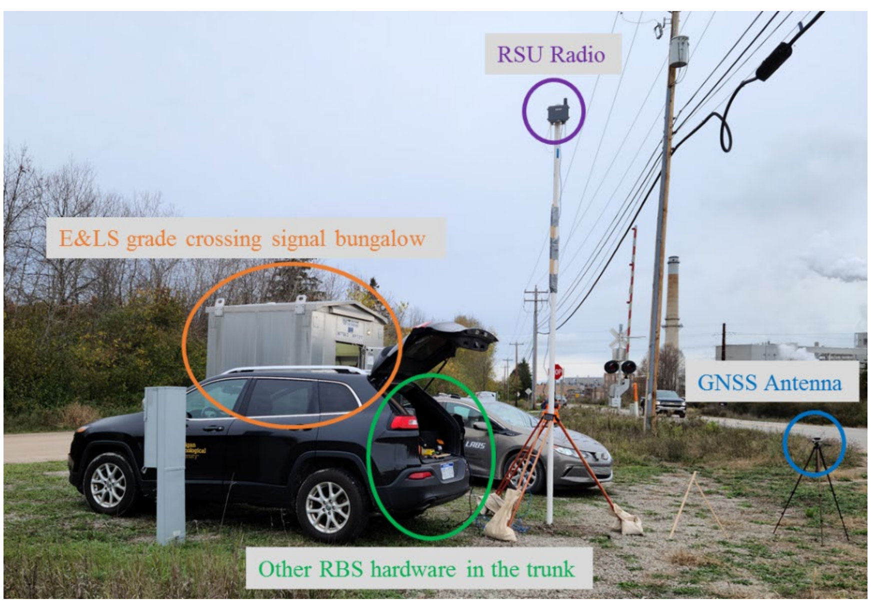

Figure 22. RBS Hardware Installation HRI 2

As shown in Figure 23, except for the RSU Radio and the GNSS Antenna, other RBS hardware (including the CP, the GNSS Module, the preemption signal source, and other required accessories) were installed in the vehicle's trunk. The trunk created a safe and waterproof workstation for the RBS hardware. In addition, a monitor, a mouse, and a keyboard, which were not part of the RCVW prototype, were also connected to the CP to allow the team to perform quick configuring and monitoring on-site. The MAP file for each HRI was generated following the steps documented in the RCVW Standard Operating Procedures (SOP) for SPaT, MAP, and RTCM Messaging (Baumgardener, 2021). The MAP file was uploaded to the CP. Please refer to the RCVW Standard Operating Procedures (SOP) for SPaT, MAP, and RTCM Messaging (Baumgardener, 2021) for all required technical steps on configuring the RCVW system.

Figure 23. RBS Hardware Hosted in the Michigan Tech Vehicle Trunk

4.2.3 Preemption Signal Source

The HRI Controller inside the bungalow could function as a preemption signal source for the RBS. However, FRA safety regulations precluded the project team from directly connecting the RBS with any equipment in the E&LS HRI equipment housing. Therefore, the project team decided to create an independent voltage-based preemption signal source to mimic the HRI Controller and connect it to the RBS CP (Figure 24). The preemption signal source consisted of a toggle switch, a DB15 interface, and a power cable. By flipping the toggle switch, a high voltage signal (i.e., 12V) representing "HRI is clear" or a low voltage signal (i.e., 0V) representing "HRI is activated" was supplied to the DB15 interface. The DB15 interface, which was connected to the CP, then forwarded the voltage-based preemption signal to the CP.

Figure 24. Preemption Signal Source

4.2.4 HRI Activation and Preemption Signal Operation

Since the RBS was not connected to the HRI Controller in the crossing, the activation of the warning devices and the operation of the preemption signal was performed manually based on communication between the field test commander (riding in the vehicle) and the signal maintainer. The communication protocol at instrumented HRIs is explained in more detail as part of the route description in Figure 35 in Subsection 4.4.2.

4.2.5 VBS Installation

The project team equipped the two Chevrolet Volt test vehicles (Figure 25) with the VBS system hardware and software. Each test vehicle was equipped with an LCD display fixed on a monitor mount (Figure 26). The monitor mount and the laptop mount were installed on the passenger seat floorboard. While this LCD display was not part of the RCVW prototype, the project team found it to be sufficiently similar to the original LCD display in the RCVW prototype. The LCD display was connected to the VBS CP via the High-Definition Multimedia Interface (HDMI) cable, The laptop mount was used to mount the laptop for vehicle Controller Area Network (CAN) bus data collection.

Figure 25. Two Chevrolet Volts Equipped with RCVW VBS

Figure 26. RCVW VBS DVI Placement

As Figure 27 shows, the VBS plate, including the CP, OBU Radio, and GNSS Receiver, were installed in the trunk of the test vehicles. The VBS plate was powered by the cigarette lighter in each of the testing vehicles.

Figure 27. RCVW VBS Plate Placement

As Figure 28 shows, the OBU Antenna and GNSS Antenna were deployed on the rooftop of each test vehicle. The remaining antenna was not part of the RCVW prototype but a part of the built-in dSPACE system that enabled vehicle CAN bus data collection in the testing vehicle.

Figure 28. VBS Antennas Placement

4.2.6 Camera Data Collection

The project team installed two webcams in each testing vehicle (Figure 29). The front camera was installed on the headrest to capture the DVI graphic and the traffic condition in the front. The facial camera was installed on the front windshield to capture the driver's facial movements.

[Figure 30](#) shows the front camera view and facial camera view of the cameras (note that the driver in the vehicle is a co-author of the report, not a participant).

Figure 29. Front Camera and Facial Camera Placement

Figure 30. Front Camera View and Facial Camera View

4.2.7 RCVW System Log Data Collection

The RCVW VBS was configured to log every RCVW message issued by the VBS, the message issue time, data from the GNSS Module, V2I messages (i.e., MAP and SPaT messages broadcasted by the RBS) received by the OBU, and system fault events. The RCVW system log can be used as supplementary data for human factor analysis.

4.2.8 CAN Bus Data Collection

As stated previously, each vehicle was equipped with a dSPACE system to capture vehicle CAN bus data. The project team connected the laptop to the dSPACE system on the vehicle and then executed the dSPACE ControlDesk software on the laptop to collect CAN bus data at 1000 Hz.

The data was then down-sampled to 10 Hz for human factor analysis. Table 4 shows the list of data fields that were collected.

Table 4. CAN Bus Data Fields

Field	CAN Bus Data Field	Unit or Format
1	Gas Pedal Position (of rotation angle)	%
2	Vehicle Acceleration	m/s^2
3	Torque at Axle	N·m
4	Acceleration in X	m/s^2
5	Acceleration in Y	m/s^2
6	Acceleration in Z	m/s^2
7	Brake Pedal Position (of rotation angle)	%
8	GNSS Speed	kph
9	GNSS Time	hh:mm:ss.s
10	GNSS Latitude	degree
11	GNSS Longitude	degree
12	HV Battery Pack Voltage	V
13	HV Battery Pack Current	A
14	HV Battery Pack State Of Charge	%
15	HV Battery Pack Current	A
16	Estimated Fuel Flow	g/s
17	Vehicle Distance Traveled	m
18	Vehicle Speed	kph

4.2.9 Technical Issues

During the preparation stage and the testing, the project team observed unexpected events regarding the RCVW system. By studying the RCVW system log, the team was able to identify these unexpected events and summarize five technical issues. The first three resulted in the RCVW System Unavailable Message displayed on the DVI. The fourth issue caused a false Active Crossing Violation Warning in the testing. The last issue on RCVW system log loss did not impact the testing but impacted the data collection, as described in the following subsections.

4.2.9.1 System Unavailable Due to Failure to Get RTK Positioning Accuracy on VBS

The RCVW VBS system is technically required to be in RTK state for acceptable operation according to the FRA RCVW SOP for Hardware and Software Configuration (Baumgardner, Paselsky, & Sanchez-Badillo, 2021). However, during the preparation stage, RTK was usually not achieved on VBS.

The project team attempted to resolve this issue by improving the survey accuracy of the survey spot for the RBS GNSS antenna, using a new survey spot, replacing the GNSS Module, and rebooting the VBS system. As none of these potential remedies were found to resolve this issue, the project team decided to configure the VBS to not rely on the RTK accuracy as a temporary solution. Investigation into this issue continued after the road test was finished. It was found that the Location Plugin in the VBS was too computationally intensive to keep up with the RCVW requirements.

4.2.9.2 System Unavailable Due to Failure to Get Location Data on VBS

During the preparation stage, the project team observed that the VBS sometimes failed to receive location data caused by the Location Plugin crashing down or the gpsd (a GPS service daemon) server (i.e., a service daemon that monitors the GNSS Module) not running well on the VBS. The project team solved this issue by restarting the Location Plugin and the gpsd server. To prevent this issue from reoccuring during the on-road testing, the project team verified the status of the Location Plugin and the gpsd server on the VBS on a regular basis and restarted them when necessary. This issue did not occur during the road test.

4.2.9.3 System Unavailable Due to Multiple HRIs being Close to Each Other

During the on-road testing, the project team observed that the VBS twice returned an error called "SPaT Data Not Received." This event did not happen frequently.

Investigation after the testing showed that this issue was caused by installing two sets of RBS at two HRIs close to each other. As a test vehicle transitioned from HRI 1 to HRI 2, the VBS locked in the MAP message of HRI 1 within an expiration time window. Therefore, the VBS was still expecting SPaT messages from HRI 1. However, since the vehicle was exiting HRI 1 and might travel out of communication range, the VBS could not receive SPaT messages from HRI 1, which would cause the error.

It should be noted that the RCVW prototype was not designed to work with multiple HRIs within close proximity of each other. This issue should be addressed in the later versions of the RCVW.

4.2.9.4 False Active Crossing Violation Warning

During the on-road testing, when a driver began to drive forward after the HRI gate was lifted, the system displayed an Active Crossing Violation Warning instead of the RCVW System Available Message. This was observed five times by the project team during the testing.

Investigation after the testing showed two potential explanations for this issue. First, the preemption signal operator may have been late in switching the toggle switch to the "HRI is clear" position. In this situation, the VBS was still operating in the "HRI is activated" state. Second, the DB15 conntector may have "loosened" from the RBS CP, resulting in low voltage (i.e., "HRI is activated" status message) sent to the CP. In both cases, the RCVW system evaluated the HRI as activated even when the warning devices were deactivated. While RCVW would permit a highway driver to advanced according to traffic rules, the VBS software would regard this as a violation and issue a warning based on wrong preemption signal status. If the preemption signal source is the HRI Controller, which does not rely on manual operation, there should be no time lag to delay the preemption signal.

4.2.10 RCVW System Log Loss

After the on-road testing, the project team determined that the RCVW did not always log events to the system log as configured. This issue occurred frequently; it was found that the log was not recorded 42.0296 percent of the time.

The investigation after the road tests showed this resulted from a misconfiguration in the journald.conf file on the CPs. It can be fixed by adding a "[Journal]" heading at the top of the file. While the log loss phenomenon had no impact on the road test, the project team was unable to trace the issue times of RCVW messages from the RCVW log file.

4.3 Human Factors Evaluation: Initial Field Test of RCVW Prototype

The project team conducted an initial field test and human factors assessment of the RCVW system by recruiting drivers to experience it on surface roads in Escanaba, MI.

Early human factors evaluations are useful for two main reasons. First, user acceptance of new technologies often drives their adoption. Second, technology is rapidly changing in connected vehicles, so a prototype evaluation in a more realistic environment provides insights into informative system development, design, and further research. The human factors assessment, which was designed within the constraints of the initial field test, was informative regarding driver perceptions of the system and their driving behavior. The setup was extensive because the field test route was on semi-rural surface roads with several HRIs. This study was empirical and exploratory and provided useful information about actual driver behavior in a real-world context that would be difficult to capture through other methods.

4.3.1 Background Research: Driver Decision-Making and Connected Vehicle Technology

Motorists' poor decision-making and non-compliance to warnings near HRIs continue to be major safety issues on the road (Klauer, Guo, Sudweeks, & Dingus, 2010) (Landry, Jeon, Lautala, & Nelson, 2019) (Lenne, Salmon, Beanland, Stanton, & Filtness, 2013) (Veinott, Linja, & Lautala, 2020) (Veinott, Lautala, Linja, & Nelson, 2021). FRA safety analyses have indicated that motorists understand general HRI information but do not always comply appropriately (Hao & Daniel, 2014). Hao and Daniel (2014) note that as the adoption of active warning devices has increased, drivers have shifted their strategies at those locations to negate some of the intended safety benefits provided by the devices.

Lenné, et al. (2011) divided driver violations into two classes of decisions: intentional and unintentional non-compliance decisions. Drivers engaging in intentional non-compliance may notice a train and active or passive warning devices, but violate them anyway (e.g., stop and go around the gates). The second category, unintentional non-compliance, is more prevalent as drivers fail to notice or attend to the devices or fail to detect the train. The RCVW prototype can potentially address both intentional and unintentional non-compliance by leveraging connected vehicle technologies and rail infrastructure and providing imminent violation and rail warning information to improve driver situation awareness and safety at HRIs.

Driving studies differ along the dimension of realism (Figure 31) and are most often conducted in the lab or driving simulators to maintain experimental control. Some studies are conducted on closed-loop tracks at automobile companies, highway, or rail training centers (Roozendaal, Johansson, Winter, Abbink, & Petermeijer, 2021). More naturalistic driving studies include incident analyses using the FRA safety database (Birrell, Fowkes, & Jennings, 2014) and video systems in personal cars such as the Naturalistic Driving Study (Lautala, et al., 2018). When introducing new technologies, driving on closed-loop routes or surface roads may provide information that is not available or noticeable in other study environments. Driving behavior in these enviornments may include speed and eye-gaze behavior. While these road studies are rare, they make up an important subset of empirical driver behavior studies. The goal of this study was to understand driver perceptions of this system after the driver experienced it in a connected vehicle environment

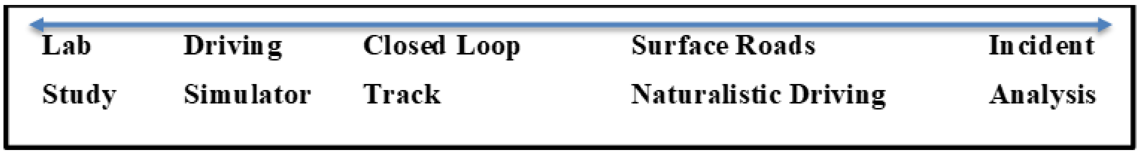

Figure 31. Human Factors Driving Research Contexts on Realism Dimension

4.3.2 Research Questions

The three research questions for the exploratory study were:

1. *Do drivers find the RCVW useful and easy to learn in a real-world driving context?*

   To explore this question, participant drivers completed two short, standard usability surveys after experiencing the RCVW at two HRIs. Drivers were interviewed briefly by one of the researchers to identify what RCVW information they recalled seeing, and to further understand their perceptions of the prototype system.

2. *Does the presence of the RCVW affect driver speed when approaching HRI with warnings activated? Does the effect depend on driver proximity to the HRI or the state of the HRI warning device (i.e., activated or not)?*

   To examine these questions, the team compared driving speed in two RCVW functional conditions and during two different driving segments: advanced warning segment (~ 200 m - 400 m before HRI) vs. closer to the HRI (within 200 m). Drivers received different warnings depending on their speed, location in the approach zone, and the state of the HRI warning devices (i.e., activated or not).

3. *Did the presence of the RCVW at an activated HRI affect driver eye-gaze behavior?*

   Part of the driver behavior analysis includes an analysis of the eye-gaze behavior. To explore this question, the team compared eye-gaze frequency outside the vehicle and at the RCVW system from coding the video data.

While the reliability of in-vehicle warning systems, such as the RCVW, is one of the key functions of a system integration test, an initial prototype test and usability assessment may provide additional information for future adoption and validation. Initial field testing leveraged best practices and any measures the team could control. Drivers were exposed to the system in a real-world scenario in the field study; with this two-pronged approach, the project team was able to examine the human-system integration and provide an early evaluation of the system.

4.4 Field Test Methods and Procedure

Because surface road field tests are rare and safety is essential in these studies, additional details about the methods and procedures to support other researchers and technology developers are provided in this section. This field test required two days of data collection and extensive preparation (e.g., system setup and institutional human subjects' approval), data processing and integration across multiple systems, and subsequent analysis.

4.4.1 Participants and Prescreening

For the field study, 15 participant drivers (i.e., 13 males and 2 females) with a current driver's license and normal to corrected vision completed a 12-mile loop in an RCVW instrumented connected testing vehicle (i.e., Chevrolet Volt) on surface roads near Escanaba, MI. Drivers were 39 years on average (range 19-62 years) with 22.9 years (SD = 12.2) of driving experience on average. Drivers reported driving 21.9 hours per week and being experienced with rail-HRIs (driving across about 38 per month). To explore their perception of HRIs, drivers were asked to rate how dangerous HRIs typically were in their experience. Participants reported low danger with an average of 3.0 (SD = 2.07) on a 10-point dangerous scale.

Drivers were recruited from the local community. To be eligible for the study, the drivers were required to have a minimum of two years of driving experience, no accident or ticket history in the last six months, and no current use of medication or recreational drugs that could affect safe driving. To reduce any potential self-selection process, recruitment ads provided the initial eligibility requirements but did not mention the RCVW system. The entire study took 60 minutes and participants received $20 to compensate for their time.

The study protocol was approved through a full review by MTU's human subjects review board in Institutional Review Board (IRB) report 1657799-6. Driving data from one driver was lost when the laptop in the Volt was inadvertently closed during the drive. Another participant did not provide consent for their video data to be analyzed. Therefore, the sample size differs slightly depending on the analysis.

To ensure safety, drivers also completed two pre-screening processes, one to determine initial eligibility and a second at-site screening on the day of the field test, which is standard in road tests. At-site screening include only the questions about accidents or moving violations after they were first recruited, and medication or recreational drug use that might affect drivers during the study.

4.4.2 Field Test: Route and Connected Vehicle Setup

The field test used vehicles instrumented with the RCVW system, as described in Subsection 4.2.2. Drivers drove a Chevrolet Volt on a 12-mile loop on surface roads with 7 HRIs near Escanaba, MI. The RCVW system and data collection setup in the Volts are described in Subsection 4.2.2. Figure 32 depicts data from the actual route with crossings numbered and Table 5 provides the types of warning devices for each of the seven HRIs along the route. It also identifies the two HRIs instrumented with the RCVW (i.e., HRI 1 and HRI 2) and the one with intentional activation by the research team (i.e., HRI 1). The team compared driver behavior at the instrumented HRIs as well as between the instrumented and baseline HRI 4 (with no functional RCVW). The posted speed was 45 mph for most of this route.

