IMPLEMENTATION REPORT

Perception-Based Adaptive Traffic Management and Data Sharing

May 2025

SMART Stage I • FY2022

August 15, 2023 – February 15, 2025

COLORADO SPRINGS
OLYMPIC CITY USA

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2 Executive Summary

The City of Colorado Springs (the City) is at the forefront of modernizing its transportation infrastructure through a staged, innovative approach to sensor-driven, adaptive traffic management. This journey began in 2016, when, in partnership with Iowa State University (ISU), the City implemented the nation's first proof-of-concept for trajectory-based signal control—what is now recognized as the first generation of high-resolution adaptive traffic management. That foundational system, currently deployed across Colorado Springs, uses radar sensors at intersections to continuously track approaching vehicles, enabling controllers to optimize signal timing in real time. The system's algorithm learns typical traffic flows, identifies bi-directional breaks between platoons of traffic, to serve side street traffic, and actively avoids creating "dilemma zones" for drivers, improving both safety and efficiency for all road users.

Building on this success, the City has leveraged USDOT SMART Grant funding to launch Stage 1 of a next-generation adaptive traffic management system. While the first-generation system proved the viability and value of real-time, perception-based signal control, Stage 1 advances this concept by integrating new perception dimensions enabled by state-of-the-art sensor hardware—including radar, LiDAR, and video analytics—as well as a sophisticated "digital twin" of intersection operations. This work not only evaluates the latest technologies but also sets the stage for a second-generation system capable of even higher-resolution perception, expanded context awareness (including real-time V2X communications with first responders, city transit, and snowplows), and dynamic adaptation to both traffic and environmental conditions.

Stage 1 of the SMART Grant Project focused on developing and field-testing these advanced technologies at two intersections representative of Colorado Springs' diverse transportation environments, including both urban and suburban-to-rural contexts. This included a rigorous evaluation of sensor performance, real-time data integration, and exploration of additional real-time adaptive controls. Simulated results demonstrated measurable improvements in intersection safety, efficiency, and protection for vulnerable road users—delivering reductions in traffic delay by up to 23.7%, fewer dilemma zone exposures, and faster emergency response times.

Stage 2 will expand deployment to 48 intersections along two key corridors, extending these benefits citywide and across El Paso County, where the City has now assumed direct management of traffic signals. By scaling up the digital twin infrastructure and continuing to refine sensor integration, the Project aims to deliver a robust, replicable model for next-generation traffic management—one that can be adopted by other municipalities nationwide. The City's approach, strengthened by technical and administrative support from HDR and a broad network of research partners, demonstrates a commitment to continuous improvement and serves as a blueprint for the future of safe, efficient, and connected urban mobility.

3 Introduction and Project Overview

3.1 Project Description

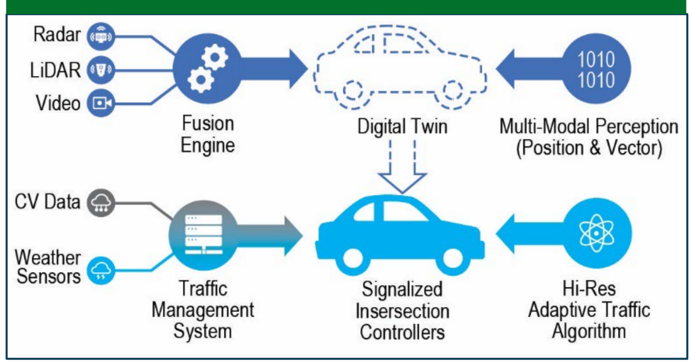
3.1.1 Motivation

The City faces significant transportation challenges as its population grows and traffic patterns become more complex. Key issues include the need to protect non-motorized road users, respond effectively to real-time environmental changes, and manage the interaction of varying traffic types, including cars, cyclists, and pedestrians. These challenges are particularly acute in areas experiencing rapid growth, where increased congestion and safety concerns threaten the efficiency and reliability of the transportation network. At-scale implementation of the Project is designed to address these issues across a variety of geographic contexts within the City and El Paso County, including urban, suburban, and rural areas. The Project will specifically target high-priority corridors, improving traffic flow and safety in regions where population density and traffic volume are increasing.

3.1.2 Technologies

The Project leverages advanced perception technologies, including radar, LiDAR, and video analytics, to monitor real-time traffic conditions. These sensors capture detailed data on the position and movement of all roadway users—vehicles, pedestrians, and cyclists—approaching, within, and exiting intersections. The system integrates this data through an open-source, standardized perception engine, creating a "digital twin" of the traffic environment. This digital twin enables automated traffic control, using algorithms to optimize signal timing, manage traffic flow, and enhance safety. Additionally, in-vehicle V2X (vehicle-to-everything) technology is being tested to further improve the accuracy of vehicle data and enhance communication between vehicles and infrastructure.

Sensor data from radar, LiDAR, and video are fused to generate a real-time digital twin of intersection activity. This multi-modal perception, combined with connected vehicle (CV) and weather sensor inputs, informs signalized intersection controllers and enables a high-resolution adaptive traffic algorithm. Together, these components support safer, more efficient traffic management for all road users.



The Project incorporates on-board units (OBUs) that are set up to act as fire trucks and snowplows to collect and transmit connected vehicle (CV) data. No roadside units (RSUs) are required for this integration due to the system's reliance on vehicle-based data transmission and cellular-based connectivity architecture, which aligns with project scope and current industry trends.

3.1.3 Goals

Stage 1 aimed to resolve the existing limitations in the first-generation system, expand its capabilities to monitor non-motorized traffic, adapt to real-time changes in weather and traffic conditions, and prioritize safety and mobility for all road users, including pedestrians, bicyclists, and the broader traveling public. It focused on enhancing traffic management by integrating advanced sensor technologies, improving safety and efficiency, and developing an automated traffic management network that adapts to changing roadway traction and visibility conditions.

The primary goals of at-scale implementation in Stage 2 are to enhance traffic management by:

1) reducing congestion and delays for commerce and the traveling public;
2) improving safety, integration and reliability of the existing transportation facilities and systems for pedestrians, bicyclists, and the broader traveling public;
3) promoting connectivity between and among connected vehicles, roadway infrastructure, pedestrians, bicyclists, the public, and transportation systems;
4) increasing the overall efficiency of the transportation network;
5) reducing vehicle pollution; and
6) improving emergency response.

Ultimately, the desired outcome is a smart traffic management system that is resilient, adaptable, and scalable, offering a model for other municipalities to implement similar solutions. Additionally, the Project aims to provide a public domain set of foundational tools for future integration with autonomous vehicles and other emerging mobility technologies.

3.1.4 Impacted Communities

At-scale implementation will target corridors that serve residents who frequently encounter transportation-related challenges such as limited access to personal vehicles, inadequate infrastructure for walking and biking, and longer commutes to reach jobs, schools, and essential services. These conditions contribute to higher exposure to traffic-related risks and reduced access to opportunities.

The Project is designed to improve safety, mobility, and connectivity by deploying advanced signal control technologies that better protect people walking, biking, and using transit. During Stage 1, community input helped shape the Project through a series of engagement activities, including public presentations and integration with other planning initiatives. These efforts informed key decisions about corridor selection and system features to better serve those with the greatest transportation barriers. By focusing on improvements where the need is highest, the Project will deliver practical, lasting benefits to residents.

3.2 Overview of Proof-of-Concept/Prototype

3.2.1 Scale of Stage 1 Deployment:

In 2016, the City of Colorado Springs and Iowa State University (ISU) launched the nation's first proof-of-concept for trajectory-based signal control—deploying a high-resolution adaptive traffic management system citywide. This first-generation system established a foundation for the next stage of innovation, demonstrating the viability of real-time, perception-driven intersection management.

Building directly on this groundwork, SMART Grant Stage 1 was designed to evaluate the latest perception technologies and lay the groundwork for a second-generation system with enhanced capabilities. Stage 1 focused on field-testing advanced sensor technologies—radar, LiDAR, and video analytics—at two representative intersections. One intersection was located in an urban/downtown environment with periodic congestion and high levels of interaction among vehicles, pedestrians, and other multimodal users. The other was at a suburban-to-rural interface, serving primarily commuter and commercial vehicles with higher speeds and fewer pedestrians.

In addition to these primary test sites, Stage 1 included the installation of a multimodal count station for monitoring both commuter and commercial vehicle volumes, and an automated weather station along a rural corridor to track adverse weather impacts on traffic operations.

To support comprehensive evaluation, all sensor technologies were also integrated into the Infrastructure Perception and Control (IPC) Mobile Laboratory—a flexible, mobile field data collection platform. The IPC lab enabled testing of sensor concepts, operational performance, and integration strategies both independently and in tandem with fixed deployments, accelerating the iterative development and validation process necessary for Stage 2.

3.2.2 Anticipated Scale of Stage 2 Deployment:

The anticipated scale of Stage 2 deployment involves a gradual scaling from two intersections in Stage 1 to a more extensive deployment of 48 intersections along two corridors. Sensors will be placed along one corridor that crosses the City through urban and suburban regions, and along one commuter access route for a rural region of the County. The locations vary to capture different urban, suburban, and rural traffic scenarios, ensuring a robust assessment of the system's performance across distinct settings. Stage 2 implementation seeks to complete methods, algorithms, software modules, and system architecture that form a replicable solution that can be implemented at any intersection in the county.

The Project will also focus on enhancing system integration across various traffic scenarios. Building on the evaluation and planning conducted in Stage 1, Stage 2 will prioritize the fusion of expanded sensor technologies to optimize intersections for all road users. In addition to integrating City and County systems, the Project will also incorporate connected vehicle (CV) platforms, including in-vehicle V2X hardware. This integration will increase the system's ability to collect, analyze, and act on real-time data, thereby improving overall traffic management and safety.

3.3 Summary of Project Activities

3.3.1 Milestones

Core activities under the SMART grant focused on evaluating cutting-edge sensor technologies and adaptive control strategies suitable for large-scale deployment to improve safety, efficiency, and adaptability in Colorado Springs' transportation system.

As part of the SMART grant, the City completed installation and field testing of advanced sensor suites at two intersections—a representative urban intersection and a suburban-to-rural interface—to capture different types of traffic conditions. Additional SMART-funded deployments included a multimodal count station to monitor a full range of users and an automated weather station to assess microclimate impacts on corridor operations. These installations generated critical real-world performance data across a spectrum of environmental and operational scenarios.

The City's project management team played a pivotal role in administering the SMART grant: aligning all partner activities, overseeing technical, reporting, and regulatory compliance, and facilitating acquisition and installation of field equipment. City staff led coordination with academic, research, and technical partners, organized meetings, collected technical deliverables, and prepared the final implementation report for the USDOT. Throughout Stage 1, the City ensured that work remained on schedule and met all federal requirements.

Under the grant, the City also conducted a comprehensive cybersecurity assessment and communications bandwidth analysis. Staff worked to expand the technical framework and datasets needed to develop a future infrastructure-based perception digital twin. Leveraging operational insights from field deployments, the team advanced the intersection control application by porting it to Advanced Transportation Controller (ATC) architecture and testing it on multiple platforms, thereby preparing the system for broader Stage 2 rollout.

Despite facing delays in procuring certain sensors and V2X equipment due to supply chain and industry factors, the City and its partners quickly adapted. They conducted field tests at alternate intersections and utilized National Renewable Energy Laboratory's (NREL) Infrastructure Perception and Control (IPC) Mobile Laboratory to maintain progress and data continuity. These adaptive approaches ensured that the SMART grant-funded activities continued to generate actionable findings and technical progress, directly informing the design of the next-generation system and setting the stage for successful at-scale implementation in Stage 2.

3.3.2 Media Coverage and Public Engagement

Stage 1 activities garnered media coverage, including a televised news segment and a City press release announcing the $1.7 million federal grant. The Project was also highlighted in public presentations delivered at the 2023 and 2024 Citizen's Public Works Academy, the Mayor's Civic Leaders Fellowship, and a meeting of the Pikes Peak Rural Transportation Authority Citizen's Advisory Board. These forums provided transparency and offered the public insight into the Project's goals and early outcomes.