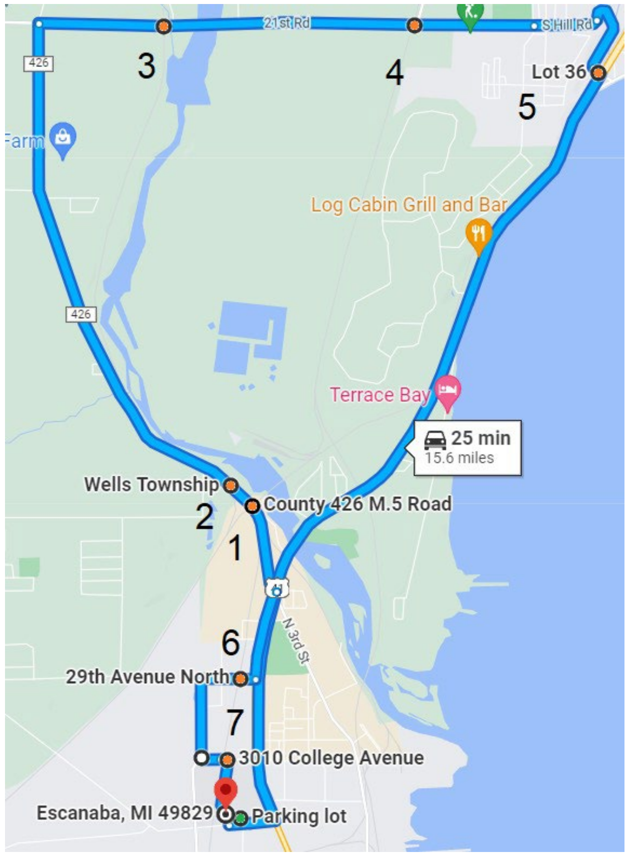

Figure 32. 12-Mile Driving Loop Map with Seven Rail Crossings Numbered

Table 5. Warning Device Types and RCVW Availability Along the Route

HRI Number	Warning Device Type	RCVW Functional	Warning Devices Activated
1	Active (Lights and Gates)	Yes	Yes
2	Active (Lights and Gates)	Yes	No
3	Passive (Crossbucks and Yield)	----	----
4	Active (Lights and Gates)	No	No*
5	Active (Lights and Gates)	No	No*
6	Passive (Crossbucks and Stop)	----	----
7	Passive (Crossbucks and Stop)	----	----

*No activation by the research team. Passing revenue trains caused activation for some of the drivers.

The driving route was chosen for its overall length, inclusion of multiple HRIs with both active and passive warning devices, relatively light highway traffic, and consistent speed limits. While the entire route included seven HRIs, only HRI 1, HRI 2, and HRI 4 were part of the current analysis. Figure 33 shows what drivers saw as they entered the two HRIs instrumented with RCVW (i.e., HRI 1 and HRI 2) and Figure 34 shows the baseline HRI without RCVW (i.e., HRI 4). For the typical driver, these HRIs look functionally similar (e.g., straight road entrance to HRI, rural setting, none with adjacent roads/short storage, posted speed, limited obstruction, etc). As indicated in Table 5, for HRI 1 the warning devices (and thus RCVW) were activated, while for HRI 2 the warnings (or RCVW) were not activated. To address the research questions, the team compared each driver's behavior at HRI 1 to their driving behavior at HRI 2 and HRI 4. HRI 4 served as a baseline control comparison.

Figure 33. HRI 1 (Left) and HRI 2 (Right) Instrumented with RCVW and Active Warning Devices (Lights and Gates) (Photo Courtesy: Google Maps)

Figure 34. Baseline HRI 4, Active Warning Devices (Lights and Gates) (Photo Courtesy: Google Maps)

The test vehicles instrumented with RCVW were first connected and tested for the proper system functioning. Each connected vehicle included an experienced observer (i.e., field test commander) on the passenger seat who conducted the initial standard vehicle safety briefing, provided route instructions to the driver, and was responsible for communicating (via text messages) the proper timing of the warning device (and RCVW) activation at HRI 1 to the signal maintainer and the RCVW signal controller. The communication steps (Figure 35) included the following:

1. Text “Departure” when the vehicle left Bay College.
2. Text “Activation” as the vehicle turned from US-41 to County 426 M.5 Rd.
3. Immediately after receiving the “Activation” text, the HRI signal maintainer activated the warning devices at RCVW instrumented HRI 1 and the RCVW signal controller activated the RCVW. Once the test vehicle had stopped behind gates at HRI 1, the signal maintainer waited for 10 seconds before deactivating the warning devices. This was followed by the deactivation of RCVW by the signal controller immediately after the lights stopped flashing.

4. If a train activated warning devices at RCVW instrumented HRI 2, the RCVW signal controller activated the RCVW. Otherwise, no action was taken.

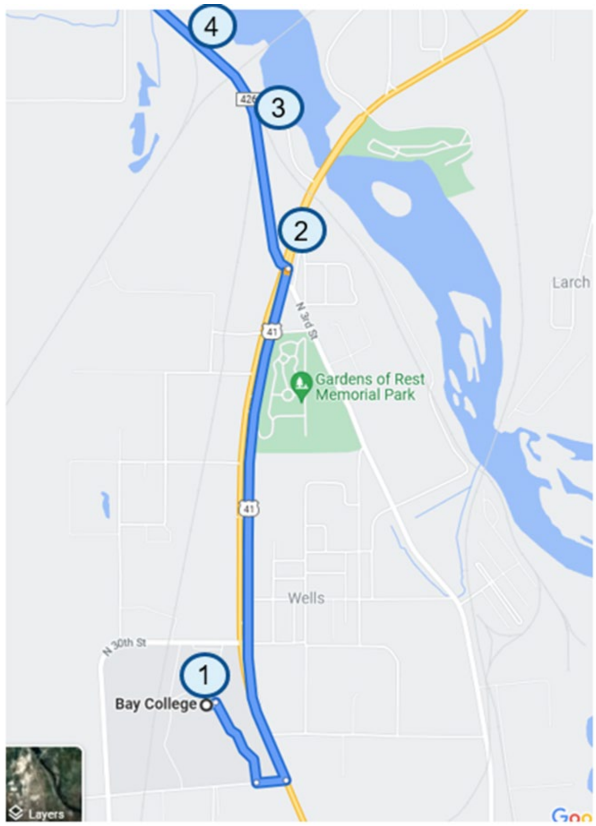

Figure 35. Communication Protocol for HRI 1 Activation

Drivers were staggered to start the route every 30 minutes. Set up started at about 6:00 am, and the first participant was scheduled for 9:00 am each day and heavier traffic times (e.g., shift changes) were avoided. As is typical with field studies, the local authorities were notified several weeks in advance of testing as E&LS rail personnel and Michigan Tech researchers were frequently working at the two instrumented HRIs. Fortunately, the weather was mild on both days of the testing with partly sunny condtions and no precipitation. Fourteen of the 15 drivers experienced light traffic.

4.4.3 Procedure

The field study was completed during a two-day period with two vehicles, two observers, and one human factors researcher collecting the pre-drive and post-drive data.

Each participant completed the study in approximately 60 minutes following the steps presented in Figure 36. Drivers who passed the initial pre-screening received the RCVW training document to review prior to the road test. On the day of the driving portion of the study, each participant was greeted at the starting point (i.e., the Bay College parking lot), completed the at-site screening and consent form, took a short HRI knowledge test, and then reviewed the five RCVW system messages and warnings. Next, each driver completed a standardized safety briefing in the vehicle with the observer, and the driver was shown the route. Drivers were instructed to drive the 12-mile route as they normally would (the in-vehicle research team member provided instructions for turns during the drive), obeying all the rules of the road, speed limit, etc. Following the 30-minute drive, each participant completed a post-drive questionnaire and a semi-structured interview with a human factor researcher. After the interview, participants were debriefed and compensated for their time.

Figure 36. Overview of Study Procedure for Each Participant

4.4.4 Questionnaire Measures: SUS, PSSUQ, and Rail Knowledge Test

For the usability analysis, the team integrated two standard system usability questionnaires that have been used to evaluate vehicle interfaces from infotainment to navigation (Götze, Schweiger, Eisner, & Bengler, 2016); (Li, Chen, Sha, & Lu, 2017); (Walch, Jaksche, Hock, Baumann, & Weber, 2017). Participants completed the 20-item survey which combined the 10-item System Usability Scale (SUS) (Brooke, 1996) and a subset of relevant items from the Post-Study System Usability Questionnaire (PSSUQ) (Lewis, 2002). Readers can find the SUS questionnaire in Appendix A and the PSSUQ questionnaire in Appendix B. The team used a 7-point Likert scale (i.e, strongly disagree to strongly agree) and an option for NA in both scales for consistency. The SUS is reliable with small sample sizes (e.g., 8-12 users) (Stetson & Tullis, 2004). Both scales have high internal reliability: SUS has an alpha coefficient of .91 (Orfanou, Tselios, & Katsanos, 2015), while PSSUQ has an alpha coefficient of .92 (Fruhling & Lee, 2005).

As crossing knowledge awareness is a factor in driver performance, participants completed a 10-item rail knowledge test that has been used in previous research (Landry, Jeon, Lautala, & Nelson, 2019); (Linja, Lautala, Nelson, & Veinott, 2020). Average knowledge test scores were 8.2 (out of 10). Consistent with the overall rail knowledge test, drivers reported that their knowledge of what to do at railroad crossings was strong (M = 9.2 out of 10 with SD = 1.58).

4.4.5 User Semi-Structured Interviews

As the RCVW is a prototype in-vehicle warning system, participants were interviewed about their experience with the system, in addition to completing the usability questionnaires.

Specific questions were:

a) You just experienced a new system; we would like to start by asking you about the information it provided. What information did the system provide? When was it provided? What did it mean?

b) What did you notice about the system (e.g., Message content, message timing, etc.)?

c) After experiencing it for this drive, in your opinion, how useful or helpful would the system be? Why or why not?

4.4.6 Speed and Location Data

CAN Bus data and video data from the research setup were used in the analysis. The different CAN Bus data fields are provided in Table 4, while Table 6 lists the data and related calculations for driving behavior analysis, followed by brief explanations of selected calculated measures.

Table 6. Data Sources and Calculated Measures for Speed, Distance and Driving Behavior Analysis

Calculated Measures	*Data Source*	*Description*
Crossing Time and Distance Calculations	CAN bus data Google maps, Video data	Crossing time and distance locations needed to be calculated from lining up the CAN and GNSS from Google maps and driving videos. Time was triangulated with the Can bus data format to connect the two data sources. These measures were compared and checked against other measures (e.g., odometer) to verify the plotted data.
Vehicle Distance from HRI	Can bus data, GNSS coordinates	Vehicle distance from the HRI was calculated based on the GNSS coordinates and the vehicles's odometer reading, reconstructed route from the vehicle CAN bus data, and Google maps. GNSS distance between two points' odometer closely matched the odometer distance.
RCVW Message/Sound timing, Crossing timing	Video data	Timing of the messaging and head-movements. Coded message start and end time, sound time, and crossing timing with two coders for reliability.
Eye-movements	Video data	To coders provided time-stamped frequency counts of three driver eye-movements during the HRI: outside the vehicle to the right, left, and at the RCVW interface.
HRI Location	Odometer, Google maps	Establish/Validate the location of the HRI and to calculate 400 m before and 50 m after each crossing point (Figure 40, Figure 41).

- CAN bus data
    - Speed from the vehicle's CAN bus (speed data were transformed for the statistical analysis but plotted using untransformed kph)
    - GNSS coordinates used longitude and latitude combined (needed up to five decimal places for accuracy)
    - Odometer readings from the CAN bus were used to establish/validate the location of the HRI and to target driving windows
- Video data was used to capture RCVW message timing, crossing timing, and three categories of eye-movement frequency and timing
- Vehicle distance from the HRI was calculated based on GNSS coordinates and RCVW messages and warnings were overlaid on the visualizations (Figure 40, Figure 41) from the video data based on time (in seconds) from the crossing.

4.4.7 Video Coding Scheme to Capture Eye Gaze Behavior

To understand if the presence and/or activation of the RCVW changed driver behavior, driver eye-gaze behavior was coded from the videos. Other measures captured were the content and timing of the RCVW messages or warnings and times for events (e.g., at HRI, gates, sound). These were integrated into the driver behavior figures presented in Subsection 4.5.3. The video coding scheme was developed collaboratively with human factors and rail experts. Eye gaze behavior included: 1) looking left out of the vehicle, 2) looking right out of the vehicle, or 3) looking at the RCVW display (middle console inside the vehicle). Eye-gaze behavior toward the observer or odometer were not part of the coding or analysis as they were not pertinent to the main research question. Two coders (i.e., researchers on the team) achieved an inter-rater reliability (Cohen Kappa > 0.7) after several rounds of gaze behavior training on a subset of crossings from the video data[1]. After this was established, one coder was able to complete the data coding for all the HRI videos.

4.5 Field Test Results

The test results included analysis of the usability assessment questionnaire responses (SUS and PSSUQ), interview responses, driving behavior, and eye-gaze behavior. The usability assessment focused on overall driver perceptions and experiences with the system, while the driving analysis focused on changes in each driver's behavior related to the presence of RCVW. While no HRIs along the route were identical, they were functionally similar for drivers in several ways. However, the team could not separate the impact of the RCVW warning on driving behavior from the HRI order, so researchers explored driving behavior compared to other HRIs.

[1] Inter-rater reliability is the extent to which two coders agree when using the coding scheme. Cohen's Kappa is a percent agreement measure for inter-rater agreement that controls for chance agreement. Cohen's Kappa of more than 0.7 is a strong inter-rater agreement.

4.5.1 Usability Assessment Questionnaires

Research Question 1: Do drivers find the RCVW prototype useful and easy to learn after experiencing it in a real-world driving context?

For Research Question 1, the team analyzed data from both the usability questionnaires and interviews. The SUS was used to assess the RCVW system's learnability and operativity, while the PSSUQ focused on interface and information quality.

Figure 37 shows the correlation matrix for all the questionnaire items used and shows that some SUS (blue text) and PSSUQ (red text) items were positively correlated. For example, as shown in the top row of the correlation matrix, the SUS item *easy to use* correlated with the PSSUQ items *organization of information was clear* and *overall satisfaction* whereas the SUS item *confident using system* correlated with the PSSUQ item *easy to learn*. Several PSSUQ items were intercorrelated as well (indicated by the frequency of blue dots near the items in red).

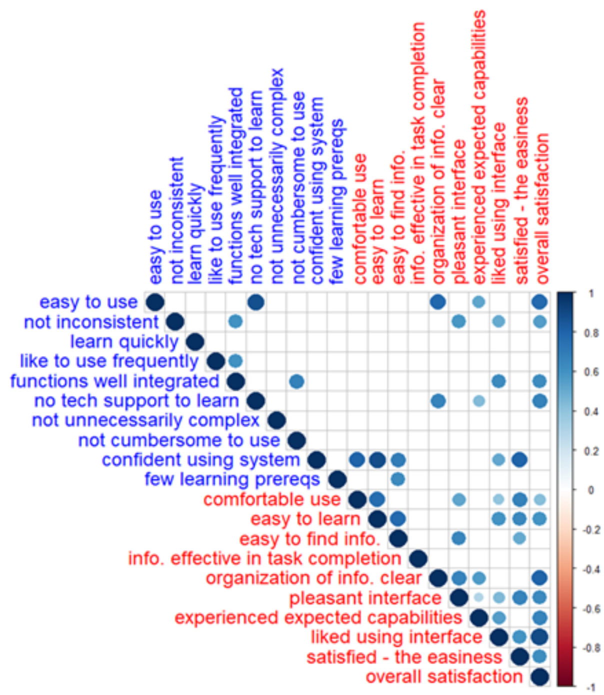

Figure 37. Significant Pearson Correlations Between SUS and PSSUQ Items (Blue Indicates the SUS Measures; Red Indicates the PSSUQ Measures; Darker Circles Indicate Higher Correlation)

Usability scales are typically reported as a total score or by scale dimensions. Figure 38 shows the overall average for each SUS dimension was high (on a 7-point scale) in terms of *Usable* (8 items) and *Learnable* (2 items), indicating the RCVW was high on both. With nominal training, participants found the RCVW easy to learn and usable.

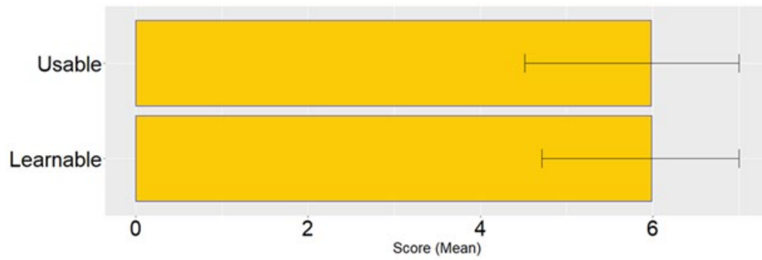

Figure 38. SUS Scale Usability Dimension Mean and Standard Error after RCVW Experience

Figure 39 shows the PSSUQ scale dimension averages for the RCVW system. Once again, drivers gave high ratings on usefulness, information quality, and overall satisfaction. Drivers had more variability in their ratings of the RCVW interface quality (largest error bar) than in other dimensions. This variability indicates that drivers differed in their opinions of interface quality. These two scales provided an initial subjective assessment. The project team also conducted short semi-structured interviews with each driver to complement and potentially unpack their perceptions of the system (e.g., the interface quality).

Figure 39. PSSUQ Usability Dimension Mean Scores after RCVW Experience

4.5.2 User Experience Semi-Structured Interviews

To futher evaluate Research Question 1, drivers were interviewed briefly to identify what RCVW information they recalled seeing and to further understand their perceptions of the prototype system. Two researchers collaboratively reviewed the interview notes. For context, the 15 drivers experienced the functional RCVW for two rail crossings (i.e., HRI 1 and HRI 2) during which they typically saw an alert, in some cases a warning, and two messages (i.e., system available or unavailable). Feedback from these drivers may support future design, testing, and research. Highlights included:

- Drivers reported that the system was useful and easy to learn.
- Most drivers accurately recalled the warnings and messages they saw.
- Eleven of 15 drivers thought the timing was good, and 4 thought it was late. None reported it was too early.
- Two reported that the RCVW helped them slow for the HRI approach.

- Drivers commented that RCVW is potentially effective for returning their attention to the road, particularly in unfamiliar or distracted environments.

The research team assessed the ability of drivers to remember which RCVW messages they saw, the timing, and any action(s) requested by the RCVW system. Eleven drivers correctly recalled which message was displayed, when they saw it generally, and what it meant. Given a 25 minute route time, this level of retention suggests good attention management (i.e., noticed and recalled after a 20 minute delay). Of course, in this initial field study, no other devices were competing for the driver's attention.

Next, drivers were asked to describe their overall experience with the system. One-third of the drivers answered that the RCVW was a straightforward, easy-to-use, easy-to-understand system. Three drivers reported that the RCVW seemed to bring their attention back to the driving task. All 15 participants thought the system provided useful information. Two participants reported that the system helped them slow down their approach speed to the HRI with the combination of auditory and visual messages. Two drivers had constructive feedback, one suggesting that the system felt intrusive by reproducing outside signals but acknowledged that it provided information while driving and supported attention management. Another driver reported being startled by the audible warning.

One sound was used as an audible warning in testing but was not a key focus of the original RCVW design. Drivers thought that the warning was loud enough, but several drivers noted there was little noise inside or outside the vehicle to compete with the warning. Most drivers reported that the audible warning was clear even when wind was present. Only 4 drivers reported that the warning timing was late, 11 reported it was timely and none reported that the timing was early.

Finally, when considering the usefulness of the system, drivers reported that the RCVW system would be useful under several different conditions. First, participants suggested that the RCVW would be useful to address driver inattentiveness (e.g., sleepiness) or distraction. Second, two drivers reported that the RCVW may be beneficial in unfamiliar or new areas (e.g., when on a trip). Overall, the usability assessment and interviews indicated that the prototype system was easy to learn and use.

4.5.3 Driving Behavior

As mentioned earlier, drivers often do not slow down when approaching an HRI, even when they should (Hao & Daniel, 2014). Therefore, driver behavior anlaysis provides additional insight to the usability data (i.e., interviews and questionnaires) analysis. Do drivers behave appropriately when they see an RCVW message or warning? Do drivers slow down after the advanced warning?

In the following sections, driver behavior is described using two measures: 1) average speed, and 2) frequency of eye-gaze behavior out the window (left or right) and at the RCVW display. Average speed during the vehicle approach to an HRI revealed whether a vehicle was slowing down in response to either RCVW warnings or the upcoming active crossing devices. Eye-gaze behavior can indicate whether drivers are changing their behavior or attention management at the different HRI/RCVW configurations. That is, are they paying more attention to their surroundings (i.e., looking out the window to the left or right near the HRI) or at the RCVW system? Because the RCVW warnings and active warning devices co-occur at HRI 1, the team could not determine the effect of the RCVW alone on driver behavior.

Research Question 2: Does the presence of the RCVW display messages (with the active crossing) affect driver speed when approaching an HRI? Does the effect depend on how close the driver is to the HRI or the state of the HRI warning device status (i.e., activated or not)?

To assess Research Question 2, drivers received different warnings depending on their speed and location within the approach zone and the state of the HRI (i.e., activate or not). Although exploratory, these analyses were useful to examine changes in each driver's behavior (e.g., whether the driver slowed down when expected). All drivers completed the same 12 mile route and experienced the 2 functional RCVW crossings first (HRIs 1 and 2). This was followed by two crossings that were considered baseline driving situations to provide an additional comparison group. This analysis was focused on the first two HRIs. The team generated data visualizations in RStudio using the CAN bus data and the video timestamps from the vehicle to triangulate location as drivers entered each crossing.

4.5.4 Driving Behavior Visualizations

One way to examine whether a driver is sensitive to the upcoming HRI is to examine vehicle speed. Plots of speed for each participant over time for HRI 1 and HRI 2 are shown in Figure 40 and Figure 41, respectively. Each driver is represented by a unique line that changes from green to blue to red. These colors represent vehicle speed on approach, at the HRI, and immediately after a vehicle has traversed a rail crossing. The starting moments of different alerts provided by the RCVW are indicated by dots (i.e., yellow, red, blue, and pink) in the figures. For HRI 1, researchers found that particpants reduced their speed after receiving the yellow 'Active Crossing Ahead Alert' (i.e., yellow dots) on the RCVW. Subsequently, a few received the 'Active Crossing Violation Warning' (i.e., red dots) and continued to slow. Since active warning devices (i.e., flashing lights and gates) were activated at HRI 1, drivers stopped before reaching the stop line (sometimes a bit further behind the stop line if another vehicle was stopped in front of them).

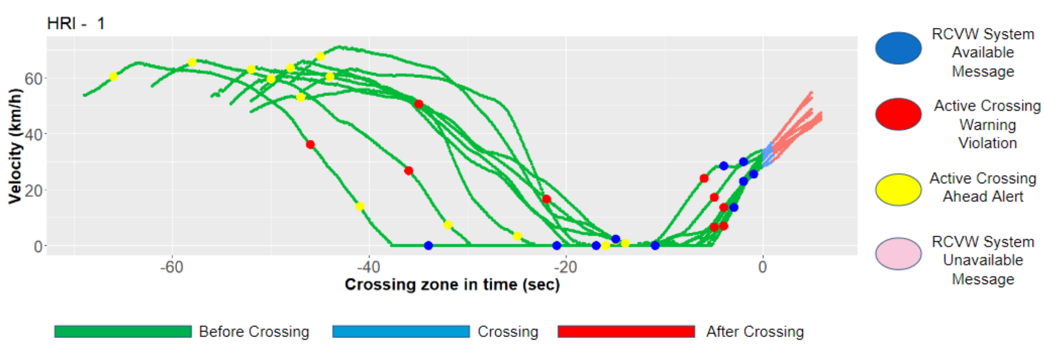

Figure 40. HRI 1 Time Series of Each Driver's Speed (km/h) Plotted by Time Over the Rail Crossing Region (~ 400 m before to 50 m after the tracks)

While HRI 2 was also instrumented with RCVW technology, there was no activation of warning devices and therefore drivers only received the RCVW System Available message (i.e., blue dots) instead of either of the activation alerts. Without any indication of a potential HRI activation, most drivers performed only minor speed reductions while traversing the HRI, as shown in Figure 41.

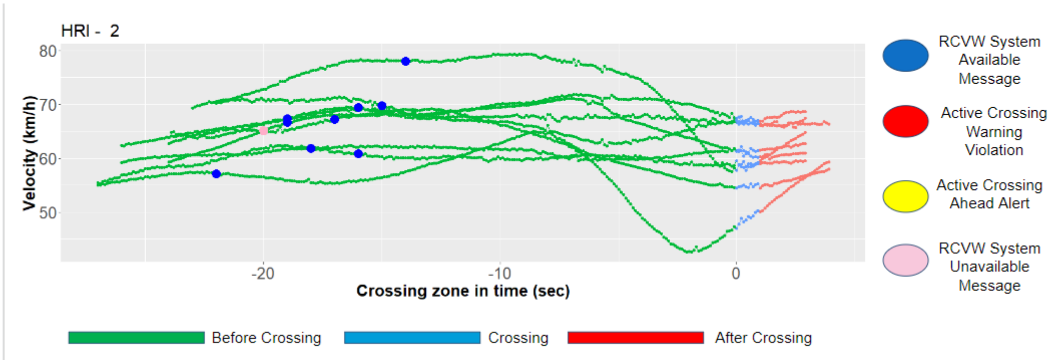

Figure 41. HRI 2 Time Series of Each Driver's Speed (km/h) Plotted by Time over the Rail Crossing Region (~ 400 m before to 50 m after the tracks)

4.5.5 Statistical Tests of RCVW Functionality on Speed using Mixed-Effects Models

To examine driver behavior when the RCVW was available but no HRI warning devices were activated versus when they were activated (e.g., bells, lights, and gates), the team analyzed CAN speed data using a mixed-effect model linear regression. These analyses included only HRIs with active warning devices. For the speed analysis, the approach to each HRI was divided into two segments: the Advance Warning Segment and the Crossing Event Segment (as seen in Figure 42). The team statistically compared drivers' average driving speeds at each HRI (i.e., HRI 1, HRI 2, and HRI 4). To evaluate the difference in driver behavior based on the type of RCVW alert and active warning devices, the team compared speed at the two driving segments when approaching HRI 1 and HRI 2. As expected, drivers reduced their speed within the Crossing Event Segment when the warning devices were activated. However, researchers were interested in finding out if they slowed down earlier (in the Advance Warning Segment) when RCVW provided an additional alert due to activation.

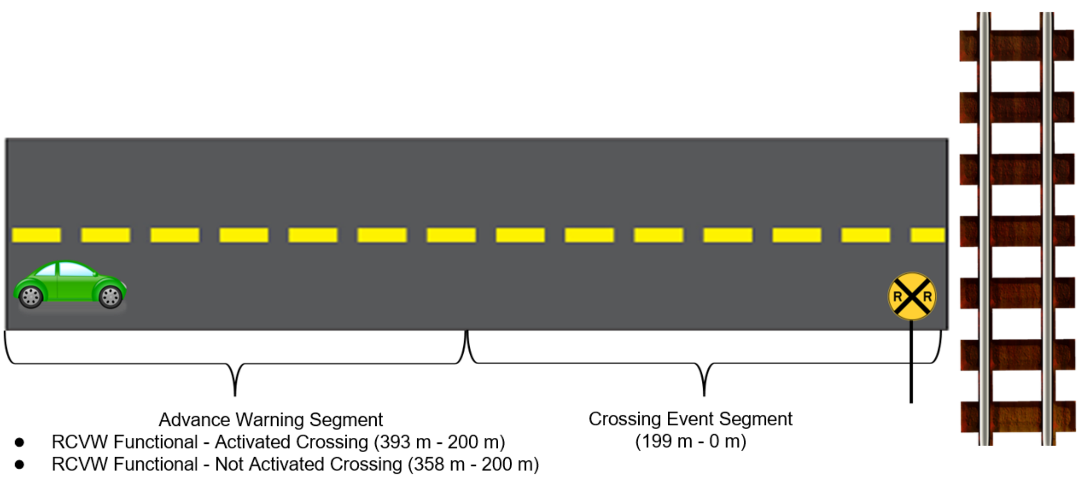

Figure 42. Advanced Warning Segments and Crossing Event Segments for Driving Speed Comparisons

Table 7 and Figure 43 show the speed averages for the three HRIs which were all equipped with flashing lights and gates. The order in which these crossings were traversed was the same for each driver, as this was an initial field test, and moving the RCVW infrastructure setup was impracticable. Comparing the two RCVW functional crossings (i.e., HRI 1 and HRI 2) in terms of speed and gaze behavior provided initial information about the impacts of RCVW as the additional in-vehicle warning. This approach statistically looks for systematic patterns for each driver on the variables of interest and minimizes the effects of individual differences due to driving style or speed. The values in the means table (Table 7) and the graph in Figure 43 suggest that each driver reduced their vehicle speed at HRI 1 compared to HRI 2 or HRI 4. Next, the team determined if these differences were statistically significant.

For all subsequent statistical analyses, team members used R via Rstudio. Researchers conducted a mixed-effects Poisson generalized linear regression via the 'Elmer' function of the lmer4 library in R. To compare speed in the two HRIs with the RCVW implemented (i.e., HRI 1 and HRI 2), and against the baseline condition (i.e., HRI 4), the team conducted a set of linear mixed-effects models via the 'Elmer' function using the lmer4 library in R that takes into account both the fixed and random effects in the experimental design. For both metrics, models were created with a within-subjects design to remove individual difference effects, thereby increasing the sensitivity of the data. The lme4 function enabled the model to capture the repeated measures (within-subject) design of the study, and results were reported as Type-3 F tests, which account for the main effect after the contribution of all other effects including interactions. The Kenward-Roger method is used by default in these tests as it offers a more precise small-sample estimator for the variance-covariance of the fixed effects parameters and the approximate denominator degrees of freedom.

Since speed data are typically skewed and violate the assumptions of linear regression, the team applied an optimal Tukey's ladder transform to driving speed. In each of the next subsections, the team reported specific comparisons of driver speed between different HRI crossing types comparing different driving segments (e.g., Advanced Warning Segments vs. Crossing Event Segments).

Table 7. Rail Crossing Comparisons by RCVW Functionality, Crossing Type and Crossing Segment Speed

	Active Warning Devices Present	RCVW Functional	Warning Devices Activated	Average Speed (SE) Advanced Warning Segment (kph)	Average Speed (SE) Crossing Segment (kph)
RCVW Functional, Warning Devices Activated (HRI 1)	Yes	Yes	Yes	59.18 (1.81)	17.67 (0.81)
RCVW Functional, Warning Devices Not Activated (HRI 2)	Yes	Yes	No	67.14 (1.56)	64.86 (1.73)
Baseline HRI w/ Active Warning Devices (HRI 4)	Yes	No	No	78.72 (2.01)	62.57 (2.32)

First, the team examined the two HRIs with RCVW (i.e., HRI 1 and HRI 2) and how driver behavior differed in these crossings. Results of a Type 3 Wald F test with Kenward-Roger df test showed a significant main effect between the HRIs ($F(1, 39) = 29.13$, $p < 0.001$) and segments ($F(1, 39) = 145.71$, $p < 0.001$) and a significant interaction between them ($F(1, 39) = 80.47$, $p < 0.001$). As can be seen in Figure 43, the statistical interaction means the differences in driver speed between the RCVW with an active device were larger at the crossing driving segment than at the advanced warning segment (200+ m out). The averages provided in Table 7 show that each driver slowed down for HRI 1 compared to HRI 2. Drivers slowed down while in the advanced segment and at the HRI when they needed to stop. Drivers slowed down as expected due to the HRI 1 configuration (i.e., warning devices and RCVW activated). Statistically, the analysis also shows that this pattern was present for each driver because of the within-subjects study design.

Next, the team examined RCVW's functional presence by comparing HRI 2 and HRI 4, which both had active warning devices, although neither was activated during the test drive. In addition, HRI 4 had no RCVW functionality. Results from the Type 3 Wald F tests with the Kenward-Roger df test showed a significant effect for crossings ($F(1, 39) = 58.56$, $p = 0.001$) and segments ($F(1, 39) = 11.08$, $p = 0.002$) and a significant interaction between them ($F(1, 39) = 37.62$, $p = 0.001$). Drivers drove slower on average at HRI 2 than at HRI 4 and when traversing the advanced warning segment than at the crossing itself. Assuming no other interference with speed (e.g., traffic), this pattern could suggest that the RCVW functionality affected speed mainly during the advanced warning segment. However, the slower speed may equally be due to the proximity of the stop condition at HRI 1. Future research is needed to examine this situation more systematically. These analyses were based on the transformed speed data, while the actual speed is represented in Figure 43.

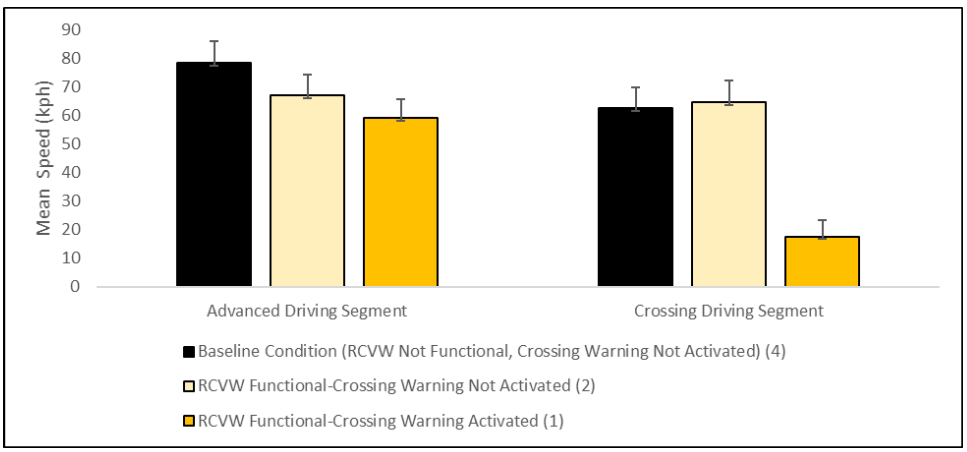

Figure 43. Average Speed for Three Active Warning Crossings on the Route: Baseline, RCVW Functional with Crossing Warning not Activated, and RCVW Functional with Crossing Warning Activated

Average speed (i.e., transformed) during the approach to different HRI configurations may suggest whether a driver is slowing down in response to either the RCVW warnings or the upcoming active warning devices. Looking behavior can indicate whether the driver is paying attention to the surroundings (i.e., looking out the windows) or on the RCVW system display.

4.5.6 Effect of RCVW and Crossing on Gaze Behavior

Research Question 3: Does the presence of the RCVW plus the active warning device affect driver eye-gaze behavior?

To explore Research Question 3, the team compared eye gaze frequency outside the vehicle and at the RCVW system, as gaze behavior allowed the team to explore what drivers were paying attention to. Researchers were interested in three specific gaze behaviors related to rail safety:

looking right or looking left outside the vehicle and looking at the RCVW system. If the frequency of eye-gaze behavior increased, it would suggest a change in attention and a potential increase in situational awareness. Eye-gaze behavior outside the vehicle (i.e., left or right) would suggest a change in attention while eye-gaze behavior toward the RCVW system would suggest drivers were noticing the information changing in the interface.

The presence of the RCVW system, especially when it provided an alert or warning, was expected to change where drivers look. First, the team examined whether the RCVW alerts impacted driver gaze behavior by comparing two HRIs where RCVW was implemented (i.e., HRI 1 and HRI 2), the results of which are shown in Figure 44. Data were analyzed using a three-gaze behavior (i.e., left, right, RCVW) vs. 2 HRI models. The results of a Type 2 Wald Chi-squared test showed a significant effect of HRI ($\chi^2(1) = 33.93$, $p < 0.001$) and gaze location (left, right outside, RCVW) ($\chi^2(2) = 7.45$, $p = 0.02$), but no significant interaction ($\chi^2(2) = 2.42$, $p = 0.3$). This means that the RCVW alerts/warnings impacted drivers' gaze behavior between HRI 1 and HRI 2. The main effect of HRI indicates that drivers looked left, right, and at the RCVW more during HRI 1 as compared to HRI 2. The main effect of gaze location indicates that drivers looked more at the RCVW system than right or left outside the vehicle (Figure 44).

Next, the team compared gaze behavior between HRI 2 and HRI 4 (i.e., baseline) (see Table 7). In this case, a Type 2 Wald Chi-squared test showed no significant effect of crossing ($\chi^2(1) = 0.25$, $p = 0.62$) or gaze location ($\chi^2(2) = 3.58$, $p = 0.17$), and there was no statistically significant interaction, meaning the gaze behavior was similar at both HRIs. Gaze behavior did not differ by gaze locations (i.e., right, left, or at RCVW) or HRI warning status. In this data set, the RCVW message (i.e., RCVW System Available) did not affect drivers looking behavior at the RCVW or outside the vehicle. One interpretation is that with the presence of the RCVW system (only available in this case), drivers were able to receive the necessary information from the system efficiently (see Figure 44). Gaze behavior frequency increased as a function of both the RCVW alerts/warnings and the warning device activation. Drivers were more attentive when the RCVW was providing alerts/warnings and the HRI warning devices were activated. However, as mentioned before, the team cannot separate these effects in the current study.