On the research and professional front, partner institutions presented findings at several conferences and contributed to peer-reviewed publications. NREL, ISU, and other partners authored white papers accepted by the Transportation Research Board (TRB) and IEEE, helping to disseminate results and tools developed through the Project. These resources, included in the appendix, offer in-depth insight into the methodologies and tools now entering the public domain.

The Project and its partner-developed tools were presented at multiple professional forums, including the TRB Annual Meeting, the Conference of Cities, the IRF Global R2T Conference, and the ASCE International Conference on Transportation and Development. These venues provided national exposure to the Project's technical achievements and open-source toolsets.

The City will continue engaging stakeholders through established forums such as the City's Transit Advisory Board (CTAB), while preparing for a structured validation period during the final three months of Stage 2. These efforts will ensure continued public involvement and a successful transition from testing to full corridor deployment.

Stage 1 of the Project built on the existing efforts of the City and its partners to prototype and develop a multi-dimensional perception system. The focus was on testing combinations of sensors and control applications to identify the most feasible and beneficial solutions for the region. Key milestones during Stage 1 include the installation of sensor technologies at two intersections—one urban and one suburban-to-rural—along with the deployment of a multimodal count station and an automated weather station. These installations provided critical data to evaluate the system's performance under various conditions. Partnerships with ISU, NREL, UA, Olsson and other stakeholders were integral to advancing these efforts. Despite some delays in procurement and contracting, the City adapted by conducting some sensor tests and data collection at alternate intersections utilizing NREL's mobile perception lab.

While Stage 1 focused on collaboration with public agency, academic and research peers, Stage 2 engagement expands to include a broader spectrum of public stakeholders, including community organizations, transit users, and first responders. Outreach and input from these groups are critical for validating the system's utility and refining its user-focused applications.

3.3.3 Deviations from Original Proposal

Stage 1 activities experienced several deviations from the original proposal, primarily related to procurement and contracting timelines, as well as refinements in technology deployment strategies. A delayed contract with the University of Alabama postponed the testing schedule for V2X technology, and widespread turnover in the LiDAR industry complicated equipment acquisition. In addition, the team encountered challenges complying with Build America Buy America (BABA) requirements, which extended procurement timelines for sensors and related software systems. While video analytics technology showed promise in post-processing contexts, Stage 1 testing confirmed that current systems do not yet offer distortionless positional and trajectory data necessary for infrastructure-based signal control, particularly under low-visibility conditions.

One notable structural change was the City of Colorado Springs' assumption of operational responsibility for traffic signals previously managed by El Paso County. This transition did not alter the geographic scope of the Project, but it did simplify governance and leadership by consolidating all relevant signal operations under a single agency. As a result, the City now serves as the sole lead agency for the Project in both name and function, improving administrative efficiency and long-term system integration potential.

Despite the above adjustments, the Project's goals remained on track. The City and its partners continued to advance the core objectives of Stage 1: validating infrastructure-based perception technologies, maturing a real-time digital twin framework, and refining trajectory-based control methods. To maintain testing momentum during procurement delays, the City deployed NREL's IPC Mobile Laboratory at alternate intersections. These efforts contributed to the development of a robust foundation for at-scale deployment in Stage 2, including integration of real-time object fusion, V2X telemetry for emergency vehicle preemption, and data-driven strategies for improving intersection performance.

Insights from Stage 1 field testing also informed key refinements to Stage 2 implementation. Based on observed reliability, radar will serve as the primary perception technology across most intersections, while LiDAR deployment has been scaled back to targeted sites due to supplier instability. Video analytics will be retained primarily for object identification confidence. These adjustments reflect the Project's commitment to cost-effective, maintainable, and scalable deployment as it prepares for broader rollout across the region. A summary of Stage 1 project activities and milestones is provided in **Table 1**.

Table 1: Stage 1 Project Activities and Milestones

Month	Activities and Milestones
August 2023 – December 2023	• Established a grant agreement with U.S. Department of Transportation (USDOT) • Completed the evaluation and data management plans • Attended Smart Grant Summit • Created the scope for a RFI for sensor technologies • Divided full project scope into separate tasks for subrecipients
January 2024 – February 2024	• Initiated coordination with vendors and stakeholders for installation logistics • Developed scope for the sensor technologies RFI • Published RFIs for sensor technologies
March 2024	• Finalized contracts with ISU, NREL • Revisited scope work and deliverables with partners given shorter timeline • Developed auto-calibration methodology for fusion engine
April 2024 – May 2024	• Finalized contracts with UA • Conducted initial testing of installed hardware through NREL's IPC lab • Started collecting data from IPC lab and pre-existing radar sensors
June 2024	• Started preliminary analysis of collected data to understand quality of data and sensor efficacy (NREL) • Collected data from second field test- Evaluated and analyzed the collected sensor data (from IPC and on-site radars) • Initiated analysis of simulations for both corridors using ISU algorithms and current volume data, as real-time data is not yet available due to slow procurement process • Procured V2X technology

July 2024 – August 2024	• Procured and installing weather station • Procured multi-modal counting station • Completed ISU traffic algorithm testing • Completed simulations & generated a report from these based on ISU algorithms • Collected data from third field test • Tested multi-sensor fusion capability • Finalized procurement of sensor hardware and support systems • Attended Smart Grant Summit • Submitted Draft Implementation Report
September 2024	• Installed sensor hardware at designated intersections • Ingest data into existing algorithms for extended testing and refinement • Began drafting the design document for the system upgrade, focusing on integration and deployment • Started preliminary analysis of collected data to understand quality of data and sensor efficacy (ISU, UA, City)
October 2024	• Analyzed outcomes from Q2 tests and refine data integration strategies • Established partner VPN access to sensors • Conducted initial testing and calibration of installed hardware (from intersections) • Monitored and collected data from the installed sensor suites • Tested multi-sensor continuous validation and health monitoring method • Deployed weather and multi-modal counting stations
November 2024	• Continued sensor data collection • Conducted analysis on collected data • Refined and optimize data integration strategies
December 2024	• Connected Vehicle technology assessment • Final NREL field testing for fusion engine
January 2025	• Finalized technology assessments (Sensors) • Deployed additional cameras at intersections • Finalized cybersecurity assessment, bandwidth analysis, weather station and vehicle counting analysis • Finalized datasets from NREL • Presented at the Standards and Technology subcommittee for TRB's Signal Systems Committee • Established data repository for NREL • NREL & ISU presentation - TRB posters
February 2025	• Finalize Implementation Report

4 Proof-of-Concept or Prototype Evaluation Findings

4.1 Findings on the performance of your proof-of-concept or prototype

The City of Colorado Springs, in partnership with Iowa State University (ISU), pioneered the nation's first trajectory-based signal control system in 2016. This initial "proof-of-concept" deployed radar sensors at signalized intersections, enabling controllers to continuously track the speed and approach distance of each vehicle. By integrating this real-time data, the controllers could intelligently select safe and efficient signal transitions—optimizing flow, reducing dilemma zone incidents, and serving as the foundation for the City's ongoing adaptive traffic management strategy. This first-generation system has remained in continuous operation across Colorado Springs, demonstrating the potential of perception-based adaptive control.

Building on this legacy, Stage 1 of the SMART Grant project focused on advancing and validating a new generation of perception technologies and adaptive control applications. Extensive field testing was conducted at both permanent sensorized intersections and through NREL's IPC Mobile Laboratory, enabling rapid deployment and iterative evaluation of different sensor configurations across multiple intersection types. This real-world testing was critical to assessing how the latest radar, LiDAR, video analytics, and V2X equipment performed in varied operational and environmental conditions.

Technologies evaluated in Stage 1 were measured against performance benchmarks that included data refresh rates, object detection accuracy, system latency, resilience to weather and lighting, and ease of integration with intersection controllers. Results demonstrated that new sensor suites and control algorithms substantially outperformed the original radar-only system, particularly in their ability to detect and track multiple road users—including pedestrians, cyclists, and transit vehicles—and in supporting higher-resolution, trajectory-based control logic.

However, field validation also highlighted important areas for continued improvement. Challenges were observed with the real-time classification accuracy of some sensor types, the synchronization of data streams from disparate devices, and sensitivity to adverse environmental conditions. Lessons learned through this process are now guiding targeted refinements, continued manufacturer engagement, and the technical strategy for at-scale deployment in Stage 2.

The findings summarized below reflect each partner's contributions and highlight the current state of technology readiness, key lessons learned, and the specific advancements made through this phase of the Project. Full technical details are available in the final reports submitted by NREL, ISU, and UA, which are included in the appendix. Reviewers are encouraged to explore those documents to better understand the unique contributions and public domain tool sets developed through this effort:

Sensor Testing Using the NREL Infrastructure Perception and Control (IPC) Mobile Laboratory: During Stage 1, NREL focused on evaluating perception technologies that could deliver real-time object detection with position, speed, direction of travel, and size/classification updates at a minimum of 10 times per second. Testing was conducted at targeted intersections in Colorado

Springs using the IPC Mobile Laboratory, which enabled rapid deployment of radar, LiDAR, and video analytics systems. RTK and public base station GPS data provided a reliable ground truth reference for evaluating accuracy. Comparative testing revealed that no single technology offers a comprehensive solution across all use cases.

Perception Technology	Advantage	Disadvantage
Radar	Demonstrated excellent distance measurement and reliable speed and position data	Limited classification capability
LiDAR	Offered good classification and positional accuracy	Suffered from lower maintainability and weather-related sensitivity
Video Analytics	Excelled in classification	Performed poorly in adverse weather and had limited distance and tracking reliability

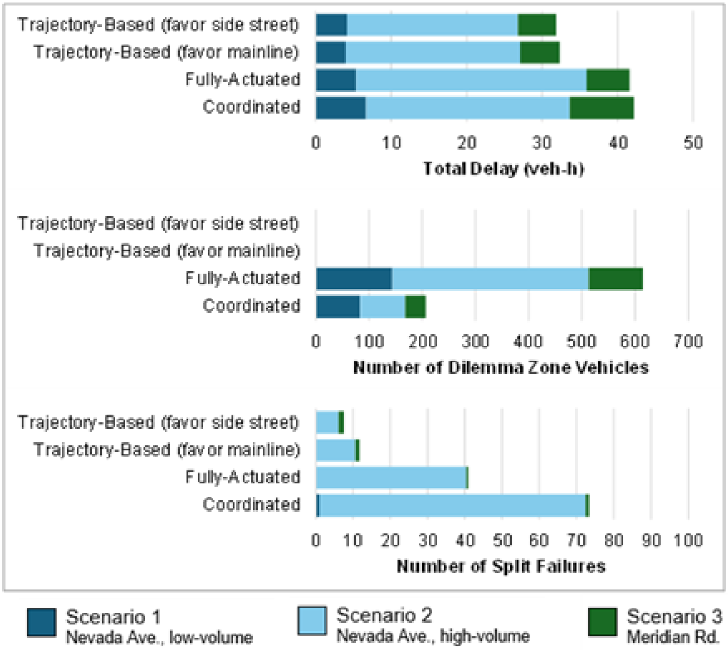
Real-world deployment conditions, including issues with data dropouts, firmware mismatches, and inconsistent time synchronization, revealed critical gaps in system resilience. These challenges directly informed improvements to the Perception Fusion application, leading NREL to implement significant fault tolerance upgrades. By the end of Phase I, the IPC system advanced to an initial release-ready state, with enhanced robustness and normalization strategies for integrating multi-sensor data streams. This outcome was made possible through iterative testing at sites such as North Powers Blvd and Palmer Park Blvd, and reflects the effectiveness of a field-based development approach that continuously validated against ground truth video analysis.

Automated and Rapid Calibration of Sensors: Over the course of Stage 1, NREL has developed and implemented their rapid calibration techniques to allow for robust sensor deployment as well as on-going health monitoring of the system. Data collected by the IPC Mobile Laboratory in Phase 1 has been used to successfully demonstrate the feasibility of rapid calibration algorithms. See the attachments for an IEEE white paper presented by NREL on this topic.

Incorporation of Connected Vehicle Data: In Stage 1, NREL emulated CV capability through use of GPS high-precision instrumentation on two vehicles that mimic the data conveyed through BSMs and other protocols. This provides statistically independent vehicle track data for calibration, periodic re-calibration, and ongoing system health monitoring. High accuracy position data from connected vehicles is critical within the IPC framework. The passage of each connected vehicle provides not only additional data, but the opportunity to validate the system accuracy based on vehicle position between the IPC fused sensor data, and that reported by the connected vehicle.

Refinement of the IPC Framework: Stage 1 testing presented real-world challenges with perception technologies—including synchronization issues, data dropouts, and variable sensor performance—which provided critical input for advancing NREL's Perception Fusion application. These lessons allowed the team to implement significant fault tolerance enhancements and shape the architecture toward a robust, deployable framework. As a result, the IPC system reached an initial release-ready state by the end of Phase I, with finalized specifications and data schemas that support normalized, scalable integration of diverse sensor inputs in live field environments.

Figure 2 ISU simulations predict substantial safety and efficiency benefits from implementation compared to fully-actuated and coordinated control methods.



Simulation Validation: In Stage 1, ISU used VISSIM traffic micro-simulation software to model two arterial routes scheduled for at-scale implementation in Stage 2, the Nevada Ave corridor (Brookside to Cheyenne/ Southgate) & Meridian Rd corridor (Londonberry to Woodmen). Due to delays in senor acquisition, ISU used alternate City-provided real-world datasets for the simulations. Streetlight traffic movement count (TMC) was used to generate origin-destination volume data, and a Hill-Climb algorithm was used to convert the TMC data to OD-data. Simulations ran for 4000 seconds with a 400-second warm-up. Signal control was coded using the Green Box Signal Controller, which integrates trajectory data with control methods. Validation compared field TMC data with simulation TMC data, which showed high accuracy with coefficient of determination values above 0.96 for both models.

Simulation of Trajectory-Based Control Methods: Using the validated simulation, tests compared the proposed trajectory-based control methods of the Project against conventional coordinated signal control that would typically be used for such corridors and fully actuated control under existing detection technology. Results show that total delay is reduced 15.8% to 23.7% by the trajectory-based methods reduction in total delay compared to coordinated control, notably reducing both mainline *and* side street delays. Trajectory-based control methods also result in a near total elimination of dilemma zone vehicles and a substantial reduction in the number of split failures. The reduction in dilemma zone vehicles is facilitated in part by the introduction of the new concept of extension priority, enabling safety-critical features to access a greater amount of maximum green time.

Safety and Efficiency Improvements: Applying knowledge from the City of Colorado Springs' implementation of trajectory-based traffic control and simulation tools from ISU's "Integration of

New Traffic Signal Actuation Concepts using Enhanced Detector Information" pooled fund effort, the ISU team provided simulations showing strong potential for safety and efficiency improvements.

- **Safety:** ISU applied crash modification factors derived from national literature to evaluate the expected safety impacts of implementing perception-based adaptive signal control on the Nevada Ave and Meridian Rd corridors. Based on 2023 crash frequencies observed along the Nevada Avenue and Meridian Road corridors (the two corridors proposed for Stage 2 implementation), ISU estimates that the Project will achieve, over ten years, a reduction of approximately 2.2 fatal crashes, 6.2 incapacitating injury crashes, 48.3 non-incapacitating injury crashes, 145.5 possible injury crashes, and 288 property damage only crashes. These reductions are projected to result directly from the deployment of the advanced signal control and perception technologies proposed for these corridors. These reductions, driven by reductions in rear-end and broadside crash risk, are expected to produce over $28 million in safety benefits over a 10-year project life.
- **Efficiency:** Simulations conducted by ISU showed that trajectory-based control reduced peak-period vehicle delay across test intersections by an average of 15.4 vehicle-hours. When scaled to Stage 2's full 48-intersection deployment, this equates to an expected daily reduction of 79.3 vehicle-hours and an annual peak-period delay reduction of approximately 33,314 vehicle-hours. These improvements in corridor throughput and delay mitigation result in over $10 million in travel time savings and reduced vehicle operating costs over a 10-year period.

Expanding Knowledgebase of Available Technologies and Applications: Since the City started the project with only a basic understanding of connected vehicle technologies and applications, University of Alabama (UA) assembled a comprehensive knowledgebase of standards and tools, allowing the City to improve its understanding of how these technologies can be incorporated within the project. UA evaluated connected vehicle equipment and services from Applied Information (AI) providing the following conclusions:

- Tracking and identifying data from properly equipped vehicles can be programmatically retrieved from AI's cloud-based service.
- Low latency tracking data is accurate enough for preemption control of intersections.

Data Accuracy: The index of visibility data from the weather station was accurate enough to be included in safety first mitigations such as red light running, and could be programmatically retrieved from Advanced Monitoring Methods' (ADVM2) cloud-based service. Other weather condition data could also be retrieved from this service. Count Station from Vivacity Labs Ltd can be used to provide accurate vehicle and pedestrian counts in locations without intersection control infrastructure. Additionally, the metric presentation tools provide a clear understanding of available data.

4.2 How your Stage 1 project met the original expectations and goals stated in your project proposal

Stage 1 testing has met the goals outlined in the project proposal:

1. **Identify the most promising sensor technologies and control applications for cost-effective implementation of the system throughout the Pikes Peak Region:**

Tests utilizing NREL's IPC mobile lab and alternate city intersections have identified improved radar technology for large-scale implementation in the region: radar remains the most reliable for 3D perception and imaging. LiDAR technology and video analytic technology has shown promise but remains unreliable and plans for LiDAR implementation in Stage 2 have been scaled back to a further testing phase. Testing has also identified certain changes to radar, LiDAR and video analytic technologies that will allow for more cost-effective testing and implementation by reducing the likelihood of dropouts and sensor errors.

- **EVO Radar Sensors:** the most mature and reliable sensor technology, easy to set up. These radars are able to accurately perceive objects at up to 300m at all times of day and in diverse weather conditions. They provide excellent position (particularly distance from intersection), speed and direction of travel data and basic object classification. Classification abilities are minimal; only able to provide basic size information for the objects they are tracking (ex. misclassified a closely bunched group of teenagers as a small vehicle). The lack of classification information can be overcome by geofencing regions of an intersection, understanding movement characteristics, and matching average speeds, as well as fusion with other sensors that have higher fidelity with object identification. Installation planned at all 48 intersections in Stage 2 implementation.
- **LiDAR:** emerging technology with great potential but reliability issues remain. Complex systems are more difficult to set up than radar**.** They are able to perceive objects at up to 200m at all times of day and in diverse weather conditions. Accuracy of speed and position metrics declines as object distance increases. Classification abilities are more accurate than radar. Performance during severe weather (heavy or frozen precipitation) remains untested. Installation planned at 8 of the 48 total intersections in Stage 2 implementation.
- **Video Analytics:** emerging technology with great potential but issues remain. Able to perceive objects near and within an intersection. Due to reliance on visual spectrum, accuracy is low in adverse weather conditions, at night, and at a distance. Reliable and highly accurate classification abilities at a close distance. Installation planned at 8 of the 48 total intersections in Stage 2 implementation.

2. **Advancing Toward a Next-Generation Adaptive Traffic Management System:**

Stage 1 resolved key limitations of the first-generation system and set the stage for a fully adaptive, next-generation solution. By rigorously evaluating new radar, LiDAR, and video analytic technologies, the City identified how to expand perception capabilities beyond basic vehicle speed and distance. These advanced sensors now provide the ability to detect precise lane positions, differentiate vehicle size and type, and capture non-motorized road users' movements (such as bicyclists and pedestrians) as they approach, travel through, and exit intersections.

While delays in contracting slowed initial integration of V2X data, ongoing collaboration with the University of Alabama (UA) ensured a clear path for incorporating these data streams. Software development also advanced significantly: NREL's real-time edge computing platform is nearly complete, enabling a digital twin environment for each intersection that fuses multiple sensor inputs in real time (a significant upgrade from their initial post-process approach). This foundation will enable full implementation in Stage 2.

Through these efforts, Stage 1 achieved its goals by laying the groundwork for widespread deployment—integrating advanced sensors, enhancing safety and mobility for all users (including those most at risk), and developing an automated, adaptive traffic management system responsive to real-world roadway and environmental conditions. Stage 2 will build on this platform, scaling deployment to 48 intersections and delivering real-world benefits across the City.

Table 2: Performance Evaluation Based on Measures from Evaluation Plan:

Performance Measure	Performance Measure Target	Performance Evaluation
How quickly can the digital twin from the fusion engine be updated?		
Time between updates	0.1 seconds between updates	Radar and LiDAR object lists refresh at 20 Hz and 10-20 Hz, respectively. NREL's fusion engine generates a unified digital twin at ~10 Hz with latency of ~50 ms. Total system delay is approximately 150 ms, meeting the target and suitable for real-time traffic control applications.
Does the system reduce travel time through the intersection?		
Travel time through intersections and corridors during peak/off-peak	Demonstrated delay reduction over existing control methods	ISU simulations demonstrated delay reductions between 15.8% and 23.7% for both mainline and side-street approaches using trajectory-based control. Annual peak-period vehicle delay is projected to decrease by ~33,314 hours across 48 intersections.
How well do all the sensors work under varied weather or lighting conditions?		
Detection accuracy during adverse conditions	Report degradation from baseline metrics	Radar and LiDAR maintain reliable tracking in snow and low-light conditions, validated by IPC lab and real-world weather station comparisons. Video analytics performance degraded during low-visibility events. Manual resets and calibration may be required to sustain operation.
What is the appropriate tolerance for error at high speed?		
Accuracy of telemetry data for fast-moving vehicles	Latency < 150 ms and positional error within 1 meter	Testing showed radar and LiDAR maintain speed and position accuracy sufficient for high-speed travel (up to 65 mph). Object tracking maintained integrity without need for predictive compensation. Sensors can identify and monitor fast-moving vehicles within safety tolerances.
What is the appropriate tolerance for error at low speed?		
Accuracy for identifying vulnerable users	Object permanence, lateral precision, classification confidence	LiDAR consistently identified stationary and slow-moving human-sized objects with strong classification reliability. Radar classification errors (e.g., mistaking tight pedestrian groups as vehicles) were mitigated using geofencing and behavior filtering. System performance meets expectations for pedestrian and cyclist detection.

Performance Measure	Performance Measure Target	Performance Evaluation
What is typical accuracy of V2X identity and position data, and typical latency for data delivery?		
Connected vehicle data transmission accuracy and speed	Accuracies consistent with SAE J2735 standard; latency < 250 ms	Initial integration tests show V2X data is transmitted within acceptable latency for preemption scenarios. Simulated GPS telemetry via probe vehicles indicates high consistency. Further testing is underway to validate full emergency preemption capability.
Performance of multimodal count station		
Compare collected data to video recordings. Evaluate automated data retrieval integration.	Data accuracy; seamless integration with broader system	Product selected following clarification on BAA compliance thresholds. Delivery and installation occurred late in Stage 1. Validation now complete
Performance of automated weather station		
Compare collected data to NWS/local weather sources and real-world conditions	Comparable accuracy; consistent availability	Weather station successfully recorded major storm events with data aligning with COS Airport and NWS records. Modem reset required during one event, highlighting need for monitoring and manual intervention protocols. System shows strong value for adaptive red-light extension logic during weather related, low-visibility periods.

5 Anticipated Costs and Benefits of At-Scale Implementation

5.1 Anticipated/Estimated Impacts of At-Scale Implementation in the Program Goal Areas

Table 3: Potential impacts of at-scale implementation

Goal Area	Anticipated Impacts	Description
Congestion and Delay Reduction	Decreased travel time, smoother traffic operations	Stage 1 simulations suggest delay reductions of up to 23.7% on the selected corridors. At-scale implementation is expected to substantially reduce congestion and delay, especially during peak hours, improving reliability for both passenger and commercial traffic.
Safety and Integration of Systems	Reduction in collisions; better multimodal coordination	Sensor fusion and trajectory-based signal control will improve intersection safety by eliminating dilemma zone exposure and enabling responsive timing. Enhanced detection of non-motorized users ensures better integration of pedestrian and bicycle movements into traffic operations.
Access to Jobs and Services	Improved connectivity to employment and healthcare	Stage 2 corridors connect rural and neighborhoods to regional job centers and health facilities. Reducing delays and improving safety will enhance access to critical services for various populations.
Cost Reduction	Reduced transportation barriers for vulnerable populations	Improved pedestrian and bicycle infrastructure benefits those without access to vehicles. The Project will reduce transportation costs and improve mobility options for many.
Economic Competitiveness	More efficient movement of goods and services	By reducing delay and improving system reliability, the Project will lower transportation costs for businesses and support economic growth along key regional corridors.
System Reliability	Fewer unplanned delays; better incident response	Real-time data from sensors and V2X communications improves the ability to adapt to incidents and maintain traffic flow, resulting in more consistent travel times and fewer unplanned delays.