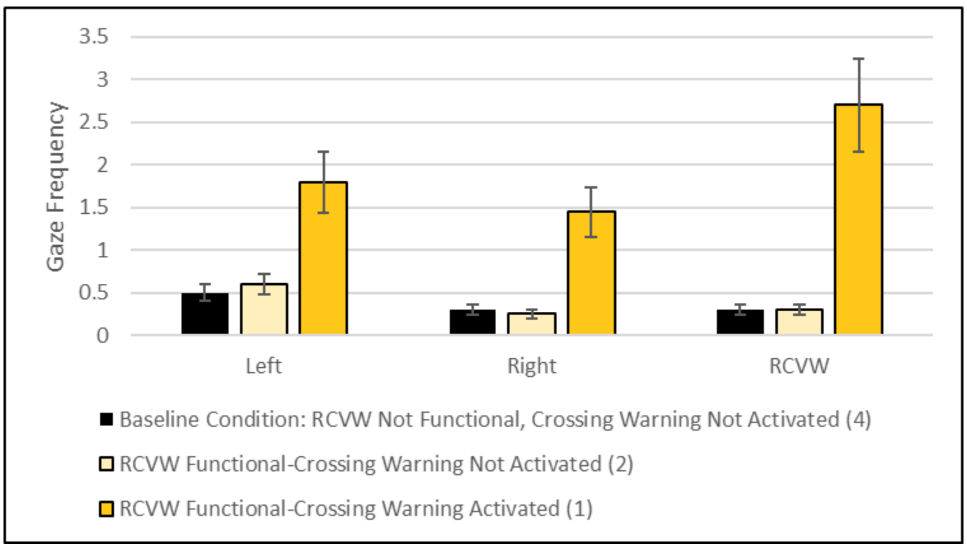

Figure 44. Gaze Frequency by Location and Crossing

4.6 Summary

This field test with the RCVW prototype system and 15 drivers provided some promising data and useful insights. The team used a multi-pronged approach for this assessment that included usability, drivers' perceptions, and driving behavior.

Based on the usability questionnaires, drivers were satisfied with the RCVW system, found it easy to learn and easy to use, and commented that it provided good information. Interface quality ratings indicated more variability than the other dimensions, which is not surprising, as the prototype development was concentrated more on technical functionality than user experience. Driver interviews reinforced these usability ratings but identified some potential contexts in which the system might be most beneficial, such as distracted drivers and drivers traversing unfamiliar roads.

Usability ratings and interviews were supported by driving and gaze behavior analyses. Drivers responded to the RCVW with the active warning in consistent and expected ways as shown by the changes in vehicle speed and gaze behavior. While team members did not ask drivers if they slowed down as a result of the RCVW alerts, the speed visualizations showed that they did. While field testing could only evaluate the RCVW together with the warning device activation, and not the relative effects of each, the statistical models indicated that some of these differences were reliable. These results suggest some interesting potential for the effects when highway vehicles are operating within the Advanced Warning Segment (i.e., more than 200 m before the HRI). Drivers' gaze behavior increased both outside the vehicle at the rail crossings and toward the RCVW system display. The gaze behavior results suggest that the RCVW caught drivers' attention. What cannot be seen from these data is if drivers are slowing down earlier or more than they would with an active crossing. Further research is needed to answer that question.

Based on the results of this initial field test and given the RCVW system is a working prototype, future research could focus on several areas. As this was an early empirical study with 15 drivers on surface roads, more controlled experiments under different road conditions and different crossing environments are reqired to potentially replicate and extend these findings. Another potential area of research could involve the integration of in-vehicle auditory messages into the RCVW system, since sound was not a key part of the initial design. These auditory alerts could provide drivers with information about how to proceed in different situations (e.g., get off track, look left/right) and leverage the extensive body of research in this area (Jeon, Lautala, Nadri, & Nelson, 2022). Finally, future research could include an assessment of the benefit of the RCVW system in the presence of more distractions in the vehicle (e.g., radio or other systems). Due to the growth of connected vehicles on the road, conducting an early system test on surface roads using mixed methods highlighted the potential for future RCVW design and research.

5. CAV Eco-Driving Control Simulation Analysis for Safety and Energy Efficiency

This section presents a simulation analysis of CAV Eco-Driving Control strategies at HRIs based on highway-rail connectivity for safety and energy efficiency. CAV Eco-Driving Control strategies can reduce stopped time and smooth acceleration/deceleration maneuvers while approaching an HRI to ensure safety. Key assumptions, the simulation framework, and numerical studies of CAV Eco-Driving Control are presented in the following subsections.

5.1 Assumptions

The CAV Eco-Driving Control simulation assumes that each train's Head-of-Train (HOT) and End-of-Train (EOT) are equipped with GNSS modules and C-V2X OBUs. It is also assumed that all active HRIs are equipped with C-V2X RSUs. Real-time train information (including HOT position, HOT speed, EOT position, and EOT speed) can be sent to C-V2X RSUs at HRIs over the C-V2X Uu interface. Using the Uu interface enables long-distance communications between the train HOT/EOT and the RSUs at HRIs. It is also assumed that each CAV Eco-Driving vehicle (i.e., a CAV with CAV Eco-Driving Control) is equipped with a C-V2X OBU such that it can receive predicted SPaT messages via direct communications over the C-V2X PC5 interface when it is within the direct communication range. Each CAV Eco-Driving vehicle is also equipped with onboard sensors that can measure sensing data, which includes vehicle position, vehicle speed, vehicle acceleration, spacing, and immediately preceding vehicle speed in real-time.

5.2 CAV Eco-Driving Control Simulation Framework

The CAV Eco-Driving Control simulation framework is shown in Figure 45. This framework requires information from both HOT and EOT so the train can predict not only arrival time but also departure time at an HRI. Trains on the railroad track send real-time HOT information (i.e., HOT position and HOT speed) and EOT information (i.e., EOT position and EOT speed) to the RSU at an HRI. Specifically, the GNSS modules installed in HOT and EOT can measure this information. The OBUs installed in HOT and EOT can send this information to the RSU, respectively. With this information, the RSU is able to predict when the train will arrive and when it will travel through the HRI. Based on the predicted train arrival and departure times, the current signal phase can be derived. In addition, timing information, including “minEndTime” (i.e., the earliest time possible at which the phase could change) and “maxEndTime” (i.e., the latest time possible which the phase could change) in the SPaT data can be derived (SAE, 2020). The RSU broadcasts this predicted SPaT message to vehicles around the crossing.

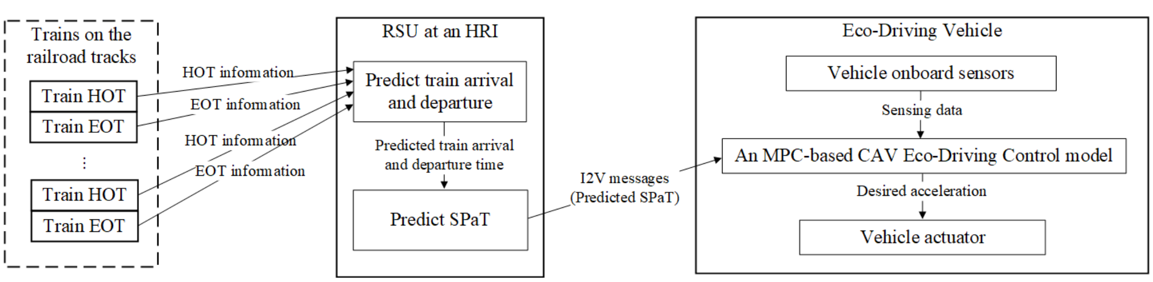

Figure 45. The CAV Eco-Driving Control Simulation Framework

The CAV Eco-Driving Control is based on a Model Predictive Control (MPC) model. The MPC-based model employs real-time sensing data (e.g., vehicle position, vehicle speed, vehicle acceleration, spacing, and immediately preceding vehicle speed) from vehicle onboard sensors as model parameters (Zhao & Zhang, 2021). It also uses the timing data in the predicted SPaT as model parameters. The objective of the model is to minimize the weighted sum of driving smoothness and energy consumption. The driving smoothness component includes tracking error and acceleration fluctuations. The energy consumption component is calculated by the Comprehensive Modal Emissions Model (CMEM) (Scora & Barth, 2006).

The MPC-based CAV Eco-Driving Control model is limited by vehicle dynamics constraints, driving safety constraints, and crossing signal constraints. By integrating energy into the objective and considering safety in the constraints, the MPC-based CAV Eco-Driving Control model is able to improve energy efficiency while ensuring driving safety. The output of the MPC-based model is the desired acceleration, which can be applied to the vehicle actuator.

5.3 Numerical Analysis

5.3.1 Simulation Setting

The project team performed a series of 1 hour simulations to evaluate the effectiveness of CAV Eco-Driving Control at an E&LS HRI in Escanaba-Wells-Gladstone, MI. As Figure 46 shows, the simulated network included a segment of a two-directional highway, a segment of the railroad, the HRI located at the intersection of the highway segment, and the railroad segment.

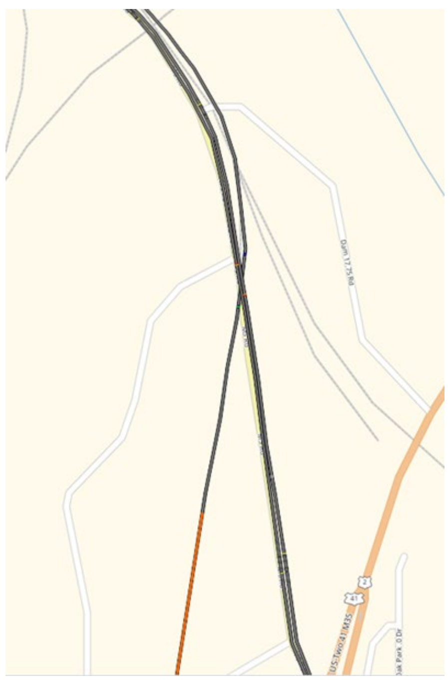

Figure 46. The E&LS HRI at 6802 County 426 M.5 Rd, Wells, MI

The simulated train entered the network from the south. It occupied the HRI starting from the time when the HOT was 25 seconds from the HRI. The HRI was occupied until the EOT passed through the HRI. Vehicles entered the network from the south or north at random times. When the vehicle was within the direct communication range (e.g., 300 meters) of the HRI and receiving predicted SPaT messages from the HRI, the CAV Eco-Driving Control module would initiate.

5.3.2 Energy Benefits of CAV Eco-Driving Control by Varying Highway Traffic Conditions

This subsection presents a study of the energy benefits under different highway traffic conditions. Highway traffic conditions are influenced by two factors, CAV Market Penetration Rate (MPR) and vehicle demand.

5.3.2.1 Varying CAV MPR

CAV MPR represents the percentage of CAVs existing in the simulated transportation network. It should be noted that only CAVs apply CAV Eco-Driving Control. Other vehicles are HDVs modeled by the Intelligent Driver Model (IDM) (Treiber, Hennecke, & Helbing, 2000). An MPR of 0 percent is the base case where no vehicles apply CAV Eco-Driving Control. The energy savings presented in the following figures were calculated by comparing the energy consumption with the corresponding base cases. In the simulations, MPR can be 0, 25, 50, 75, and 100 percent. Impacted vehicles are defined as CAVs or HDVs that encounter an occupied HRI. Figure 47 and Figure 48 show the average stopped time and average energy savings compared to the base case for the impacted vehicles when vehicle demand is 480 vehicles per hour (i.e., veh/hour), predicted HRI-occupied time is 85 seconds, and train frequency is five trains per hour (i.e., train/hour).

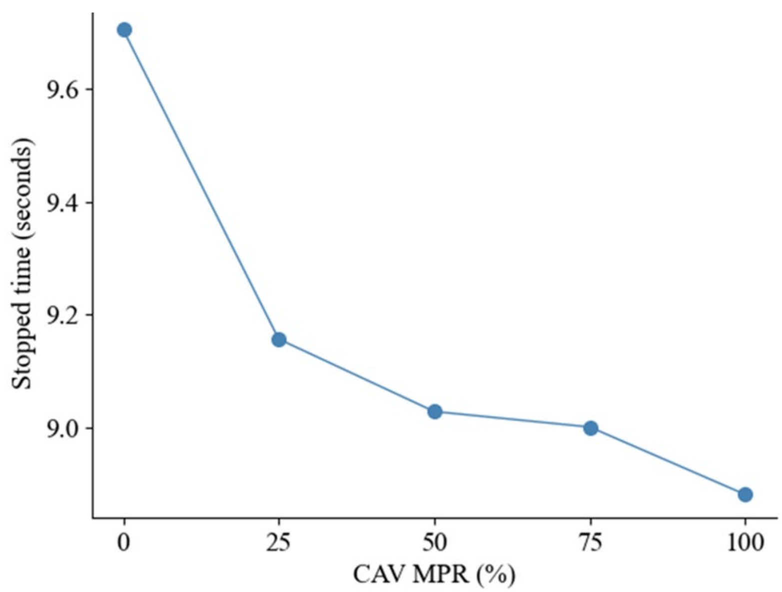

Figure 47. Average Stopped Time of Impacted Vehicles Under Varying CAV MPR With 480 veh/hour

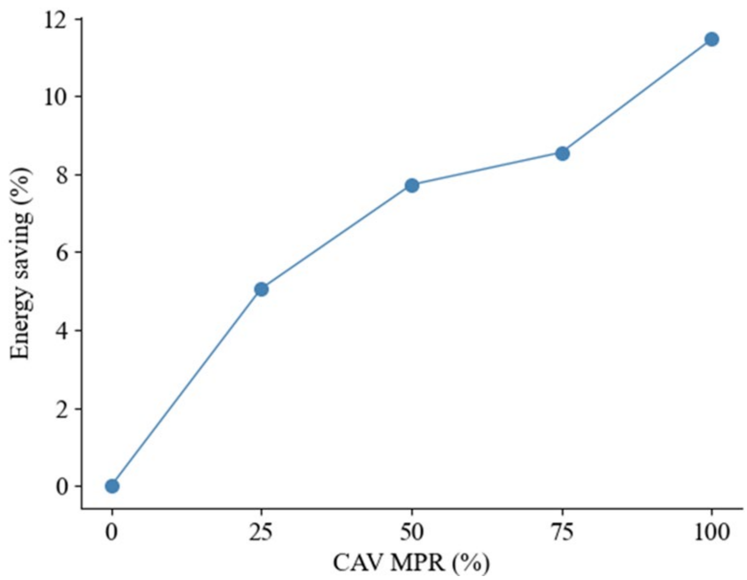

Figure 48. Average Energy Saving of Impacted Vehicles Under Varying CAV MPR With 480 veh/hour

As shown in Figure 47, the average stopped time of impacted vehicles decreased by 9.23 percent as CAV MPR increased from 0 to 100 percent. This result indicated that the CAV Eco-Driving Control was able to reduce idle time for vehicles approaching an occupied HRI. Figure 48 shows that the average energy saving of impacted vehicles increased as CAV MPR increased. The average energy savings for impacted vehicles under 100 percent CAV MPR is up to 11.6 percent. This is because more vehicles are able to apply CAV Eco-Driving Control when the CAV MPR becomes larger.

5.3.2.2 Varying Highway Vehicle Demand

Vehicle demand was varied in the simulations to observe how the benefits would change under different highway traffic congestion levels. The vehicle demand was fixed at 120 veh/hour, 240 veh/hour, 360 veh/hour, 480 veh/hour, and 600 veh/hour. Here, 120 veh/hour represents the lightest traffic condition, and 600 veh/hour represents the heaviest traffic condition. Figure 49 to Figure 53 show the average energy savings, average stopped time, and maximum queue size when CAV MPR is 100 percent, predicted HRI-occupied time is 85 seconds, and train frequency is five train/hour.

Figure 49 shows that the maximum queue size increased from 2 to 12 as vehicle demand increased from 120 veh/hour to 600 veh/hour. As the highway traffic increased, more vehicles lined up in the queue before the HRI. This is further illustrated by Figure 50 and Figure 51, where vehicle trajectories of the one-hour simulation are shown. Since CAV MPR was fixed at 100 percent, all vehicles represented by red lines are CAVs. The blue dotted lines signify the HDVs in the corresponding base case. In this scenario, five trains traveled through the HRI during the one hour simulation. It was observed that when approaching an occupied HRI, CAVs were able to decelerate more smoothly than HDVs. When the vehicle demand was 120 veh/hour, the queue length was no larger than two vehicles. When the vehicle demand was 600 veh/hour, the queue length could be as high as nine vehicles.