Goal Area	Anticipated Impacts	Description
Connectivity and Integration	Enhanced V2X and infrastructure interoperability	Deployment of V2X systems and data-sharing infrastructure will connect vehicles, traffic systems, and multimodal users, improving situational awareness and enabling coordinated responses to changing conditions.
Private Sector Partnerships	Opportunities for integration with telecom and OEMs	The Project provides a framework for collaboration with technology vendors, OEMs, and telecom providers, including those supporting in-vehicle systems, to support testing and data sharing for future deployments.
Energy and Environmental Impact	Lower emissions and fuel consumption	Reductions in idling, delay, and crash-related disruptions will lower fuel use and emissions. Improved access to active transportation options also supports healthier, low-emission travel choices.
Resiliency	Improved response to weather and system disruptions	Weather stations and sensor-based adjustments improve safety during microclimate events. The Project increases the region's ability to maintain mobility during interstate closures and severe weather conditions.
Emergency Response	Faster, safer routing for first responders	Connected vehicle telemetry enables intersection preemption for emergency vehicles, reducing response times, enhancing safety for emergency operations across the corridor, and ultimately saving lives.

In addition to the expected benefits to the local community, the Project will provide far-reaching benefits for transportation systems outside the City. Tools produced through implementation across diverse traffic management challenges will reside in the public domain for further development and adoption by other agencies, producing similar benefits across the nation.

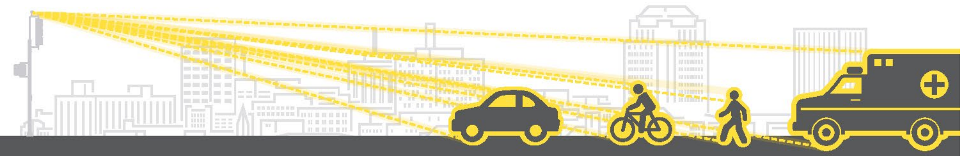
The Project will also expand the possibilities of sensors already in place at many intersections across the country, such as radar. The City sees potential future expansion of the Perception-Based Adaptive Traffic Management and Data Sharing system to create even smarter intersections. For example, the digital twin object list created by sensor fusion could be incorporated into an app to audibly inform vision-impaired pedestrians when it is safe to cross. The system could also extend the perception of autonomous vehicles, reducing the uncertainty associated with intersections and more seamlessly integrating autonomous vehicles with human-driven vehicles.

5.2 Anticipated Costs of At-Scale Implementation

The costs detailed in **Table 4** reflect an estimate of the scale of Stage 2 deployment needs. These costs have been refined and updated throughout Stage 1.

Table 4: Estimated cost of at-scale implementation

Stage 2 Activities	Estimated Costs		
Item	Cost/Unit	# of Units	Total
ISU	N/A	N/A	$852,000
UA	N/A	N/A	$471,000
UNCC	N/A	N/A	$550,000
NREL	N/A	N/A	$3,600,000
Olsson	N/A	N/A	$3,800,000
Cyber Services	N/A	N/A	$450,000
Publication & Documentation	N/A	N/A	$550,000
Public Engagement	N/A	N/A	$300,000
Installation	$14,000	48	$672,000
Servers, workstations and interconnectivity	N/A	N/A	$30,000
Cellular Interconnect	$4,000	12	$48,000
Auxiliary cabinet	$1,000	48	$48,000
Radar perception system (sensor and hub)	$24,000	48	$1,152,000
LiDAR Perception System (Sensor and Hub)	$25,000	7	$175,000
Video Perception System (sensor and hub)	$45,000	4	$180,000
Connected vehicle (in-vehicle and cloud service)	$7,000	20	$140,000
Advanced Transportation Controllers	$3,000	48	$144,000
Firewalls & Communication System for Intersections	N/A	N/A	$610,000
Enclosures, cabling, and miscellaneous installation hardware	$750	48	$36,000
Software licenses and service fees	$12,000	3	$36,000
Weather station equipment and service	$21,500	5	$107,500
Total Direct Cost			$13,951,500
Contingency (6%)			$837,090
Total Project Cost			$14,788,590



5.3 Comparison of Benefits and Costs

Trajectory-based control simulations conducted by ISU during Stage 1 estimate total safety and efficiency benefits of approximately **$67.3 million** over a 10-year life cycle. This estimate is based on deployment at 48 intersections along the Nevada Ave and Meridian Rd corridors, and reflect peak-hour delay reductions, crash prevention benefits, and improved travel conditions for both major and minor road users.

Simulations performed during Stage 1 project activities suggest a total peak period delay reduction of 15.4 vehicle hours across the modeled intersections on Meridian Rd and Nevada Ave. Scaled to Stage 2 implementation levels of 48 intersections, the project is expected to reduce total daily peak period delay by 79.3 vehicle hours. Annualized using a 260-day year to account for weekdays, this results in an annual peak period delay reduction of approximately 33,314 vehicle hours, assuming current traffic volumes. A major source of benefit, this delay reduction translates to travel time savings benefits and would be expected to produce emissions reduction benefits.

In addition, the project is expected to significantly improve safety along Meridian Rd. and Nevada Ave by reducing rear-end and broadside crashes at intersections equipped with the new technology. Specifically, based on crash modification factors (CMF) of 0.564 for rear-end crashes and 0.65 for broadside crashes, and using 2023 average annual crash rates, the project is projected to prevent approximately 2.2 fatal crashes, 6.2 incapacitating injury crashes, 48.3 non-incapacitating injury crashes, 145.5 possible injury crashes, and 288.1 property damage only crashes over a 10-year period along the two corridors. These reductions represent a substantial safety benefit for the traveling public, directly supporting the project's core objectives of decreasing crash frequency and severity at signalized intersections.

However, the anticipated benefits of the Project extend far beyond the local community. Stage 2 implementation aims to develop methods, algorithms, software modules, and system architecture that can serve as a replicable solution for intersections across the United States. By focusing on a robust testing and development infrastructure along two key corridors, encompassing 48 intersections that represent a wide variety of traffic scenarios, population densities, neighborhood contexts, and microclimates, the Project will ensure that the solutions developed are both adaptable and scalable. This diverse testing environment will allow the City to identify the most cost-effective implementation approaches, prioritizing future deployments that maximize safety and efficiency benefits.

The continued testing of sensor technologies and control applications in Stage 2 is crucial to refining the system and ensuring that the most effective solutions are identified before broader expansion. By supporting this rigorous testing in Colorado Springs, the SMART Grant effort will help establish a cost-effective, publicly available system that can be adopted by agencies across the country, delivering similar benefits nationwide.

5.4 Baseline Data for At-Scale Implementation

Stage 1 deployment of next-generation sensors at a downtown intersection and a rural to suburban interface intersection will provide baseline speed and ATSPM metrics. Comparison of baseline numbers to speed and ATSPM metrics at those same intersections after Stage 2 corridor-wide implementation will allow efficiency analysis of improved sensors and control algorithms.

Police reports from before and after Stage 2 implementation will provide crash count comparisons to evaluate safety enhancements; according to the PPACG Traffic Crashes Map, there were 1,715 crashes at intersections on the Stage 2 implementation corridors (Nevada Ave and Meridian Rd) from 2018 to 2022 and four intersections designated as locations of high crash frequency (at least 50 crashes in 4 years).

6 Challenges & Lessons Learned

6.1 Legal, Policy, and Regulatory Requirements (e.g., NEPA, BABA)

The pilot Stage 1 project included improvements at a small number of intersections – these same improvements will encompass the entirety of Stage 2 work at 48 additional intersections. USDOT determined that Stage 1 was not subject to NEPA clearance, so it is expected the same finding will apply to Stage 2.

6.2 Procurement and Budget

The Buy American Act (BAA) added some complexity to the procurement process. The challenges of procuring compliant products at reasonable costs without relying on statutory waivers resulted in delays and lengthy discussions with vendors, who often had to conduct their own research to confirm compliance. Although understanding of the requirements improved over time, potential future restrictions could further complicate the project timeline.

Anticipating that program policies and regulatory compliance may take time to navigate, planning accordingly through specific requirements in RFPs/RFIs, leveraging existing vendor relationships, and ensuring that project team members are knowledgeable about these policies and regulations will be essential to a successful project delivery.

6.3 Technology Suitability / Integration with Incumbent Systems

Emerging technologies such as LiDAR and video analytics present both opportunities and challenges in the traffic management context. In this use case, radar has proven to be the most stable and deployment-ready solution, delivering consistent real-time perception with minimal setup complexity and high reliability under diverse environmental conditions. As a result, radar will form the foundation of the Stage 2 deployment across all 48 intersections.

LiDAR, while offering higher classification fidelity, demonstrated limitations related to data completeness and system complexity. Stage 1 testing revealed challenges with real-time data capture and sensor integration, especially under conditions requiring continuous operation and high availability. Though promising for post-analysis applications, LiDAR currently lacks the consistency required for large-scale real-time traffic management. Continued refinement in Stage 2 will explore how LiDAR may support complementary functions, with a focus on manageable deployment and maintainability.

Video analytics, though a longstanding component in traffic systems, remains volatile in high-precision, real-time applications due to its dependence on lighting, weather conditions, and evolving software ecosystems. The pace of change in video platforms poses additional integration risks, making stability and long-term support more difficult to guarantee in this context. In Stage 1, video analytics did not meet the fidelity or reliability thresholds required for use as a primary input to the control system. However, it may remain useful for secondary or retrospective analysis.

Time synchronization between multi-sensor systems continues to be a critical challenge, particularly as different vendors implement proprietary methods for timestamping and data alignment. This issue directly affects the reliability of fused perception and automated decision-making. Stage 2 will prioritize continued refinement of NREL's fusion engine to address these integration barriers, standardize data handling protocols, and improve real-time system performance.

Ultimately, the Project's success depends on integrating intelligent infrastructure components that accurately perceive all intersection users and share this information with traffic control systems and, eventually, autonomous vehicles. The lessons learned through Stage 1 underscore the importance of scalability, maintainability, and system-wide coherence. By continuing rigorous field evaluation and refining deployment strategies in Stage 2, the City will be able to provide concrete, evidence-based guidance to other agencies considering similar deployments.

6.4 Data Governance

Data management and sharing methods are inconsistent between academic institutions, federal research groups and public agencies. Data governance requirements from SMART Grant administration are appreciated, because they provide a broad accessible framework for consolidation of the project's results.

6.5 Internal Project Coordination & Partnerships

The loss of a key project coordinator presented challenges, necessitating a period of adjustment. Regular meetings, clear expectations, consistent communication, and regular reminders of project objectives were crucial. The role of a dedicated project manager was vital for maintaining task focus and accountability across the Project's multiple partnerships.

6.6 Community Impact

Safety and traffic flow benefits have already been described; however, deployment of new technologies and the management systems that utilize them is not risk free. Just like we have done with previous advancements of our traffic management system, we will carefully plan staged deployments that include rapid rollback options to mitigate risk and inconvenience for the traveling public. Before each deployment we have full traffic team meetings to ensure there are no conflicting projects and keep everyone informed of risks to watch for and mitigation options. We also deploy observers in the field to provide immediate feedback if hazards develop.

6.7 Public Acceptance

Gathering meaningful feedback from local communities during implementation of such a complex technology has proved challenging: the more effectively the system manages traffic and protects the public from hazards, the less noticeable the efforts should be. It has been productive to integrate public outreach into existing initiatives such as the City's Transit Advisory Board (CTAB) and prioritize project alignment with community needs that have been revealed through the City's other public outreach initiatives.

7 Deployment Readiness

7.1.1 Requirements for Successful Implementation

Successful implementation of the Project at scale requires not only advanced technology and robust partnerships, but also sustainable staffing strategies and institutional knowledge. The Stage 2 workplan is organized into four primary task areas—Management, Development, Documentation, and Deployment—each encompassing activities critical to ensuring technical functionality, implementation readiness, and long-term sustainability.

A key requirement is the seamless integration of sensor technologies into existing traffic management systems, supported by reliable data fusion and real-time analytics. Effective coordination across internal and external teams, including academic and research partners, will be essential. The City has already demonstrated its capacity to manage similar efforts: the first-generation system—still operational today—was successfully developed, deployed, and maintained by City staff in partnership with Iowa State University beginning in 2016.

As part of Stage 2, the City is taking deliberate steps to build operational resilience, including planning for staff continuity. This includes investing in cross-training, cultivating long-term institutional expertise, and evaluating contingency staffing strategies to address potential vacancies or shifting budget conditions. Ongoing community engagement will also help ensure that the system continues to meet the needs of various road users.

7.1.2 Key Obstacles to Scaling the Project

Scaling the Project introduces several challenges. The evolving nature of certain technologies—particularly LiDAR and video analytics—poses questions about long-term stability, accuracy, and maintainability in real-world traffic environments. While these technologies show promise in post-analysis and targeted applications, real-time performance continues to require refinement.

System integration is another critical challenge. Different sensor types and software platforms must be synchronized to ensure accurate and reliable real-time data. Regulatory compliance, including Build America Buy America (BABA) provisions, may lead to procurement delays or limitations on technology selection. Additionally, future budget cycles will need to account for system upgrades and ongoing support.

7.1.3 Strategies and Demonstrated Progress

The City has already overcome many early-stage obstacles and has built a strong foundation for scaling. During Stage 1, the City adapted to sensor procurement delays by leveraging NREL's mobile IPC lab and conducting tests at alternate intersections. The team's ability to adapt to unforeseen challenges reflects a culture of responsiveness and resilience.

The City has also invested in long-term relationships with project partners—including NREL, ISU, UA, and UNCC—who share its vision and bring specialized expertise. These relationships reduce startup time and allow the Project to evolve collaboratively as testing data becomes available. A phased deployment approach provides a structured opportunity to validate performance before full implementation.

7.1.4 Uncertainties and Risk Mitigations

Key uncertainties remain regarding technology performance in diverse conditions and the effort required for long-term maintenance. To mitigate these risks, the City has incorporated continuous evaluation and feedback loops throughout Stage 2. Cybersecurity is being actively managed through design oversight, and vendor coordination. These efforts aim to protect system integrity and prepare the City for future threats.

7.1.5 Understanding Maintenance and Operating Requirements

The City's ongoing experience operating the first-generation radar-based system has already informed many of the operating requirements for the new platform. Still, Stage 2 will generate new insights. Continuous system monitoring, sensor calibration tracking, and issue logging will inform proactive maintenance schedules. Additionally, feedback from City technicians—many of whom participated in Stage 1 testing—will help refine system design, configuration, and field support protocols.

To maintain readiness, the City is developing operational playbooks and is documenting support procedures during deployment. Staff knowledge transfer and alignment between engineers, technicians, and management remains a top priority.

7.1.6 Capacity to Prevent Technical Debt

Preventing technical debt requires forward-looking investment. The City is addressing this by prioritizing ongoing training, documenting system dependencies, and fostering strong working relationships with its partners. Academic and research collaborators will continue to support design decisions, software development, and future innovation. The City's experience maintaining and updating its first-generation system is a clear indicator that future upgrades will be managed with diligence and foresight.

7.1.7 Impact on Job Opportunities

This Project is not replacing labor, it is expanding technical capacity. By building on and modernizing existing infrastructure, the City will create new job opportunities in system installation, configuration, maintenance, and data analytics. Contracted services will support competitive wage standards, and all hiring will comply with federal requirements regarding fair labor practices.

The City is also committed to ensuring long-term job quality. Stage 2 implementation is expected to support skilled local labor, while partnerships with academic institutions will open the door to workforce development pathways.

8 Wrap-Up

The City has made significant strides in advancing traffic management through the SMART Grant program. Stage 1 established a strong technical foundation, and the momentum carried into Stage 2 demonstrates clear potential for measurable improvements in safety, efficiency, and system sustainability. This Project is not only addressing current challenges, but also laying the groundwork for the future of intelligent transportation infrastructure, both locally and nationally.

As the system transitions into at-scale implementation, the Project offers numerous opportunities for expansion. The Perception-Based Adaptive Traffic Management and Data Sharing system—featuring real-time object tracking, multi-sensor fusion, and V2X integration—has demonstrated strong adaptability to various contexts. These capabilities could be extended to other corridors, applied to freight and transit operations, and serve as a testbed for the safe integration of autonomous vehicles. With continued refinement, the system positions Colorado Springs to serve as a national model for future-ready, perception-enabled transportation networks.

Crucially, the work conducted by the City's research and implementation partners has generated a robust suite of publicly available tools, methods, and insights that will shape the next generation of traffic control. The final reports produced by NREL, ISU, and UA, included as appendices to this document, present key contributions to this framework:

- **NREL** advanced the real-time fusion engine, digital twin design, and calibration strategies for infrastructure-based perception and developed a comprehensive system architecture for scalable deployment.
- **ISU** conducted detailed simulations of trajectory-based signal control, demonstrating a reduction of 15.8% to 23.7% in vehicle delay and quantifying crash reduction benefits from intersection upgrades.
- **UA** developed the V2X data path to support emergency vehicle prioritization, validating latency thresholds and providing hardware-software integration guidance.

Together, these deliverables form an open, extensible tool set that will reside in the public domain—available to local, regional, and national agencies seeking proven, cost-effective approaches to intersection safety and efficiency. The Project's alignment with federal innovation goals positions Colorado Springs to lead broader conversations about the future of multimodal infrastructure.

The Project's deployment strategy also lays the groundwork for private-sector participation. By establishing public-domain tools and demonstrating scalable, standards-based implementations, the Project encourages telecom, automotive, and sensor firms to align their products and investments with public-sector needs. This creates opportunities for co-investment in infrastructure and technology that benefits both private innovation and public transportation goals.

Moving forward, the City remains committed to leveraging this momentum—translating early findings into long-term operational improvements, informing future research, and encouraging widespread adoption of infrastructure-based perception systems that improve mobility for all users.

IMPLEMENTATION REPORT

Perception-Based Adaptive Traffic Management and Data Sharing

Appendix A – Iowa State University

- **A1 – Simulations Report**
- **A2 – Benefit Analysis**
- **A3 – Benefit Analysis Calculations**

COLORADO SPRINGS
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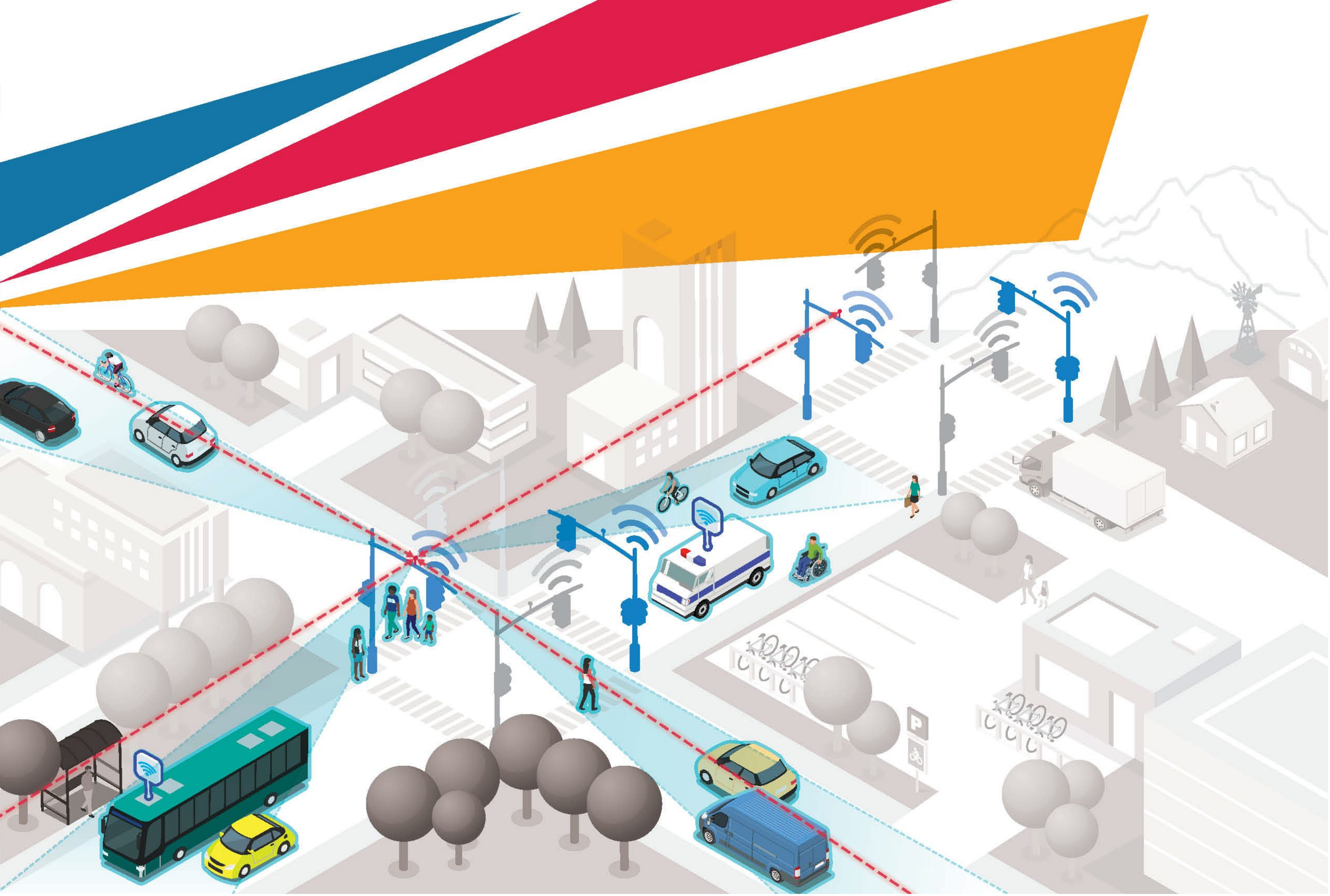
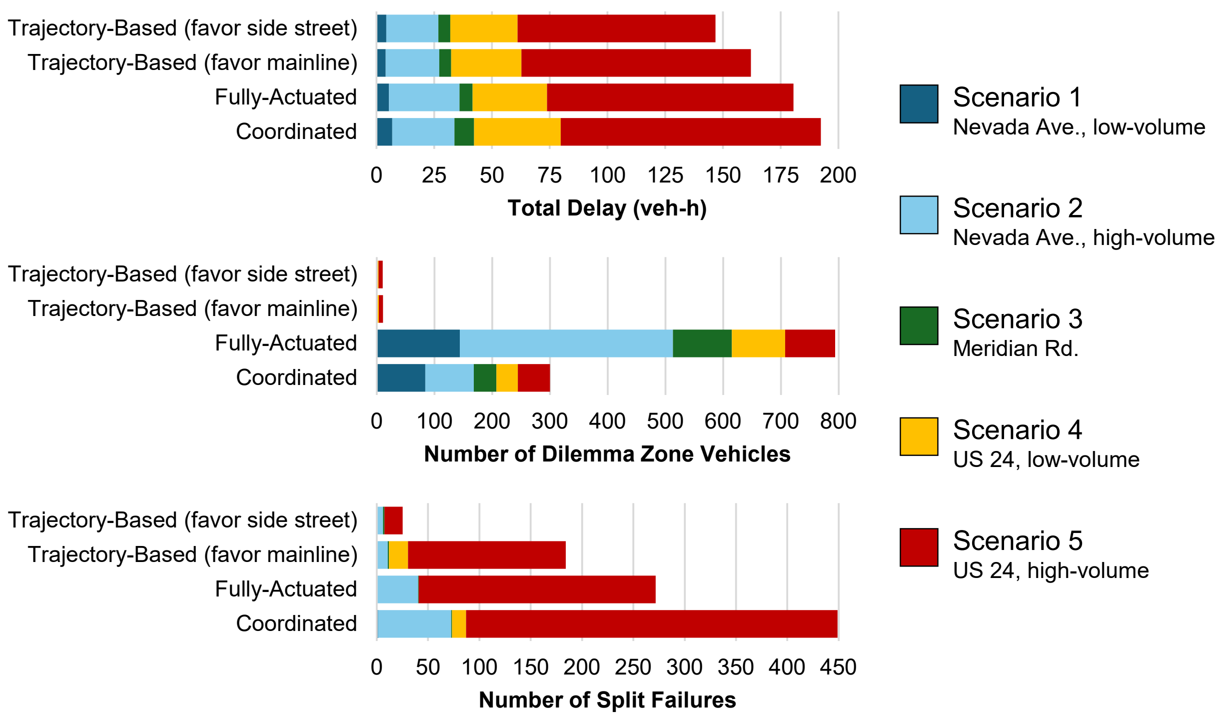