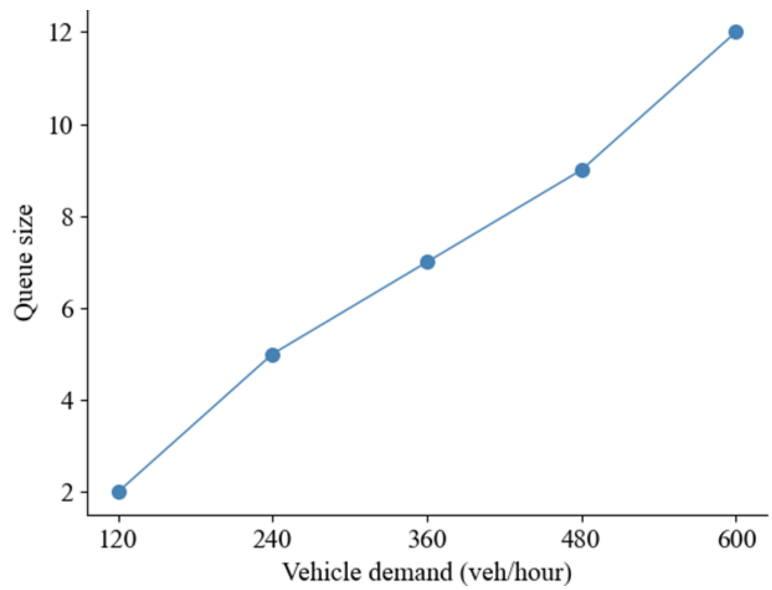

Figure 49. Maximum Queue Size at the HRI Under Varying Vehicle Demand

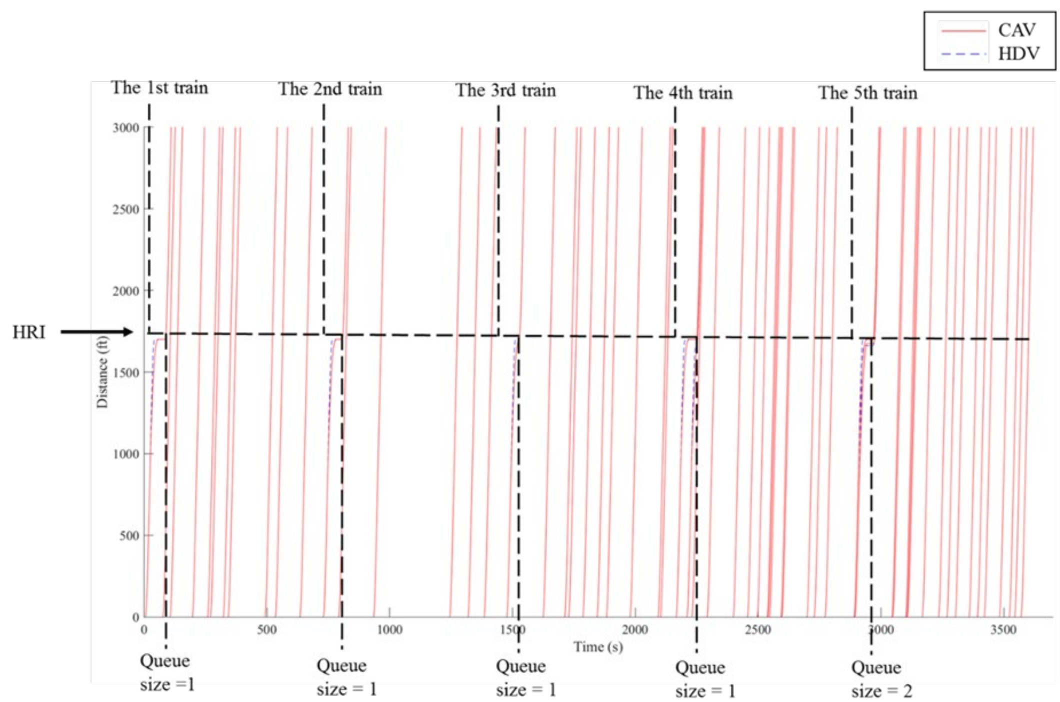

Figure 50. Trajectories of CAVs and HDVs Approaching From the South When Vehicle Demand is 120 veh/hour

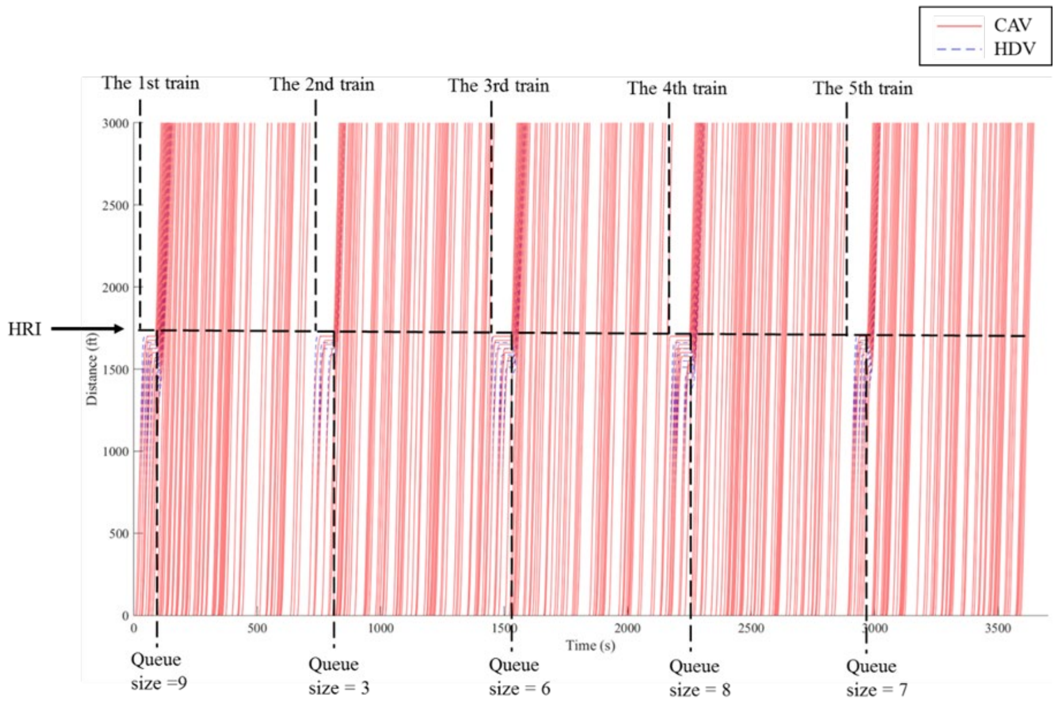

Figure 51. Trajectories of CAVs and HDVs Approaching From the South When Vehicle Demand is 600 veh/hour

Figure 52 shows the average stopped time of impacted vehicles. The stopped time increased by 9.76 seconds as vehicle demand went from 120 veh/hour to 600 veh/hour. This indicates that vehicle demand greatly influences the highway traffic condition and thus impacts the stopped time significantly. Figure 53 shows that the average energy savings of impacted vehicles decreased by 9.52 percent as vehicle demand increased from 120 veh/hour to 600 veh/hour. As the figure shows, the network becomes much more crowded when vehicle demand is larger, and CAV Eco-Driving Control gains fewer energy benefits.

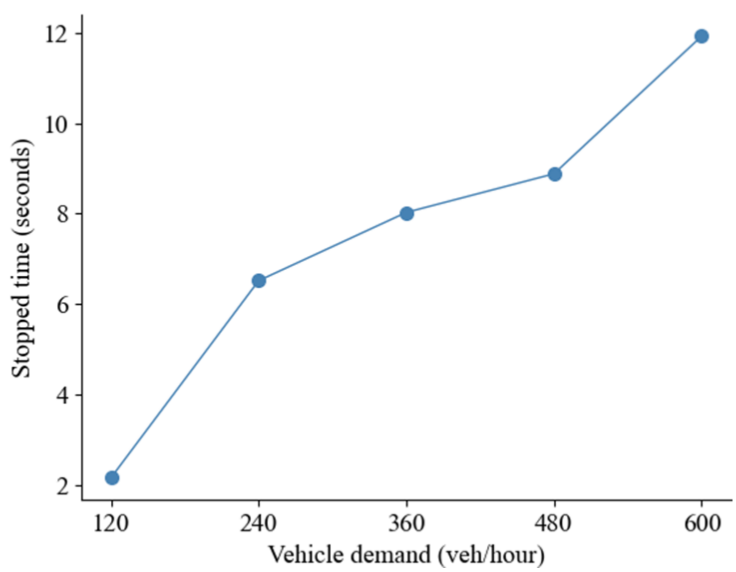

Figure 52. Average Stopped Time of Impacted Vehicles Under Varying Vehicle Demand

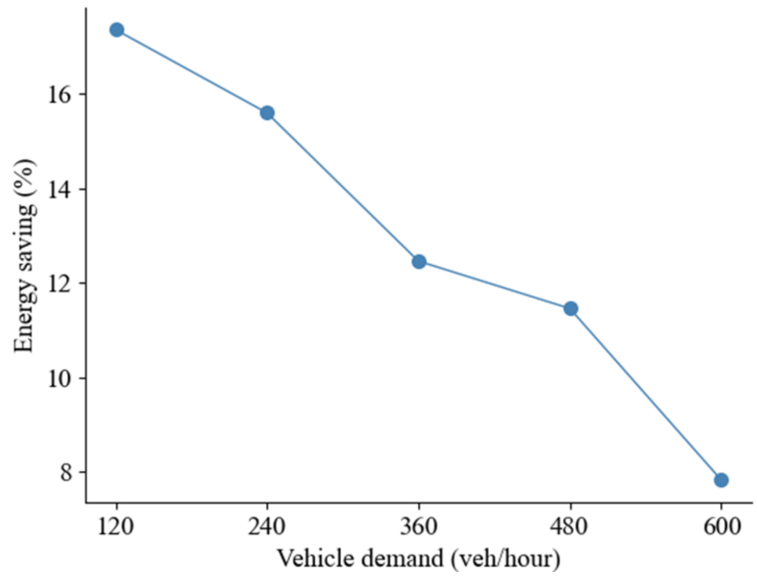

Figure 53. Average Energy Saving of Impacted Vehicles under Varying Vehicle Demand

5.3.3 Energy Benefits of CAV Eco-Driving Control by Varying Train Traffic Conditions

This subsection presents a study of the energy benefits under different train traffic conditions. Train traffic conditions are influenced by three factors: train length, speed, and frequency. Train length and train speed together determine how long an HRI would be occupied by a single train. The project team used a predicted HRI-occupied time to represent the combination of these two factors. In addition, this subsection presents a study of the impact of random train schedules to see whether CAV Eco-Driving Control gains similar benefits when the train schedule is random.

5.3.3.1 Varying Train Length and Speed

The predicted HRI-occupied time is defined as the amount of time that a single train would occupy the HRI. It was calculated as a function of both the train length and the train speed. In the simulations, train length was fixed at 0.5 miles and 1 mile. The train speed was varied at 40 mph, 60 mph, and 80 mph. The 25 second warning time before the train arrives at the HRI is also counted in the predicted HRI-occupied time. Therefore, the predicted HRI-occupied time is the sum of train length divided by train speed and the 25 second warning time. In the simulations, this number was varied at 47.5 seconds, 55 seconds, 70 seconds, 85 seconds, and 115 seconds.

Figure 54 and Figure 55 show the average stopped time and average energy savings for the impacted vehicles with CAV MPR at 100 percent, vehicle demand at 480 veh/hour, and train frequency at five train/hour. From Figure 54, the average stopped time of impacted vehicles increased by 16.26 seconds as the predicted HRI-occupied time increased from 47.5 seconds to 115.0 seconds. There are two potential reasons for this: 1) more vehicles encountered the occupied HRI, and 2) vehicles needed to wait longer before the HRI. As shown in Figure 55, the average energy savings for impacted vehicles increased by 2.53 percent as the predicted HRI-occupied time increased from 47.5 seconds to 115.0 seconds. This is because more CAVs had the opportunity to encounter an occupied HRI as it was occupied for longer periods.

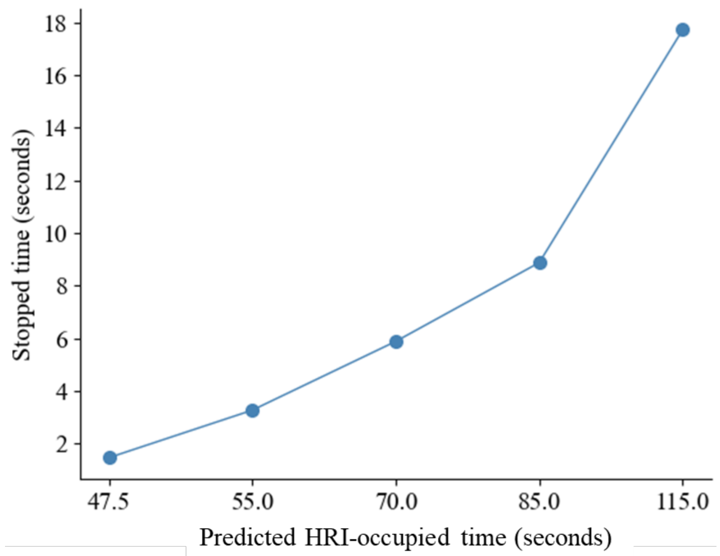

Figure 54. Average Stopped Time of Impacted Vehicles Under Varying Predicted HRI-Occupied Time With 480 veh/hour

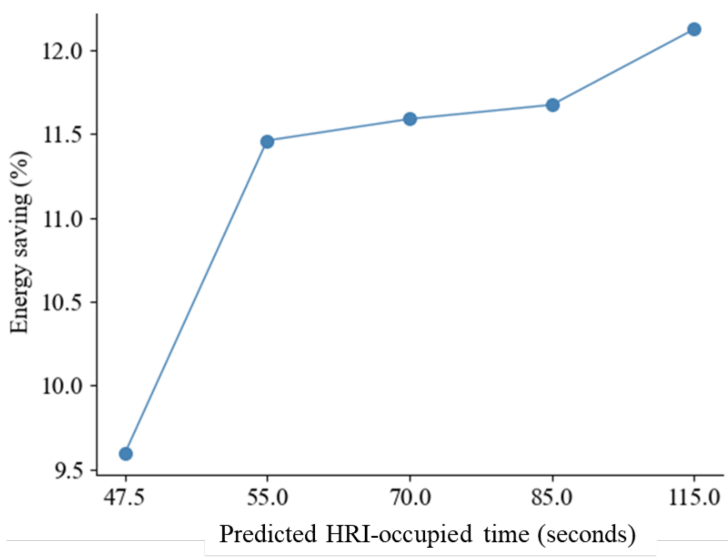

Figure 55. Average Energy Saving of Impacted Vehicles Under Varying Predicted HRI-Occupied Time With 480 veh/hour

5.3.3.2 *Varying Train Frequency*

Train frequency represents how many trains pass through the HRI during the one-hour simulations. It can be 2 train/hour, 5 train/hour, 10 train/hour, and 15 train/hour. Higher train frequency means the HRI would be occupied more frequently.

Figure 56 and Figure 57 show the average stopped time and average energy savings for the impacted vehicles with CAV MPR at 100 percent, vehicle demand at 480 veh/hour, and predicted HRI-occupied time at 85 seconds. From Figure 56, the average stopped time increased by 11.48 percent as train frequency increased from 2 train/hour to 15 train/hour. This is because more vehicles would encounter an occupied HRI as more trains travel through. As Figure 57 shows, the average energy saving of impacted vehicles increased by 0.94 percent as the train frequency increased from 2 train/hour to 15 train/hour. This indicates that more energy benefits can be gained at an HRI with higher vehicular and train traffic.

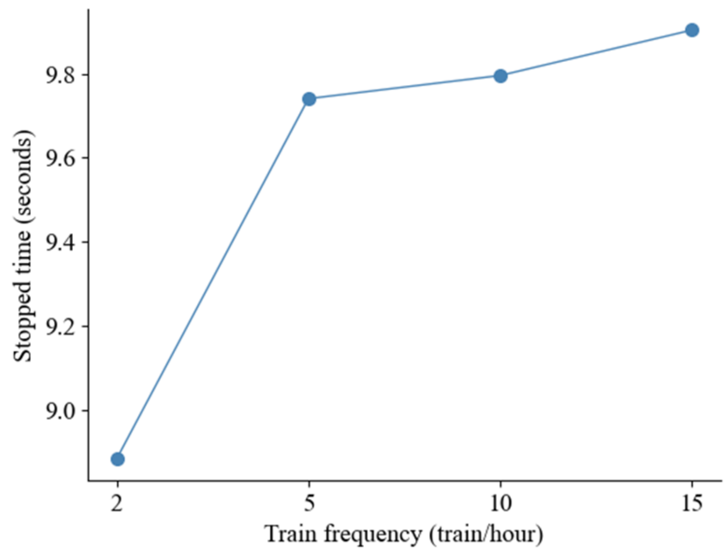

Figure 56. Average Stopped Time of Impacted Vehicles Under Varying Train Frequency With 480 veh/hour

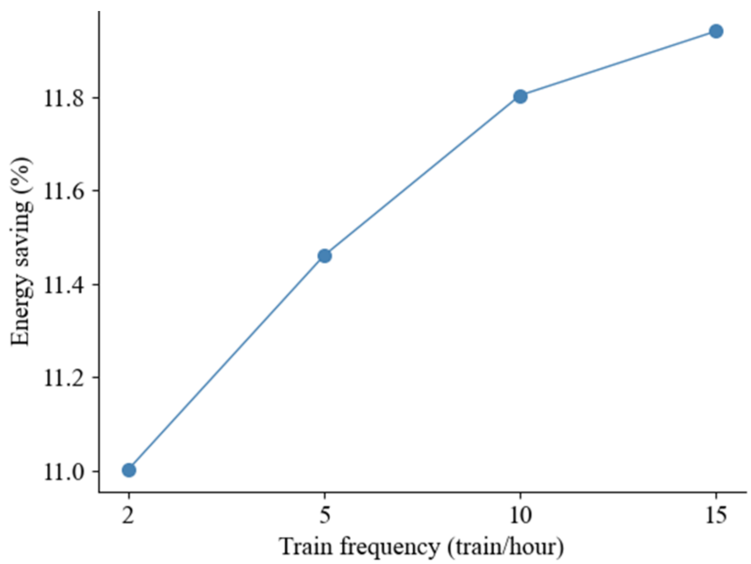

Figure 57. Average Energy Saving of Impacted Vehicles Under Varying Train Frequency With 480 veh/hour

5.3.4 Impact of Random Train Schedule

In the previous subsections, fixed train schedules were used, meaning that all scenarios with the same train frequency would use the same fixed train schedule. This subsection presented a study of the energy benefits from using random train schedules. In this test, 30 different train schedules were generated randomly. Different schedules still employed the same train frequency, but the departure times of the trains were varied. Figure 58 shows the average energy saving for impacted vehicles with vehicle demand at 480 veh/hour, predicted HRI-occupied time at 85 train/hour, and train frequency at 5 train/hour. As CAV MPR increased from 0 to 100 percent, the average energy savings for all impacted vehicles increased by 9.15 percent. This result is very close to the fixed train schedule case presented in Subsection 5.3.2.

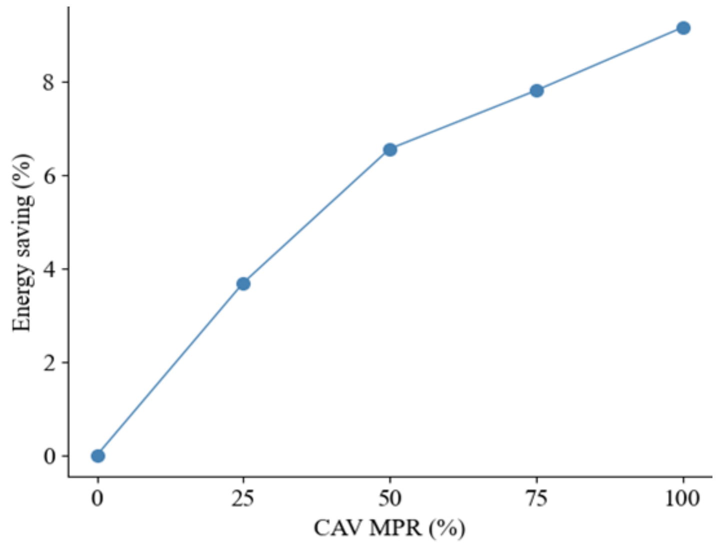

Figure 58. Average Energy Saving of Impacted Vehicles under Varying CAV MPR using Random Train Schedule with 480 veh/hour

5.3.5 Energy Benefits of CAV Eco-Driving Control by Varying Highway and Train Traffic Conditions

This subsection summarizes the results of all testing scenarios by varying highway traffic conditions (i.e., CAV MPR and vehicle demand) and train traffic conditions (i.e., predicted HRI-occupied time and train frequency). Figure 59 shows the average stopped time of impacted vehicles and Figure 60 shows the average energy saving of impacted vehicles.