A1 – Simulations Report

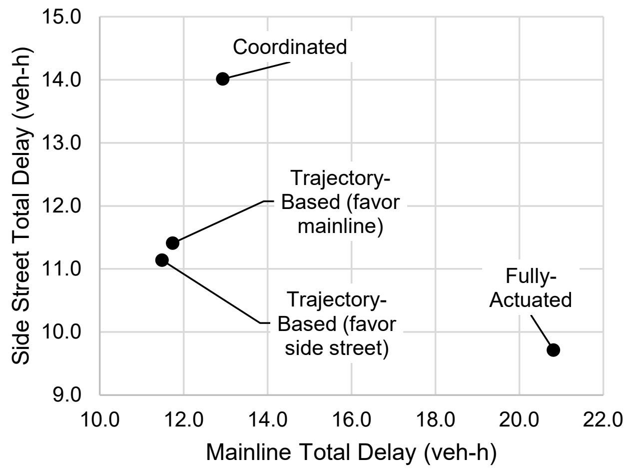
Results Briefing

During Stage I of the SMART grant, the research team conducted simulation tests of the control algorithms for specific corridors in the Colorado Springs area. The tests compared the proposed trajectory-based control methods against conventional coordinated signal control that would typically be used for such corridors, as well as fully-actuated control under existing detection technology. Two trajectory-based options were tested including one method that tends to favor the side street and another method that tends to favor the mainline movements. Five simulation scenarios were included in these tests, representing a variety of corridor types and volume levels. The results are summarized in the figures below, including the total delay, number of dilemma zone vehicles, and number of split failures.



The results show that delay is reduced moderately by the trajectory-based methods, with a 15.8% or 23.7% reduction in total delay compared to coordinated control depending on the selected control option. This is accompanied by a near total elimination of dilemma zone vehicles with trajectory-based control, and a substantial reduction in the number of split failures. The reduction in dilemma zone vehicles is facilitated in part by the introduction of the new concept of extension priority, enabling safety-critical features to access a greater amount of maximum green time, a feature that was first proposed and previously field tested in Colorado Springs.

The chart to the right shows the differences between delay experienced by the mainline and side streets for Scenario 2. Similar patterns were observed for other scenarios. This illustrates the typical tradeoff in performance between serving the mainline and serving the side street. Typically, coordination reduces mainline delay at the cost of higher side street delay. The two trajectory-based methods have similar performance and are able to reduce mainline delay (in this case doing better than coordination) with less cost to the side streets. In other words, the trajectory-based methods are able to enjoy "the best of both worlds" by combining the flexibility of fully-actuated control with platoon accommodation strategies.



The mainline delay reductions are achieved with the introduction of trajectory-based actuation methods that identify and accommodate platoons using two strategies (the "favor mainline" option more aggressively pursuing coordination). This allows some degree of coordination to take place without the use of a fixed cycle length or a corresponding pattern. By reducing the number of plans that need to be maintained in the field, this mode of operation will not only benefit traffic but also make signal timing easier to maintain.

EXTENDED SUMMARY, UPDATES AND FUTURE PLANS ON SMART GRANT

This section was an earlier draft that includes some additional technical details. I have not revised this section (and I added to these results by including some additional scenarios from the PFS simulation tests) but have kept it in case you find any of the included material useful.

METHODOLOGY

This section presents the control methods, control and simulation scenarios and a brief description on simulation framework.

Control Methods

For this study, we have implemented two trajectory-based control methods and evaluated the performance benefits against the base scenario (fully-actuated control) and PTV VISTRO optimized coordinated-actuated signal control. The trajectory-based control methods were developed as part of a pooled fund study project [1], where we focused on developing and evaluating new actuation-based signal control using advanced sensor data. Table 1 presents a brief description of the control methods we tested for the PFS. Details of these methods can be found at [1].

Table 1 Summary of trajectory-based actuated control methods tested in PFS.

Trajectory-based Control Method	Description	Primary Objective
Immediate Gap-out (IG)	Rather than wait for a passage timer to expire, the gap is directly measured using vehicle trajectory data.	Reduce wasted green time
Queue Clearance (QC	Each vehicle that stops during red is “flagged” as a queued vehicle, and an extension is placed at the start of green until all queued vehicles have departed the intersection.	Reduce number of split failures
Decision Zone (DZ) Protection	Each vehicle on the approach is assessed to determine whether it is within a Type II dilemma zone (“decision zone”). If any vehicles are in a DZ, a green extension is placed.	Reduce number of rear-end crashes
Secondary Extension (SE) for Platoons [2]	Platoons of vehicles are identified in advance and characterized in terms of their size and density. Then, contingent on the spare capacity at the intersection, the green is extended to ensure service of the platoon.	Promote smooth traffic flow
Free Optimization (FO) [3] (Mainline gap identification)	Traffic on the major street is assessed and compared against an expected volume to assess a gap in major street traffic. A green extension is placed while traffic is above the threshold, but is released so that the side street phases can be served while there are relatively few vehicles on the major street.	Promote smooth traffic flow
Adaptive Gap (AG)	The current gap value in effect is adjusted according to the ratio of traffic on the current-phase barrier group to the amount of traffic awaiting service on the other barrier group.	Equitable allocation of capacity

Simulation Environment

To implement and test the signal control methods, we have used traffic micro-simulation software PTV VISSIM. We previously developed Green Box Signal Controller (GBSC) [4], [5], [6] to develop and test trajectory based control methods in simulation. GBSC is a robust, highly customizable, multi-phase multi-ring signal controller which can explicitly integrate trajectory data with control methods. Detailed description of the signal controller can be found at [4], [5],

[6]. Figure 2 presents the green box signal controller. In the figure, the green box displays signal status, the white box presents vehicle related data and the simulation controller can start/ stop/ control the simulation speed.

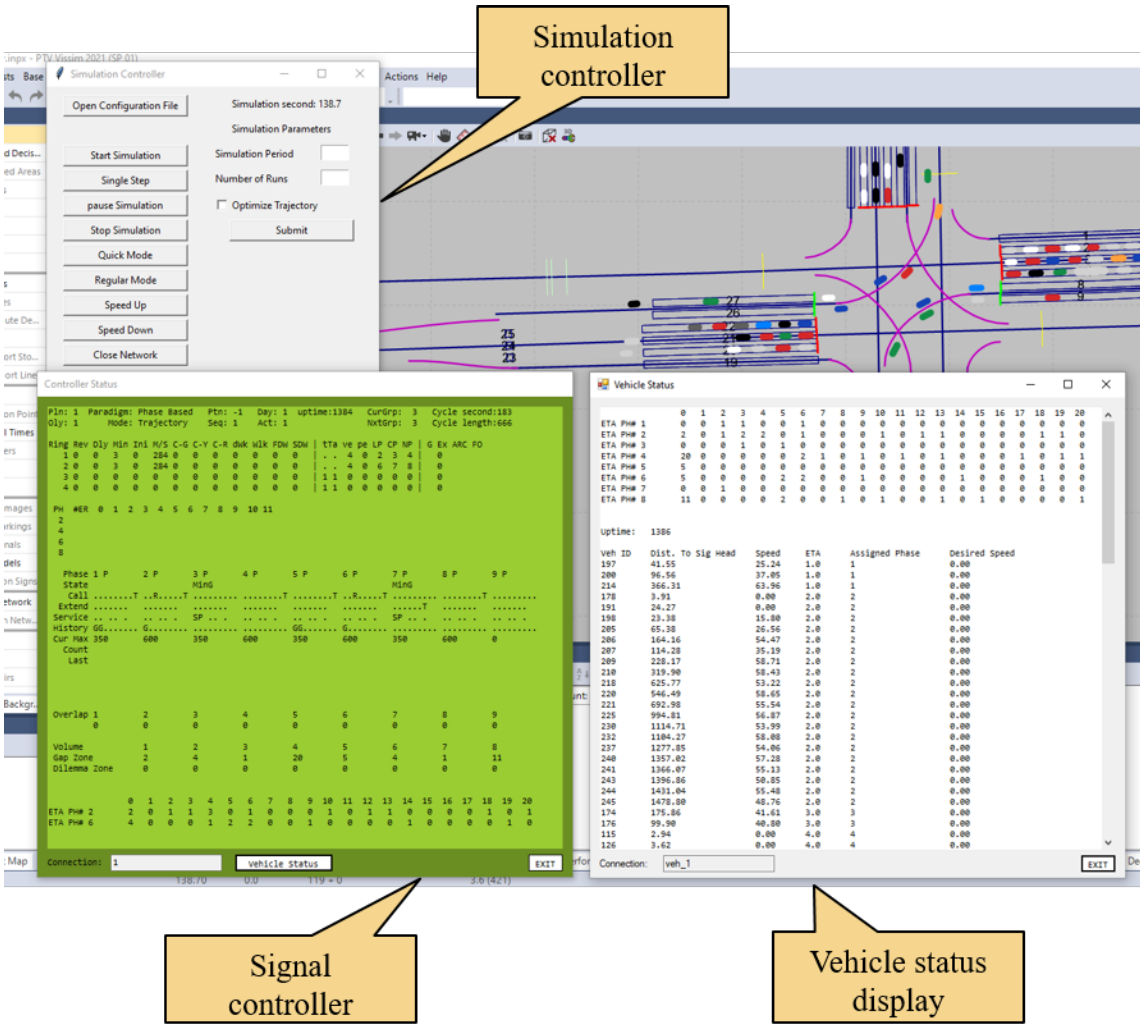


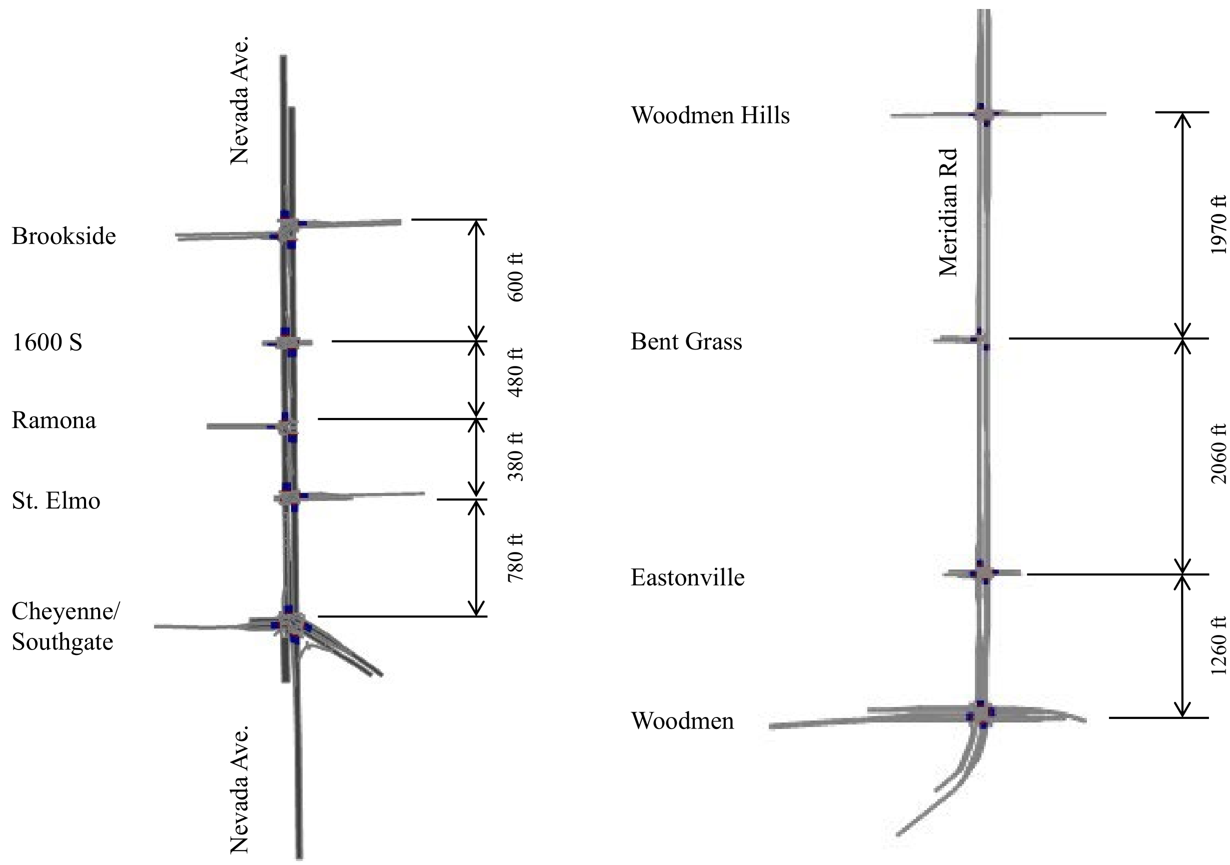
Figure 1 GBSC environment

Simulation Models

This study uses two arterial routes in City of Springs, CO and developed base models in traffic micro-simulation software VISSIM. The first model is in Nevada Ave corridor from Brookside to Cheyenne/ Southgate and the second one is Meridian Rd corridor from Londonberry to Woodmen. The Nevada Ave corridor has 5 signalized intersections with multi-modal traffic and the Meridian Rd corridor is in a suburban area with four signalized intersections. For both of the models, streetlight traffic movement count (TMC) was used to generate origin-destination volume data. A Hill-Climb algorithm was used to convert the TMC data to OD-data. We selected the morning peak period (8 AM-9AM) volume for both of the arterials. We created another hypothetical scenario by scaling up (with scaling factor 3) the Nevada corridor to present a near saturated volume configuration. So, altogether we have three configurations

1. Nevada- low volume

2. Meridian Rd.
3. Nevada- high volume



(a) Nevada Ave.

(b) Meridian Rd

Figure 2 Selected arterial routes

Control Scenarios

The trajectory-based scenarios we used in this study are a combination of IG, DZ, QC, AG and (either SE or FO). We have selected IG and QC to improve operational efficiency, DZ to improve safety performance. The key difference between the first and second trajectory-based strategy is how progression along corridor is managed.

To evaluate the performance benefits, we have developed two conventional control methods, the first one is fully actuated method which uses field signal timing data for Nevada-Low volume and reasonable assumptions for Meridian Rd and Nevada-high volume. The signal timing for the coordinated-actuated control is optimized using PTV VISTRO. Below we have listed the control methods used in this study

1. Conventional control- Fully actuated control

2. Conventional control- coordinated-actuated control
3. Trajectory-based control- IG+QC+DZ+AG+SE
4. Trajectory-based control- IG+QC+DZ+AG+FO

We ran each of the simulation scenarios for each of the control methods for 4000 seconds and used the first 400 seconds to warm up the simulation.

RESULTS AND ANALYSIS

This section presents performances of each of the control methods in the form of total delay, major and minor movement delay, total number of split failures, and total number of vehicles in dilemma zone at the onset of yellow. Major movement delay sums up delay for major through movements for all intersections and minor movement delay sums up delay for each of the other movements for all intersections. Split failure is identified when a vehicle stopped at the intersection at red, but couldn't clear the intersection within next green. As per the recommendations of Signal Timing Manual [7], a vehicle is in dilemma zone if it's estimated arrival time is within 2.5-5.5 seconds at the onset of yellow. Total split failure, total number of vehicles in dilemma zone and total delay is the summation of split failure, number of DZ vehicles and delay for all movements and for all intersections.

Total Delay Comparison

Figure 3 presents the reduction in total delay for the coordinated actuated control and trajectory-based controls in comparison with the fully-actuated control. A negative value indicates an increase in delay, and a positive value indicates a decrease in delay.

Results suggest, both of the trajectory-based control methods experienced 10-20% reduction in delay compared to the fully-actuated method whereas coordinated-actuated control experiences higher delay for Nevada-low volume and Meridian Rd. For the Nevada-high volume scenario the coordinated-actuated control also experienced less reduction in delay compared to the trajectory-based methods. So, clearly, trajectory-based methods outperformed the conventional methods.

In between the two trajectory-based methods, total delay is quite similar. This is understandable as the only difference between the control methods is how they manage progression along arterial.

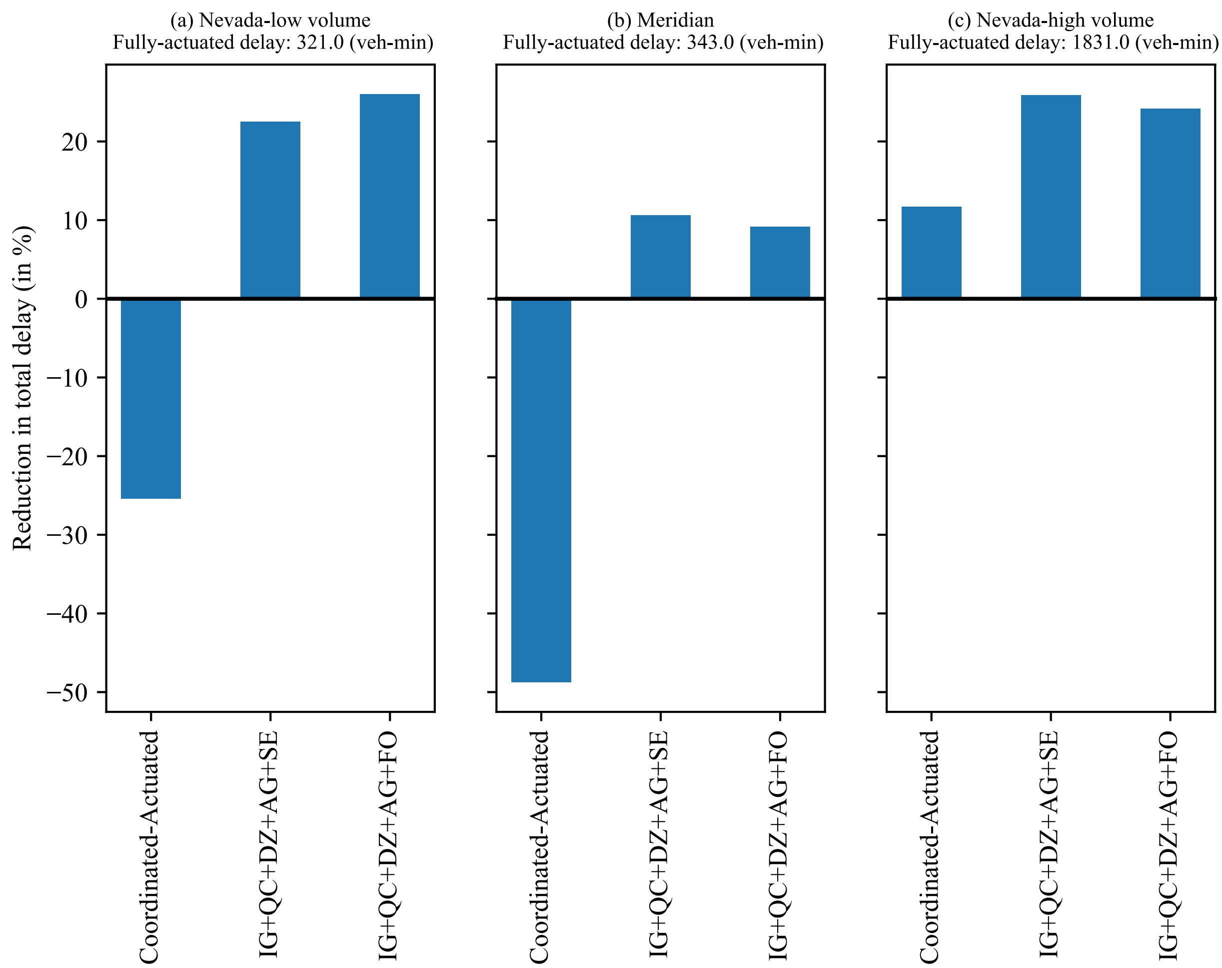


Figure 3 Total delay comparison

Nevada-low volume scenario and Meridian Rd.

Figure 4(a) compares major and minor movement delay and Figure 4(b) presents the total number of DZ vehicles for each of the control methods. In figure 4(a), both of the trajectory-based methods are in the bottom left corner, which indicate both of them are experiencing low major and minor movement delay compared to the conventional methods. The fully-actuated control is experiencing similar performances in the minor movement but the cost at major movement is higher. The coordinated-actuated control experienced higher delay for both type of movements.

As per figure 4(b), with trajectory-based control no vehicle experienced DZ. On the other hand, for both of the conventional methods, substantial number of vehicles experienced DZ. Note that, none of the control methods experienced split failure as this is a low volume scenario.

Figure 5 is similar to figure 4. The only key difference is the coordinated actuated control experienced low major movement delay.