Each figure consists of 25 3D plots. The x-axis of each 3D plot signifies predicted HRI-occupied time and the y-axis represents train frequency. The z-axis of the 3D plot represents the average stopped time or average energy savings. The 25 3D plots are organized in a 5 by 5 matrix with 2 axes. The first axis is CAV MPR and the second axis represents vehicle demand. The changing pattern of the average energy saving along each dimension can be observed in this figure.

As shown in Figure 59, the average stopped time was shown to increase significantly as vehicle demand increased. Each 3D plot shows that the average stopped time increased as the predicted HRI-occupied time increased. As shown in Figure 60, the average energy saving increased significantly as CAV MPR increased. It can be concluded that the average stopped time is mainly impacted by vehicle demand and predicted HRI-occupied time, which represents the highway traffic conditions and railroad traffic conditions, and the average energy savings was mainly impacted by the CAV MPR.

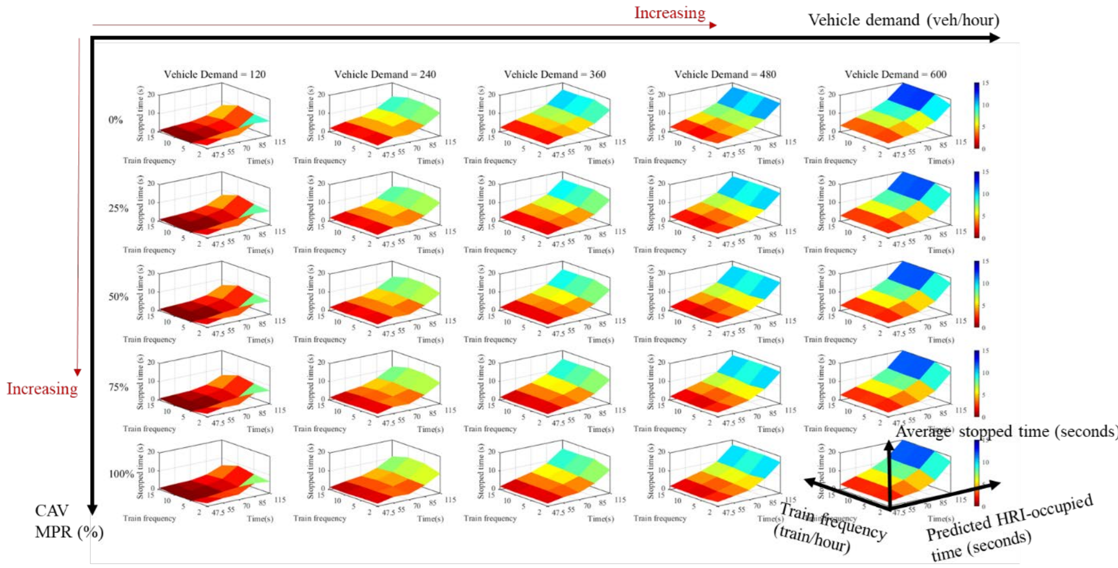

Figure 59. Average Stopped Time of Impacted Vehicles

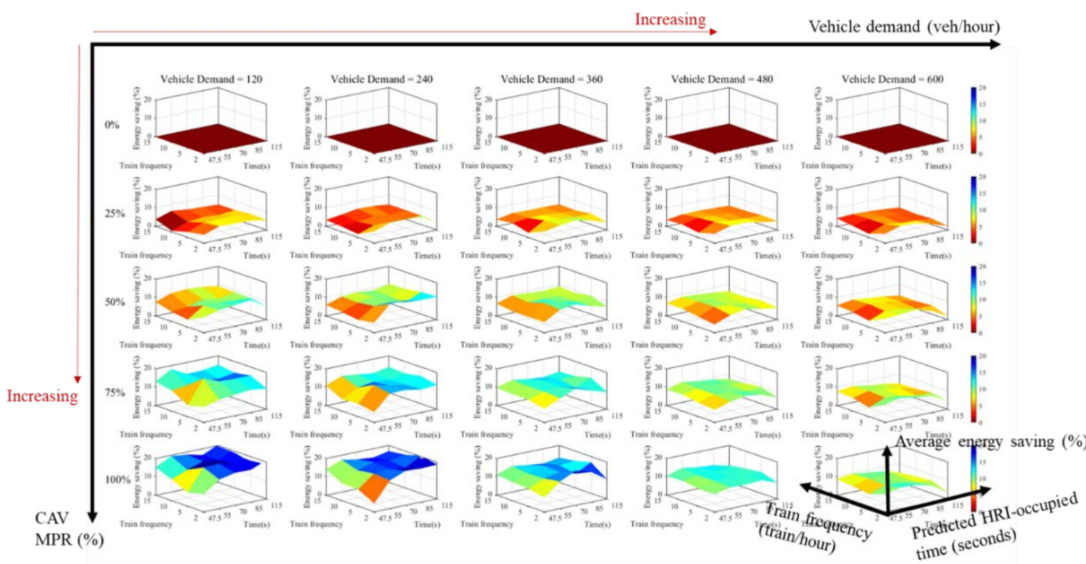

Figure 60. Average Energy Saving of Impacted Vehicles

5.3.6 Energy Benefits of CAV Eco-Driving Control by Varying Energy Weighting Factor

This subsection presents a study of the potential energy benefits using varying energy weighting factors. The value of the energy weighting factor in the CAV Eco-Driving model is an important parameter that reflects the level of preference for saving more energy. Figure 61 shows the results with CAV MPR at 25 percent, vehicle demand at 120 veh/hour, predicted HRI-occupied time at 47.5 seconds, and train frequency at 2 train/hour. The average energy consumption of impacted vehicles decreased as the energy weighting factor became larger. This is the consequence of putting more weight on the energy term in the MPC-based CAV Eco-Driving Control model.

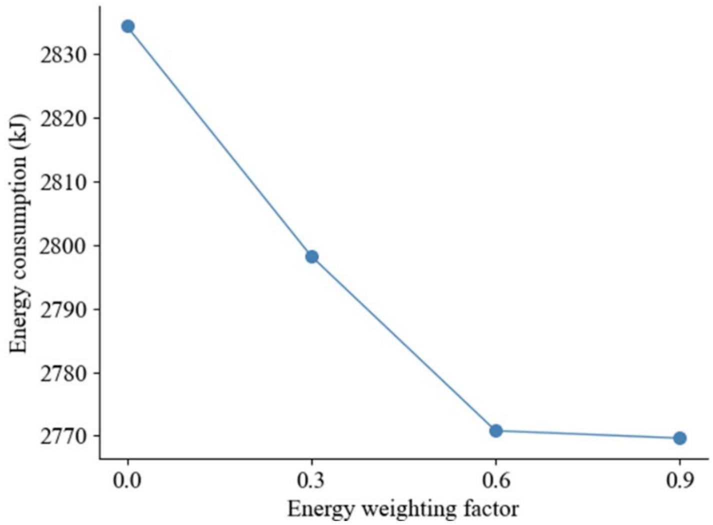

Figure 61. Average Energy Consumption of Impacted Vehicles Under Varying Energy Weighting Factor

5.4 Summary

This section proposed a safe and efficient CAV Eco-Driving Control strategy for highway vehicles at connected HRIs using V2I information for safety and energy efficiency. Safety is ensured in the MPC-based CAV Eco-Driving Control model constraints. Energy benefits are gained by reducing the number of full stops and idle time of the vehicle, and by smoothing acceleration/deceleration maneuvers while the vehicle approaches an HRI. Numerical analysis showed that, when CAV MPR increases, more energy benefits can be gained. The average energy saving of impacted vehicles increases by 11.6 percent compared to the base case, as CAV MPR increased from 0 to 100 percent. It showed that the average stopped time is mainly impacted by vehicle demand and predicted HRI-occupied time, representing the highway and railroad traffic conditions and the average energy saving is mainly impacted by the CAV MPR. It also demonstrates that the CAV Eco-Driving Control gives similar energy benefits when the train schedule is fixed and random, while the energy saving increases as the energy weighting factor becomes larger. There are, however, some challenging issues to be addressed for real-world applications. First, drivers of non-CAVs may be annoyed by CAVs at HRIs since CAVs may slow down ahead without apparent reason (i.e, non-CAV drivers may not know that CAVs consider energy beneft during driving). Second, the impact of the presence of other highway signalized intersections near the HRI is still unknown. Lastly, real-time HOT and EOT information is not typically provided by railroads for non-railroad purposes..

6. CAV Eco-Routing Simulation Analysis for Mobility and Energy Efficiency

This section presents the results of a simulation analysis of the CAV Eco-Routing strategy at HRIs with highway-rail connectivity for mobility and energy efficiency. A CAV subscribing to Eco-Routing services can choose a time- and energy-efficient route from a set of available routes between an origin and a destination. The Eco-Routing service predicts travel time and energy consumption for each route from a set of available routes using C-V2X information of train approaching to and departing from HRIs. CAV Eco-Routing key assumptions, simulation framework, and numerical studies are presented below.

6.1 Assumptions

The CAV Eco-Routing simulation assumes that the HOT and EOT of each train are equipped with GNSS modules and C-V2X OBUs. It is also assumed that all active crossings are equipped with C-V2X RSUs. Real-time train information, including HOT position, HOT speed, EOT position, and EOT speed is transmitted to C-V2X RSUs at HRIs over the C-V2X communication Uu interface. The Uu interface enables long-distance communications between the train HOT/EOT and the RSUs at HRIs. In addition, all signalized intersections in the highway network are assumed to be equipped with C-V2X RSUs. An RSU at a signalized intersection can obtain SPaT data directly from the signal controller of the intersection. All vehicles in the highway network, including background vehicles, are connected vehicles that can broadcast Basic Safety Messages (BSMs) at 10 Hz via direct communications over the C-V2X PC5 interface. RSUs at HRIs and intersections can receive BSMs from those CAVs. CAV Eco-Routing vehicles (i.e., CAVs with the Eco-Routing service) receive predicted travel information for each HRI and signalized intersection over the C-V2X Uu interface along their available routes. Before a CAV Eco-Routing vehicle departs from its origin, it can choose a route from the available routes based on the pre-trip predicted travel information. The HRI geometry of each HRI is known by the CAV Eco-Routing vehicle so MAP messages are not necessary to be sent or received.

6.2 CAV Eco-Routing Simulation Framework

The CAV Eco-Routing service relies on highway-rail connectivity using C-V2X technologies, which involves communications between trains and RSUs and between vehicles and RSUs. Figure 62 demonstrates the CAV Eco-Routing simulation framework.

As shown in the figure, an RSU at an HRI receives real-time HOT information (i.e., HOT position and HOT speed) and EOT information (i.e., EOT position and EOT speed) and predicts SPaT data following the procedure described in Subsection 5.2. Vehicles within direct communication range of the HRI also broadcast BSMs so that the RSU at the HRI can receive BSMs from these vehicles. With the predicted SPaT message containing the predicted timing information and the received BSMs representing the current highway traffic conditions, the RSU can predict vehicle travel time, queue size, and travel speed. This predicted travel information is sent to CAV Eco-Routing vehicles before departure. A similar procedure can be seen in the signalized intersection. The RSU at the signalized intersection receives SPaT data from the signal controller directly. Using the SPaT data and received BSMs, the RSU can also predict travel information, including vehicle travel time, queue size, and travel speed. This predicted travel information is also sent to CAV Eco-Routing vehicles before departure.

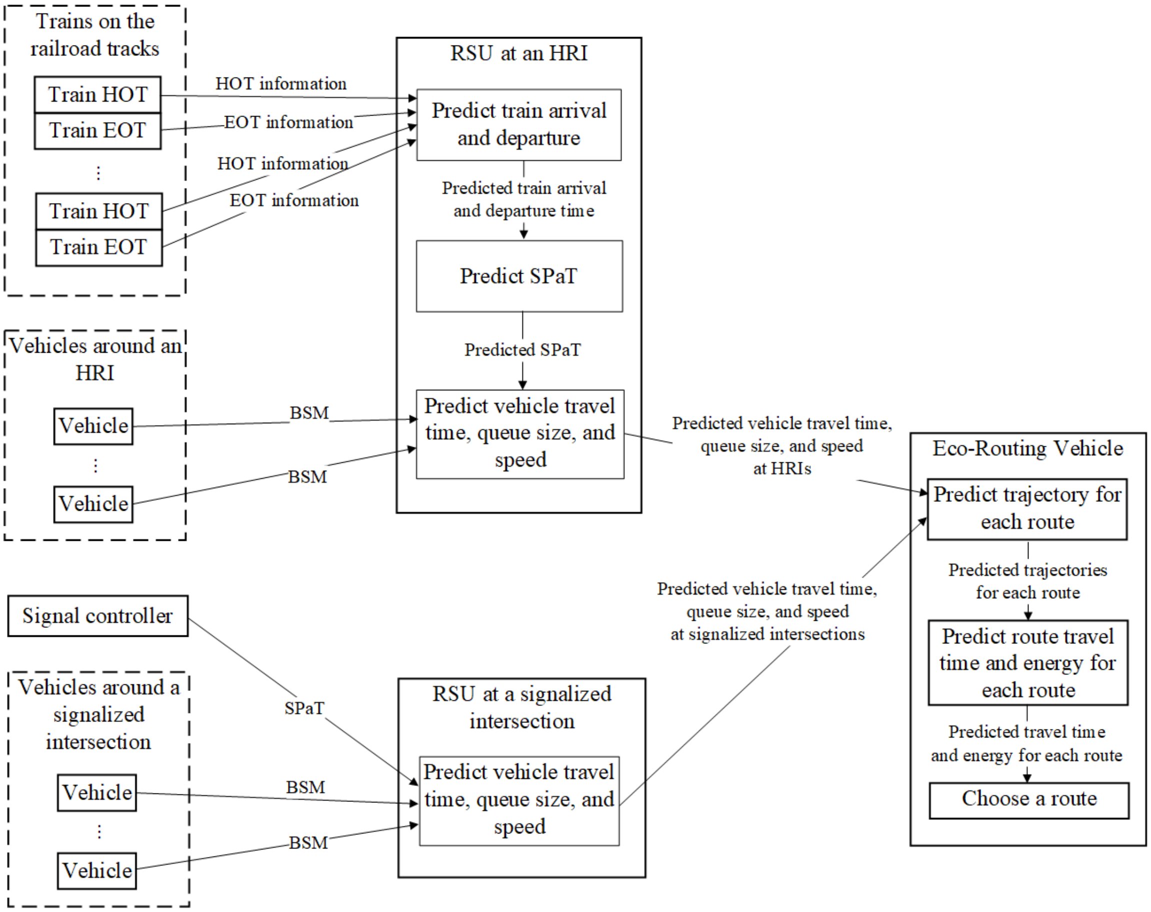

Figure 62. The CAV Eco-Routing Simulation Framework

Every CAV Eco-Routing vehicle subscribes to the CAV Eco-Routing service and receives predicted travel information from RSUs at HRIs and signalized intersections. The CAV Eco-Routing vehicle can use the predicted travel information to calculate the trajectory, predicted travel time, predicted energy consumption of each available route. The route choice is made by the trade-off between the predicted travel time and predicted energy consumption of each route. The project team uses the CMEM (Barth, M., et. al, 2000) model to calculate the energy consumption of a vehicle in kilojoules (kJ). A CAV Eco-Routing vehicle will choose the route with the least weighted sum of time and energy.

6.3 Numerical Analysis

6.3.1 Simulation Setting

The project team performed a series of two-hour simulations to evaluate the effectiveness of the CAV Eco-Routing on a transportation network. A simplified transportation network for Escanaba-Wells-Gladstone, MI, was used in this simulation (see Figure 63). This network includes major roadways in the city, one railroad track with one active HRI, and four signalized intersections. The Bay College parking lot was the predefined origin and 5090 21st Rd, Gladstone, MI, was the predefined destination for CAV Eco-Routing vehicles. The team assumed that all the vehicles from the origin to the destination subcribe to the Eco-Routing services (i.e, 100 percent CAV MPR), while vehicles outside the origin and destination (or background vehicles) do not subcribe to the Eco-Routing services. There are three routes available between the origin and destination: route one had the longest route; route two had the shortest route with an HRI; and route three had the second shortest route with no HRIs. To create a more realistic traffic environment, background vehicles that do not apply the CAV Eco-Routing were added to the network.

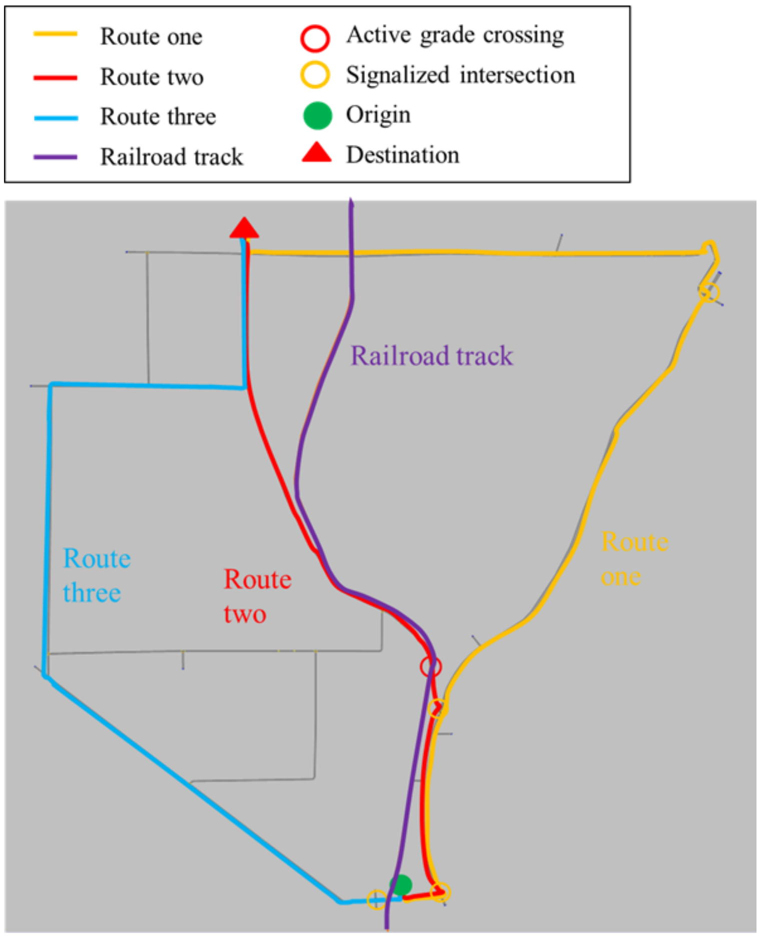

Figure 63. A Simplified Escanaba-Wells-Gladstone Transportation Network

For the two-hour simulation, 14 trains were scheduled to depart and pass through the HRI. The train departure interval was 9 minutes. Each train was 2 miles in length moving at a velocity of 20 mph. The train schedule is shown in Figure 64. From the time when the HOT was 25 seconds away from the HRI to the time when the EOT traveled through the HRI, the HRI was occupied by the train. In this simulation, every train occupied the HRI for 25 seconds + (2/20) * 3600 seconds = 385 seconds. During the two-hour simulation, the 14 trains occupied the HRI for 385 seconds * 14 = 5390 seconds = 1 hour 29 minutes and 50 seconds. That means the HRI was occupied in 5390 seconds / 7200 seconds = 74.86 percent of the 2 hours.

Figure 64. Train Schedule

Subsection 6.3.2 describes the analysis results from the testing vehicles through the simulations. Eight groups of vehicles traveled from the origin to the destination. Each group consisted of three vehicles traveling on route one, route two, and route three, respectively. The three testing vehicles in the same group departed one after another (Figure 65). CAV Eco-Routing was not applied in this test. The travel time and energy consumption of vehicles driving on the three routes was compared in the simulations.

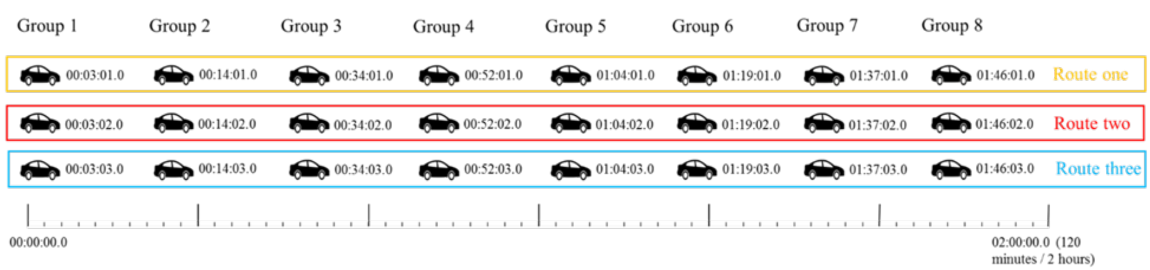

Figure 65. Departure Times of Eight Groups of Vehicles

Subsections 6.3.3 to 6.3.5 present the results of a study of the mobility benefits and energy benefits of the CAV Eco-Routing, and a sensitivity analysis of train information fidelity. Pre-trip routing was performed by 101 CAV Eco-Routing vehicles before they departed from the origin. The departure times of the CAV Eco-Routing vehicles were generated randomly. The mobility benefits and energy benefits were calculated from the simulations, and sensitivity analyses on train information fidelity were performed.

6.3.2 *Preliminary Analysis of Three Routes using Testing Vehicles*

The team performed two simulations. The eight groups of vehicles shown in Figure 65 were added to the network in both simulations. In the first simulation, there were no background vehicles or trains in the network. Only traffic signals at signalized intersections were found to interrupt the vehicles; otherwise, vehicles traveled with free-flow speed with no interuption to provide free-flow traffic for the eight groups of vehicles (i.e., “free-flow vehicles”). In the second simulation, background vehicles and trains also were added to the network. The eight groups of vehicles (i.e., “testing vehicles”) were interrupted by the background highway traffic, train traffic, and traffic signals at signalized intersections.

The three vehicles in each group traveled on three different routes. Table 8 and Table 9 show the route travel distance, average travel time, average energy consumption, and average stopped time before the HRI for free-flow vehicles and testing vehicles, respectively.

Table 8. Aggregated Results of Free-Flow Vehicles

Route	Route Travel Distance (feet)	Average Travel Time (seconds)	Average Energy Consumption (kJ)	Average Stopped Time Before the HRI (seconds)
Route One	51581.04	907.00	20576.20	0
Route Two	31467.03	550.75	12613.00	0
Route Three	43047.31	793.12	16063.57	0

Table 9. Aggregated Results of Testing Vehicles

Route	Route Travel Tistance (feet)	Average Travel Time (seconds)	Average Energy Consumption (kJ)	Average Stopped Time Before the HRI (seconds)
Route One	51581.04	919.37	20354.37	0
Route Two	31467.03	824.12	13963.18	236.87
Route Three	43047.31	801.50	15989.04	0

For free-flow vehicles (Table 8), Route Two (i.e., the shortest route) required the least travel time and least energy consumption among the three available routes, making it the best route when there was no background highway traffic or train traffic. Route Three was the second-best route in terms of travel time and energy consumption. Route One was the worst route since it had the largest average travel time and largest energy consumption. Since there was no railroad traffic present in this simulation, no free-flow vehicles stopped before the HRI.

For the testing vehicles (Table 9), the impact of railroad traffic caused Route Two to require more travel time than Route Three although Route Two was the shortest route. A testing vehicle traveling on Route Two was predicted to stop before the HRI for 236.87 seconds on average. Route Three was the least time-consuming route. However, Route Two was still the most energy-efficient route. In the next subsections, the tradeoffs between travel time and energy consumption are presented. Route One always dominated since it was always the most time-consuming and energy-consuming route. This can explain why, as shown in the next subsections, no CAV Eco-Routing vehicles selected Route One.

As shown in Table 8 and Table 9, the average travel times of Route One and Route Three for testing vehicles were larger than those for free-flow vehicles. This meant that the background highway traffic had an impact on the traffic condition and resulted in larger travel times. Route Two was the best route in terms of travel time and energy consumption in free-flow traffic, although it was not necessarily the best route under the free-flow traffic condition. This indicated that considering only route travel distance may not provide a good route choice. Therefore, considering actual traffic conditions was necessary for the CAV Eco-Routing.

Figure 66 shows the trajectory of a free-flow vehicle and a testing vehicle in Group Five that traveled on Route Two. Both vehicles ran into red lights and stopped at signalized intersections. The two trajectories were similar until the testing vehicle stopped before the HRI for 355 seconds.

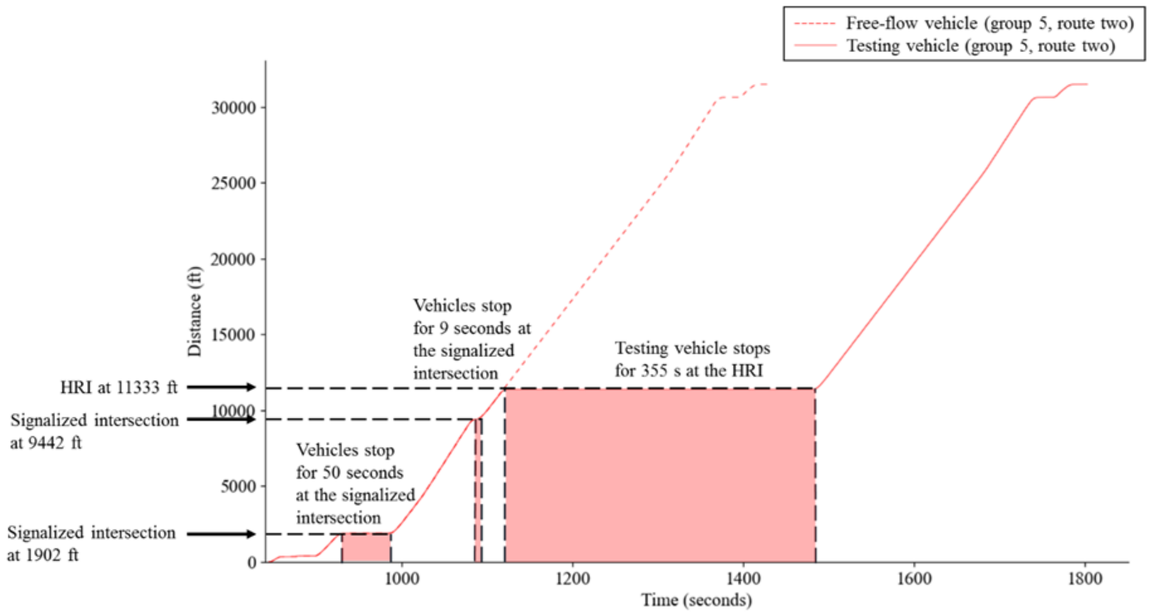

Figure 66. Trajectories of a Free-Flow Vehicle and Its Corresponding Testing Vehicle

Figure 67 shows that the energy consumption of the testing vehicle increased by about 2000 kJ when it was stopped before the HRI. This was due to the vehicle engine still operating to satisfy the power demand from vehicle accessories (e.g., the air conditioner, the power steering device, the power brake system, and other electrical loads) even when the vehicle was stopped.

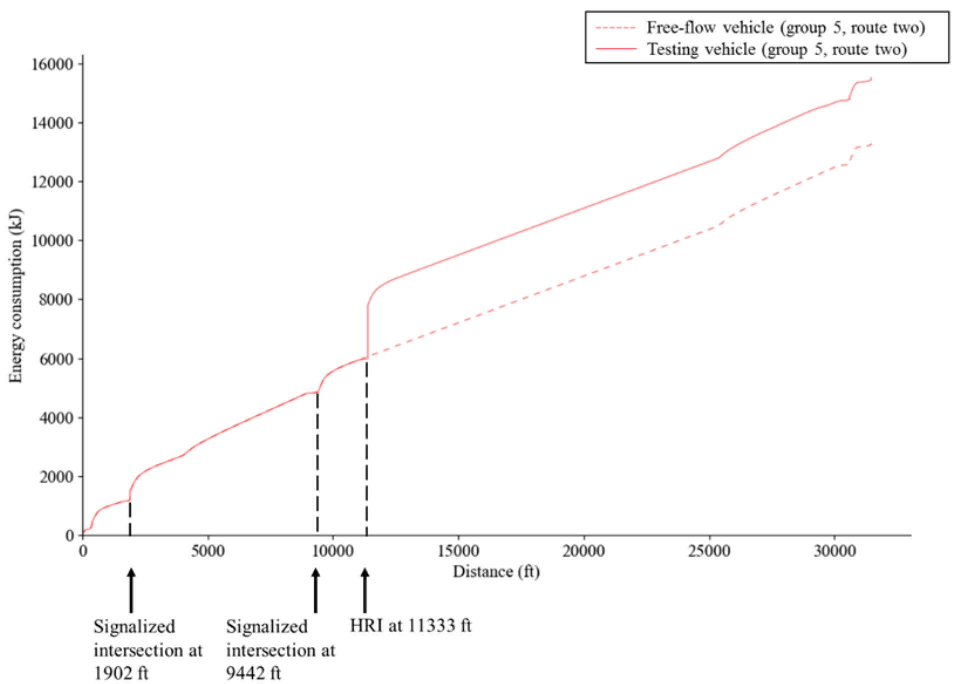

Figure 67. Energy Consumption of a Free-Flow Vehicle and Its Corresponding Testing Vehicle

Figure 68 shows the trajectories of vehicles approaching and traveling through the HRI. The HRI was occupied for 385 seconds when Train 7 approached and passed through the HRI. When the HRI was occupied, vehicles formed a queue before the HRI.

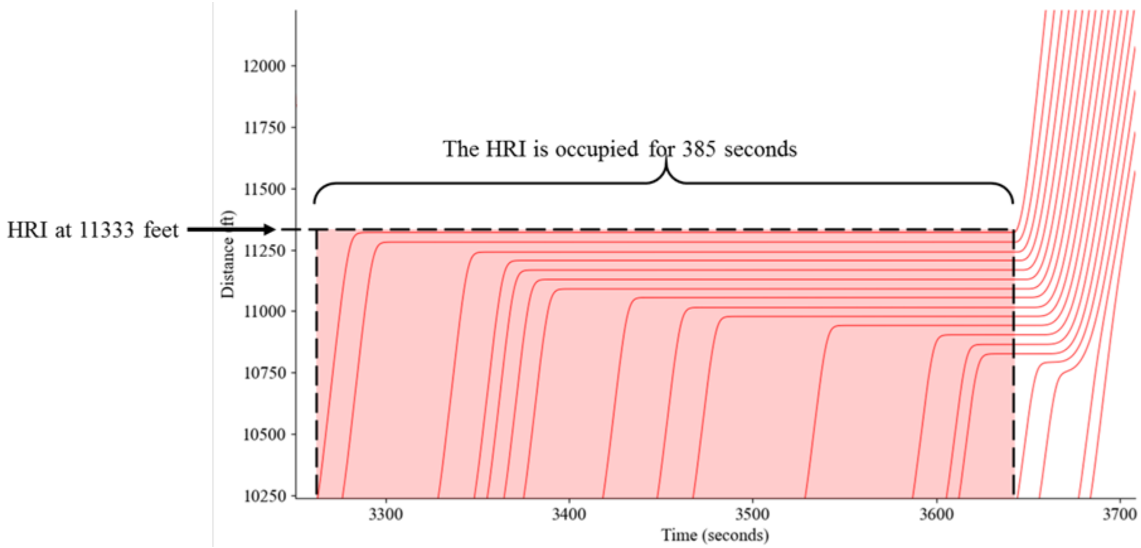

Figure 68. Trajectories of Vehicles Traveling through the HRI

6.3.3 Mobility Benefits of CAV Eco-Routing

This subsection presents the study results for the mobility benefits of the CAV Eco-Routing service through a series of simulations. In the simulations, the 101 CAV Eco-Routing vehicles applied CAV Eco-Routing to make pre-trip routing decisions. Different values of train information advance time were employed in the simulations.

The value of advance time was used to determine how soon ahead of time the train information was shared with the RSU (this information can influence the pre-trip routing decisions of CAV Eco-Routing vehicles). Since the travel time from the origin to the HRI was less than 4 minutes, the maximum advance time was set to 4 minutes in this simulation and a larger advance time was not necessary. With advance time fixed at 0 minutes, the train HOT and EOT information was sent to the RSU when the train arrived at the HRI. With advance time fixed at 1 minute, the HOT and EOT information was sent to the RSU 1 minute before the train arrived and the HRI warning devices activated. As the advance time increased, the train information was received by the RSU earlier, influencing the predictions made by the RSU. Figure 69 to Figure 71 show how the advance time influences route choices and travel times for all CAV Eco-Routing vehicles. In this experiment, the energy weighting factor was set to 0.25, and no train information measurement error was added.

Figure 69 shows the CAV Eco-Routing vehicles' route share. Route One was never chosen because it was dominated by Route Two and Route Three in terms of travel time and energy consumption in all scenarios (see Subsection 6.3.2); therefore, only Route Two and Route Three are shown in Figure 69. As the advance time increased, fewer vehicles selected Route Two, and more vehicles selected Route Three. The percentage of vehicles that selected Route Three increased by 37 percent, from 3 to 40 percent when the advance time increased from 0 to 4 minutes. This is because predictions made by the CAV Eco-Routing model are more accurate when the train information is given earlier. With the more accurate predicted travel time, CAV

Eco-Routing vehicles can make better route choices to avoid being stopped in front of the HRI for long periods.

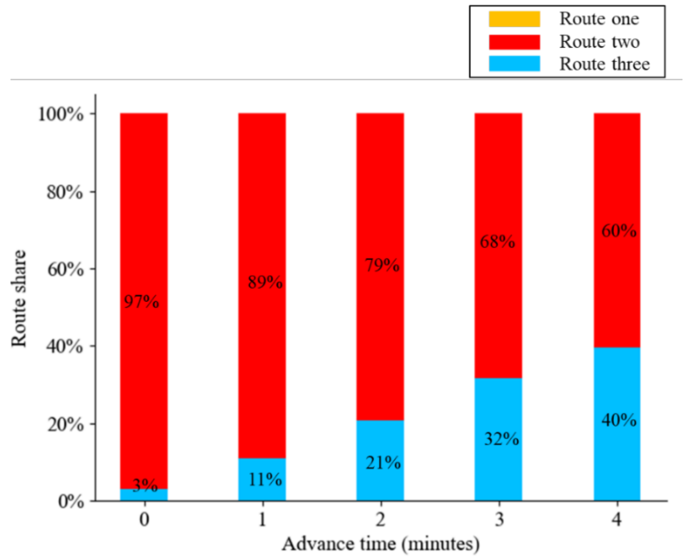

Figure 69. Route Choice Shares Under Varying Advance Time

After the pre-trip routing was completed, every CAV Eco-Routing vehicle in the simulator departed from the origin and traveled the chosen route. The vehicle trajectory of each CAV Eco-Routing vehicle was recorded, from which the project team calculated the simulated travel time for the whole trip. Figure 70 shows the average simulated travel time of all CAV Eco-Routing vehicles. As the advance time increased, the average simulated travel time decreased, showing that a larger advance time results in larger travel time savings. The average simulated travel time decreased by 10 percent as the advance time decreased from 0 to 4 minutes.

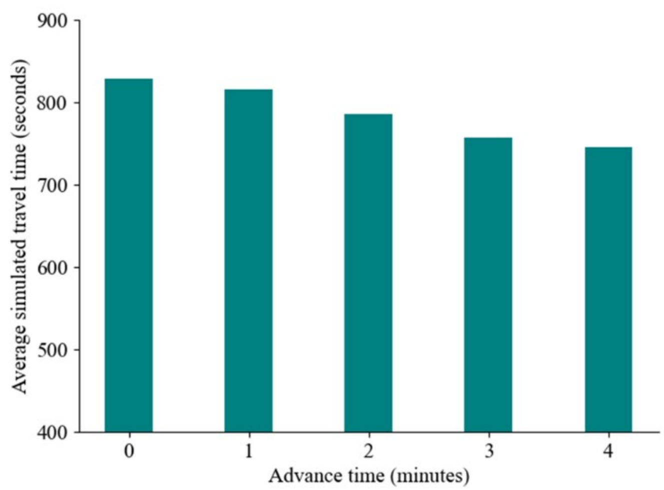

Figure 70. Average Simulated Travel Time Under Varying Advance Time

The project team also compared the predicted travel time calculated by the CAV Eco-Routing model and the simulated travel time from the simulator. Figure 71 shows the travel times averaged over all CAV Eco-Routing vehicles that choose Route Two. With larger advance time, the train approaching information can be shared earlier, so the predicted travel time given by Eco-Routing services is closer to the simulated travel time given by the simulator, making it a better reference for the pre-trip routing. The difference between the average predicted travel time and the average simulated travel time decreased by 95.10 percent as the advance time increased from 0 to 4 minutes, which indicated a significant improvement in travel time prediction.

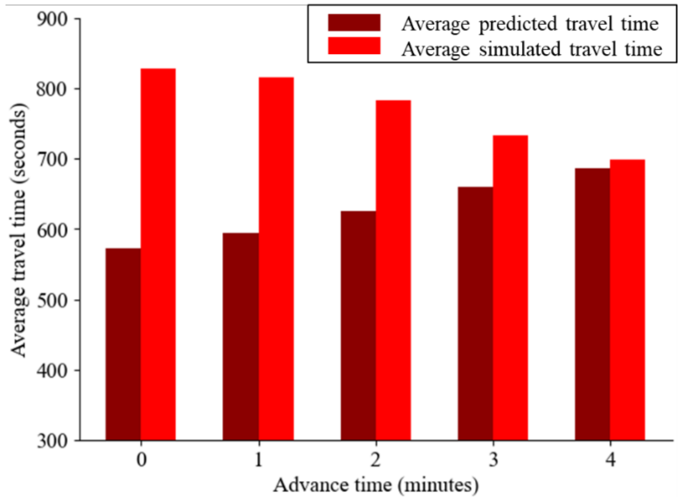

Figure 71. Average Predicted Simulated Travel Time of Route Two vs Average Simulated Travel Time of Route Two

6.3.4 Energy Benefits of CAV Eco-Routing

This subsection studies the energy benefits of CAV Eco-Routing through a series of simulations. In the simulations, 101 CAV Eco-Routing vehicles applied CAV Eco-Routing to make pre-trip routing decisions. Different values of energy weighting factor were used in the simulations.

The value of the energy weighting factor in the CAV Eco-Routing model is an important parameter that reflects the level of preference for saving energy over saving travel time and the tradeoff between energy consumption and travel time; it ranges in value from 0 to 1. A smaller value of the energy weighting factor means the model puts less weight on energy consumption and more weight on travel time. The zero-energy weighting factor is the extreme case where predicted energy consumption is not considered at all; in this case, the route choice is made purely based on the predicted travel time. A larger value of the energy weighting factor means the model puts more weight on energy consumption and puts a smaller weight on travel time. The 1.0 energy weighting factor is the extreme case where the predicted energy consumption totally decides the route choice, and predicted travel time is not considered.

Figure 72 shows the tradeoff between energy consumption and travel time when energy weighting factor = 0, 0.25, 0.5, 0.75, 1.0. In this experiment, no train information error was added, and the advance time was set to 4 minutes. It was observed that, as the energy weighting factor increased, the average simulated travel time increased and the average simulated energy consumption decreased, the result of putting more weight on energy consumption when performing pre-trip routing. As the energy weighting factor decreased, the average simulated travel time decreased and the average simulated energy consumption increased, the result of putting a smaller weight on energy consumption. As the value of the energy weighting factor increases from 0 to 1.0, the average simulated energy consumption decreases by 3.96 percent.

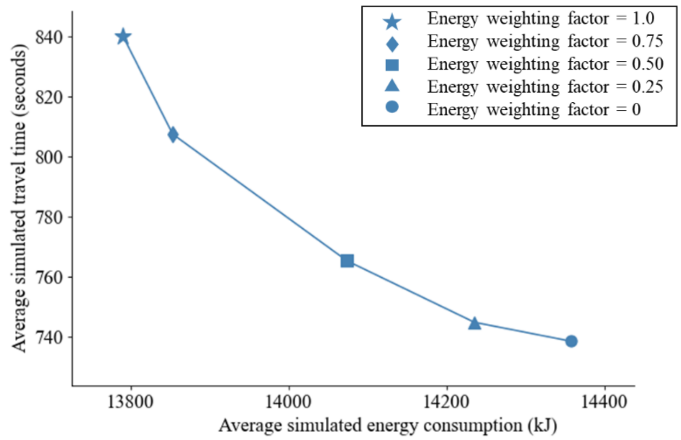

Figure 72. The Tradeoff Between Energy Consumption and Travel Time

Figure 73 shows the route choices when the energy weighting factor was increased from 0 to 0.25, 0.5, 0.75, and 1.0. No vehicles selected Route One because it was the most time-consuming and most energy-consuming route in all scenarios. Since Route Two was the most energy-efficient route, as the energy weighting factor increased more vehicles selected Route Two instead of Route Three. When the energy weighting factor was fixed at 1.0, all CAV Eco-Routing vehicles selected their routes based on only the predicted energy consumption, so all vehicles chose Route Two. The percentage of vehicles that chose Route Two decreased by 48 percent, from 48 to 0 percent as the energy weighting factor increased from 0 to 1.0.

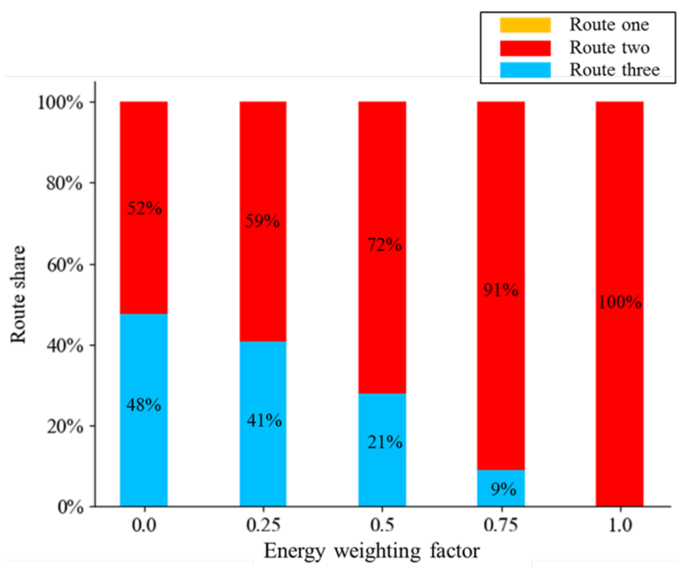

Figure 73. Route Choice Shares Under Varying Energy Weighting Factor

6.3.5 Sensitivity Analysis on Train Information Fidelity

The train information, including HOT position, HOT speed, EOT position, and EOT speed, was measured from onboard sensors where errors are inevitable. The measurement errors would influence pre-trip route choice. Ten error levels, defined in Table 10, were used to test the sensitivity of the model on the train information. Error level 0 signifies no error. In the test, the energy weighting factor was set to 0 and the random error with the corresponding standard deviation of an error level specified in Table 10 was added to the ground truth train information. The pre-trip CAV Eco-Routing model employed the biased train information in route choice selection.

Table 10. Standard Deviations of Different Error Levels

Error Level	0	1	2	3	4	5	6	7	8	9
HOT Position Error Std (m)	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5
EOT Position Error Std (m)	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5
HOT Speed Error Std (mph)	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5
EOT Speed Error Std (mph)	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5

The predictions made by the CAV Eco-Routing model were impacted by two error sources. The first error source was train information measurement error (i.e., HOT position error, HOT speed error, EOT position error, and EOT speed error). This is represented by the error level defined in Table 10. The second error source was prediction error (i.e., lack of future information due to insufficient advanced time). This is represented by the value of advance time. Figure 74 shows the average simulated travel time of all CAV Eco-Routing vehicles of varying error levels and advance times.

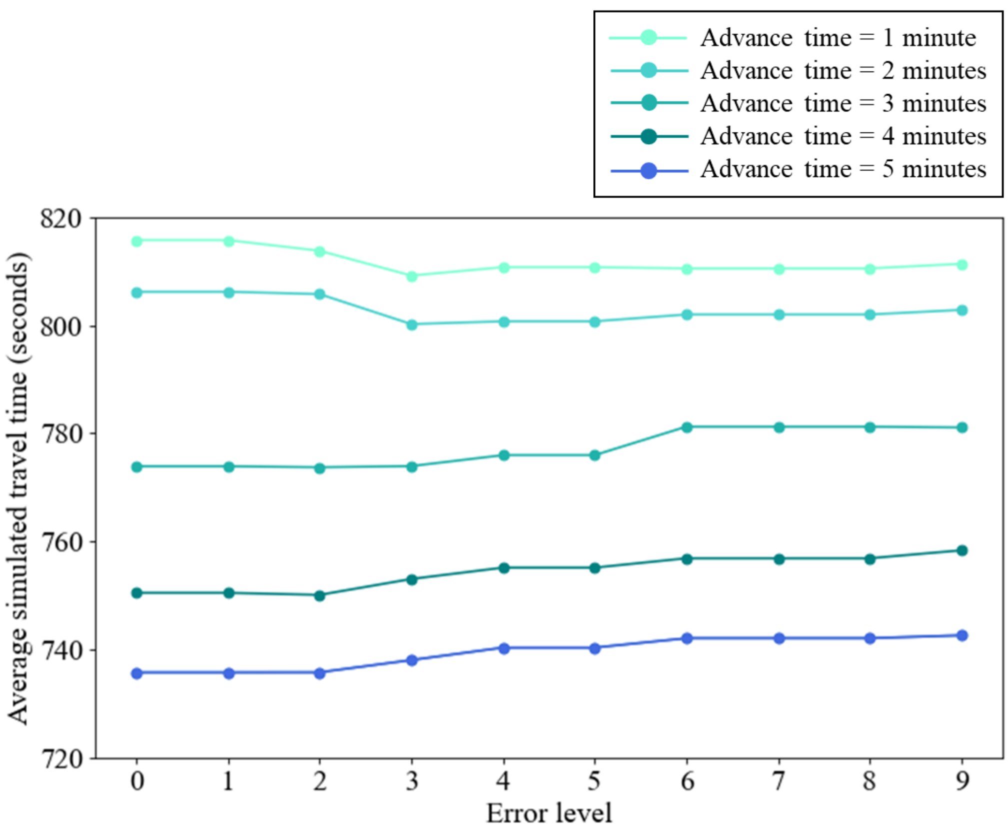

Figure 74. Average Simulated Travel Time Under Varying Error Level

When advance time was configured at 0 minutes and 1 minute, the prediction error became the dominating error source, resulting in erroneous predictions and worse route choices. As shown in

Figure 74, the average simulated travel time shows an obvious monotone trend when advance time was set to 0 minutes and 1 minute. When advance time = 2 to 4 minutes, the train information error was the dominating error source. As the error level increased, the average simulated travel time increased. This was because more significant errors lead to a worse route choice.

It was also observed that when advance time = 2 to 4 minutes, the average simulated travel time did not change significantly as the error level increased from level 0 to level 2. For this experiment, error level 2 can be considered the maximum error level that is tolerated by the CAV Eco-Routing model.

6.4 Summary

This section proposed a CAV Eco-Routing strategy that provides pre-trip Eco-Routing service for vehicles for mobility and energy efficiency. CAV Eco-Routing leverages the highway-rail connectivity so predicted travel information can be shared with Eco-Routing vehicles. CAV Eco-Routing vehicles can make route choices before departure according to the predicted travel information. In the simulation, numerical analysis showed that the value of advance time would influence the performance of the application. The travel time prediction error decreased by 95.10 percent as the advance time increased from 0 to 4 minutes. As a result, the average simulated travel time decreased by 10 percent as the advance time decreased from 0 to 4 minutes. Therefore, by providing predicted travel information for vehicles, CAV Eco-Routing can gain up to 10 percent travel time savings in the simulation scenario. There is a tradeoff between mobility benefits and energy benefits, which can be balanced by the energy weighting factor. As the value of the energy weighting factor increased from 0 to 1.0, the average simulated energy consumption decreased by 3.96 percent. Therefore, CAV Eco-Routing can achieve up to 3.96 percent energy saving by increasing the energy weighting factor in the simulation scenario.

7. Conclusion

This project included economic assessments, driver behavior analysis through road testing, and simulation analyses to study the use of CAV technologies at HRIs to enhance safety, mobility, and energy benefits via highway-rail connectivity.

The project team developed a data-driven economic evaluation tool to assess the effectiveness of HRI safety countermeasures under mixed traffic of CAVs and non-CAVs. A case study was presented to estimate the benefits of deploying RCVW-type technology in Kentucky and Michigan. Based on the analysis, benefits for Kentucky ranged from $207 to $350 million for active crossings and $66 to $112 million for passive crossings. Benefits for Michigan ranged from $253 to $428 million for active crossings and $131 to $222 million for passive crossings. Nationwide predicted benefits ranged from $8.70 to $14.7 billion for active crossings and $6.84 to $11.6 billion for passive crossings.

The project team deployed RCVW at real-world HRIs using connected vehicles. Fifteen drivers were recruited to drive a pre-determined loop on surface roads with 7 HRI events. Vehicle data, videos, and surveys were collected to analyze the effects of RCVW on driver behavior, perceptions, and experiences. It was shown that drivers were satisfied with the system, found the RCVW application easy to learn and use, and commented that it provided good information. The human factor analysis showed that drivers responded to RCVW activation in consistent and expected ways and RCVW affected their speed and gaze behavior.

The project also simulated CAV Eco-Driving and Eco-Routing strategies at HRIs. The CAV Eco-Driving simulation demonstrated energy benefits while ensuring safety. The average energy saving of impacted vehicles under 100 percent CAV MPR was up to 11.6 percent in the simulation scenario. CAV Eco-Routing simulation was shown to gain up to 10 percent travel time savings by providing predicted travel information to vehicles. CAV Eco-Routing saved up to 3.96 percent energy by increasing the energy weighting factor in the simulation scenario.

The project team identified four future areas of research that might be valuable to extend the outcomes of this project. First, future research on RCVW will need more controlled experiments under different road conditions and HRI environments to potentially replicate and extend these findings. Second, it is worth considering implementing the CAV Eco-Driving Control and CAV Eco-Routing on a hardware prototype so the applications can be tested in the real world. Third, the proposed CAV Eco-Routing in this project can be extended to be transferable for general cases since this project only focused on the Escanaba-Wells-Gladstone transportation network with a set of predefined routes. Finally, it would be worth testing C-V2X communication technologies for highway-rail connectivity in a real-world environment.

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Appendix A.
System Usability Scale (SUS) Usability Questionaire

The SUS Survey

	The System Usability Scale Standard Version		Strongly disagree 1	2	3	4	Strongly agree 5
1	I think that I would like to use this system.		○	○	○	○	○
2	I found the system unnecessarily complex.		○	○	○	○	○
3	I thought the system was easy to use.		○	○	○	○	○
4	I think that I would need the support of a technical person to be able to use this system.		○	○	○	○	○
5	I found the various functions in the system were well integrated.		○	○	○	○	○
6	I thought there was too much inconsistency in this system.		○	○	○	○	○
7	I would imagine that most people would learn to use this system very quickly.		○	○	○	○	○
8	I found the system very cumbersome to use.		○	○	○	○	○
9	I felt very confident using the system.		○	○	○	○	○
10	I needed to learn a lot of things before I could get going with this system.		○	○	○	○	○

Appendix B.
Post-Study System Usability Questionnaire (PSSUQ) Usability Questionaire

The PSSUQ Survey

Overall, I am satisfied with how easy it is to use this system.

	1	2	3	4	5	6	7	
Not at all	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

It was simple to use this system.

	1	2	3	4	5	6	7	
Not at all	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

I felt comfortable using this system.

	1	2	3	4	5	6	7	
Not at all	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

It was easy to learn to use this system

	1	2	3	4	5	6	7	
Not at all	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

It was easy to find the information I needed.

	1	2	3	4	5	6	7	
Not at all	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

The information was effective in helping me safely complete the driving tasks and scenarios.
1 2 3 4 5 6 7 Not at all ◯◯◯◯◯◯◯ Strongly Agree
The organization of information on the system screens was clear.
1 2 3 4 5 6 7 Not at all ◯◯◯◯◯◯◯ Strongly Agree
The interface of this system was pleasant
1 2 3 4 5 6 7 Not at all ◯◯◯◯◯◯◯ Strongly Agree
I liked using the interface of this system
1 2 3 4 5 6 7 Not at all ◯◯◯◯◯◯◯ Strongly Agree
This system has all the functions and capabilities I expect it to have
1 2 3 4 5 6 7 Not at all ◯◯◯◯◯◯◯ Strongly Agree
Overall, I am satisfied with this system
1 2 3 4 5 6 7 Not at all ◯◯◯◯◯◯◯ Strongly Agree

Abbreviations and Acronyms

ACRONYM	DEFINITION
AADT	Annual Average Daily Traffic
ACC	Adaptive Cruise Control
BAA	Broad Agency Announcement
BSM	Basic Safety Message
CACC	Cooperative Adaptive Cruise Control
CAN	Controller Area Network
CAV	Connected and Automated Vehicle
CDA	Cooperative Driving Automation
CMEM	Comprehensive Modal Emissions Model
CMF	Crash Modification Factors
CV	Connected Vehicle
C-V2X	Cellular Vehicle-to-Everything
CRF	Crash Reduction Factor
CSW	Curve-Speed Warning
ddRailCAT	Data-Driven Rail Safety Assessment for Connected and Autonomous Transportation
ddSAFCAT	Data-Driven Safety Assessment for Connected and Autonomous Vehicles
DOT	Department of Transportation
DUI	Driving Under the Influence
DVI	Driver-Vehicle Interface
DVSS	Dynamic Vehicle Safety Systems
DSRC	Dedicated Short Range Communication
EARS	Early Alert Response System
EOT	End-of-Train
E&LS	Escanaba & Lake Superior
FCC	Federal Communications Commission
FCW	Forward Collision Warning
4G	Fourth Generation
FRED	Front-to-Rear-End Device

5G	Fifth Generation
FRA	Federal Railroad Administration
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HDMI	High-Definition Multimedia Interface
HDV	Human-Driven Vehicle
HOT	Head-of-Train
HRI	Highway-Rail Intersection
IDM	Intelligent Driver Model
IEEE	Institute of Electrical and Electronics Engineers
IRB	Institutional Review Board
ITS	Intelligent Transportation System
IVP	Integrated Vehicle-to-Infrastructure Prototype
IVR	In-Vehicle Receiver
LCD	Liquid Crystal Display
LTE	Long-Term Evolution
MAC	Medium Access Control
MPC	Model Predictive Control
MPR	Market Penetration Rate
NEI	Not Enough Information
NR	New Radio
OBE	On-Board Equipment
OBU	On-Board Unit
OWI	Operating While Intoxicated
PSSUQ	Post-Study System Usability Questionnaire
PTC	Positive Train Control
RTCM	Radio Technical Commission for Maritime Services
RCVW	Rail Crossing Violation Warning
RLVW	Red Light Violation Warning
RTK	Real-time Kinematics
RSE	Roadside Equipment
RSU	Road Side Unit

RBS	Roadside-based Subsystem
SAE	Society of Automotive Engineers
SPaT	Signal Phase and Timing
SOP	Standard Operating Procedures
SUS	System Usability Scale
3GPP	Third Generation Partnership Project
TTA	Trackside Transmitter Assembly
TTC	Transportation Technology Center
USDOT	US Department of Transportation
VANET	Vehicular Ad-Hoc Network
VBS	Vehicle-based Subsystem
VPAS	Vehicle Proximity Alert System
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
WAVE	Wireless Access in Vehicular Environments