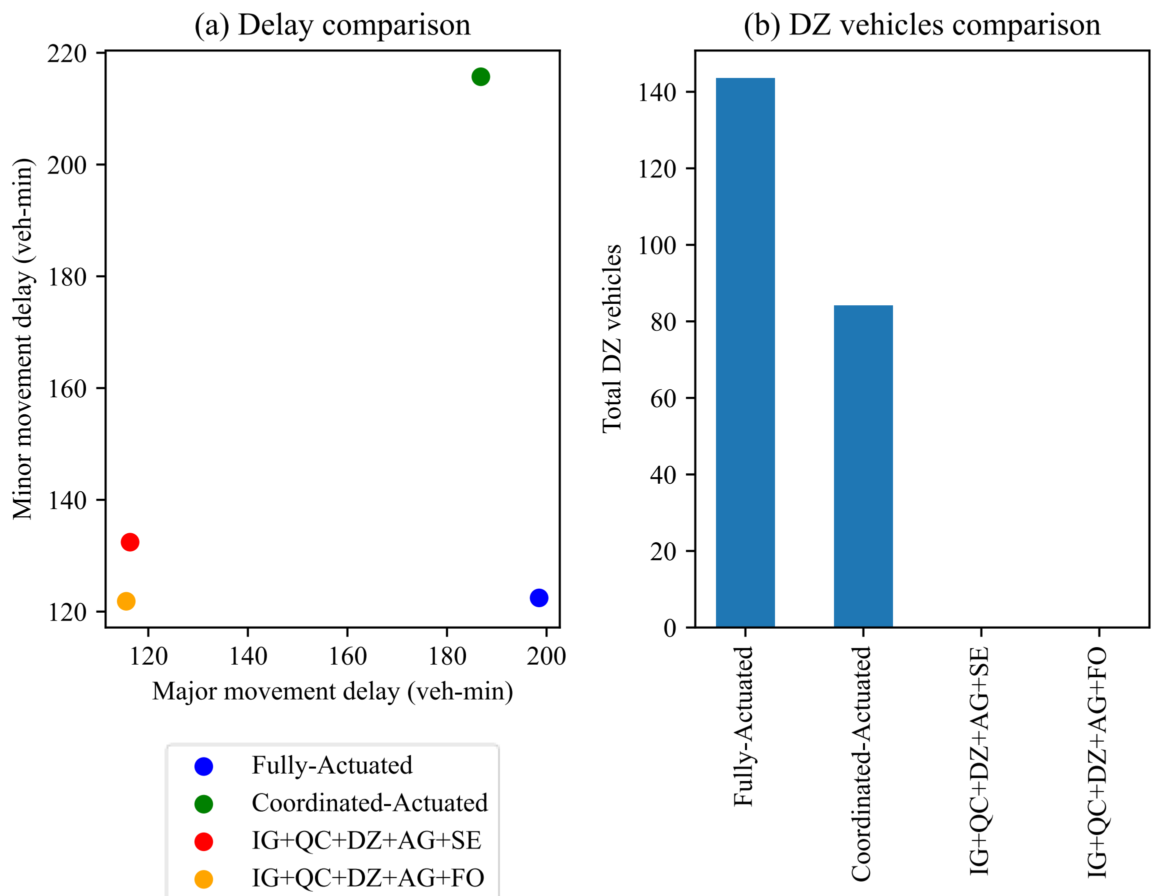


Figure 4 Performance measures for Nevada-low volume scenario

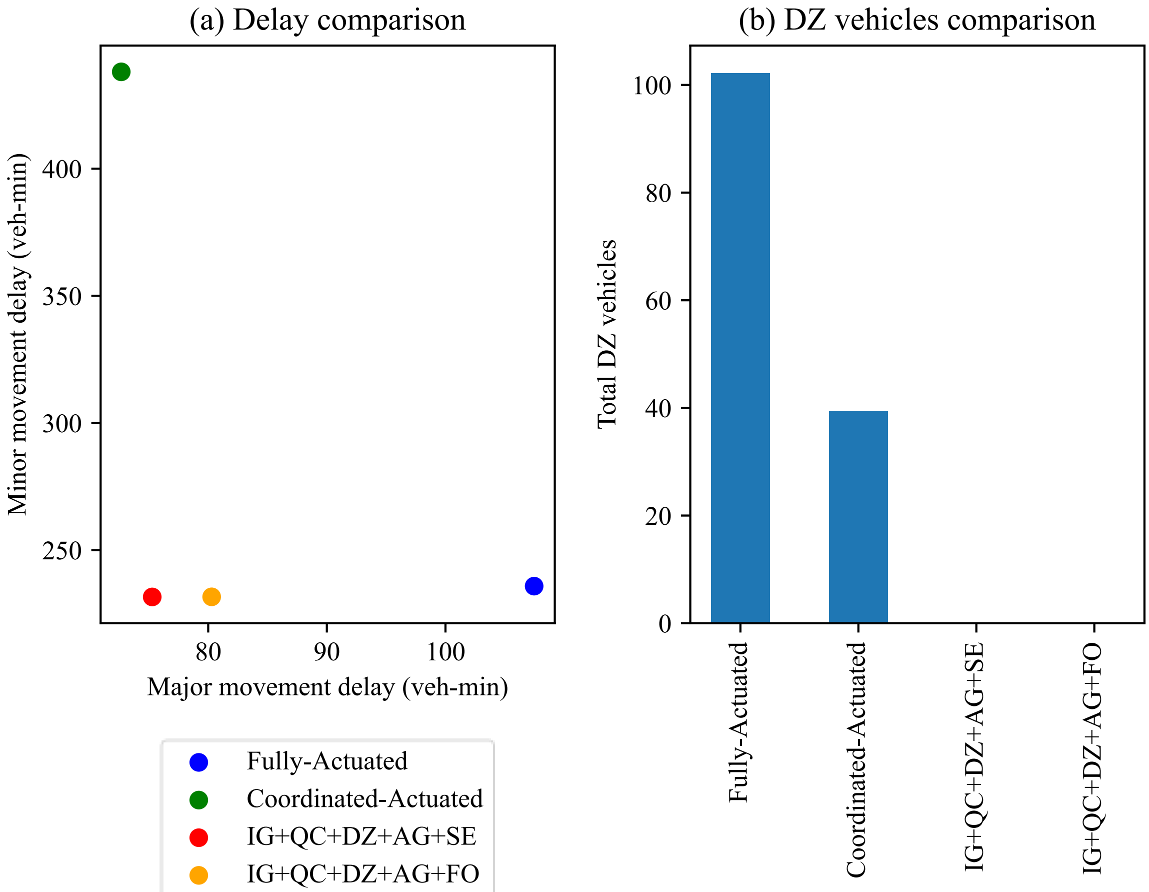


Figure 5 Performance measures for Meridian Rd.

Nevada-high volume scenario

Figure 6(a) compares major and minor movement delay and Figure 6(b) presents the total number of DZ vehicles and split failures for each of the control methods. In figure 6(a), fully-actuated methods experienced lowest delay in minor movement but experienced a substantially higher delay in the major movement. Coordinated-actuated control experienced low major movement delay at the cost of high minor movement delay. The trajectory-based methods experienced even lower delay in major movement, with a substantially less delay in minor movement compared to coordinated-actuated.

In addition, figure 6(b) suggests, trajectory-based control methods experience low number of DZ vehicles and split failures compared to conventional methods.

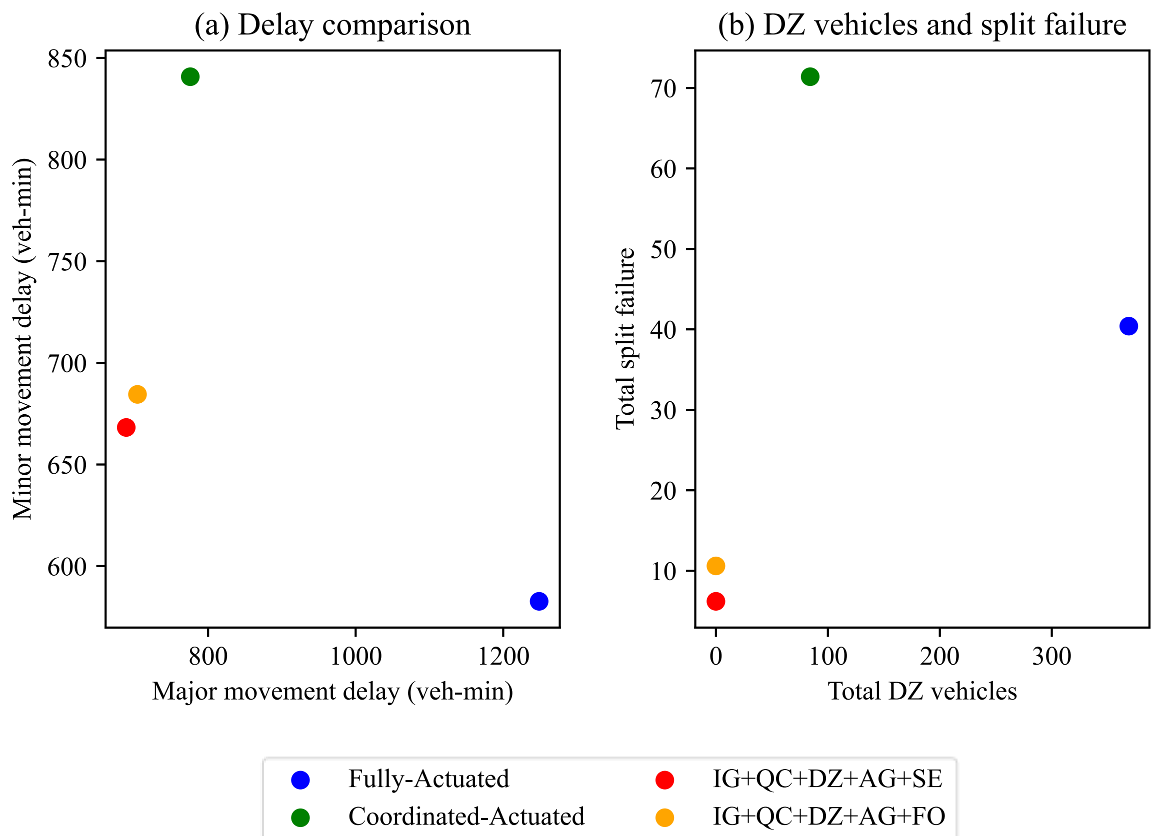


Figure 6 Performance measures for Nevada-high volume scenario

Cost-Benefit Analysis

CONCLUSIONS

The preliminary results present improved performances for trajectory-based methods in terms of total delay, split failure and number of DZ vehicles. These control methods also experience similar major movement delay compared to coordinated actuated control. However, unlike the coordinated-actuated control, the cost in minor movement delay is also low. Most importantly, trajectory-based methods experienced negligible amount of DZ vehicles and split failure, which are substantial amount of safety benefits over conventional methods.

For the rest part and next phase of this study, we are planning to include peer-to-peer communication for better progression, optimize the control parameters, and ensure equity by making traffic signal more pedestrian and vulnerable road user friendly. We believe the proposed control methods would be able to reduce emission, ensure equity, and improve operational and safety performances.

REFERENCES

[1] A. Shams, N. Dobrota, B. Cesme, and C. M. Day, "INTEGRATION OF REAL-TIME VEHICLE TRAJECTORIES INTO ACTUATED TRAFFIC SIGNALS TO IMPROVE LOCAL INTERSECTION AND ARTERIAL CONTROL," *Trajectory-based real-time traffic signal control using advanced sensor data*, p. 116, 2023.

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[4] A. Shams and C. M. Day, "Advanced gap seeking logic for actuated signal control using vehicle trajectory data: proof of concept," *Transportation research record*, vol. 2677, no. 2, pp. 610–623, 2023.

[5] A. Shams, C. M. Day, and S. Mahmud, "Digital Twin of Physical Intersection to Trajectorybased Traffic Signal Controller," in *2023 IEEE International Automated Vehicle Validation Conference (IAVVC)*, 2023, pp. 1–6. doi: 10.1109/IAVVC57316.2023.10328104.

[6] C. M. Day and D. M. Bullock, "Investigation of self-organizing traffic signal control with graphical signal performance measures," *Transportation Research Record*, vol. 2620, no. 2620, pp. 69–82, 2017, doi: 10.3141/2620-07.

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A2 – Benefit Analysis

Benefit Estimation

Benefits are calculated for deployment of trajectory-based control on two corridors: the Nevada Ave. corridor, traversing most of Colorado Springs, including urban and suburban environments, and the Meridian Rd. corridor, in El Paso County, including a suburban/rural interface. Estimated benefits are obtained considering safety and efficiency improvements. Safety benefits were estimated by applying crash modification factors to crash rates on these two corridors, while efficiency benefits were estimated with the use of microsimulation analysis of the two corridors.

Safety Benefit

First, crash data was obtained from Colorado DOT to measure recent crash counts. Crash data from Meridian Rd. were available from 2021–2023, while crash data from Nevada Rd. were available from 2019–2023. Relevant crashes were identified by searching for "intersection" or "intersection-related" crashes of rear-end and right-angle types. To estimate crash reductions, crash modification factors (CMFs) were obtained:

- The Crash Modification Factor Clearinghouse provides CMFs for dilemma zone protection with advanced warning systems ranging from 0.564–0.988 (*1*). A value in the middle of this range, 0.776, was used for estimating crash reduction.
- A recent study (*2*) showed a reduction in right-angle crashes due to red light running with the implementation of advanced dilemma zone protection. A CMF of 0.65 was obtained in this study.

The average crash rate per year was calculated from the crash counts, and the CMFs were applied to identify the rate of prevented crashes per year. The monetary value of each crash was quantified using data from USDOT's *Benefit-Cost Analysis Guidance for Discretionary Grant Programs* (*3*). This document provides crash values using 2023 dollars, which were used for this analysis. Finally, a 10-year project life was assumed to estimate the total benefit, using a 3.1% interest rate, as recommended by the same USDOT guidance (*3*). Table 1 shows the reduction in crashes per corridor and the tabulation of the number of crashes prevented per intersection per year. Crashes and crash values are shown using the KABCO scale. The estimated value of the safety benefit for the two corridors over a 10-year period was $28,268,341.

Table 1. Estimation of safety benefit.

Crash Counts	K	A	B	C	O
Meridian Rd. (2021-2023)					
Rear-end crashes	0	0	3	15	26
Right-angle crashes	1	0	4	6	8
Nevada Ave. (2019-2023)					
Rear-end crashes	0	2	12	51	93
Right-angle crashes	0	3	15	36	90
Crash Rates	K	A	B	C	O
Meridian Rd. (2021-2023)					
Rear-end crashes	0	0	1	5	8.7
Right-angle crashes	0.3	0	1.3	2	2.7
Nevada Ave. (2019-2023)					
Rear-end crashes	0	0.4	2.4	10.2	18.6
Right-angle crashes	0	0.6	3	7.2	18
Crash Modification Factors					
Rear-End Crashes (*1*)	0.776				
Right-Angle Crashes (*2*)	0.650				
Estimated Prevented Crashes Per Year	K	A	B	C	O
Meridian Rd. (2021-2023)					
Rear-end crashes	0.00	0.00	0.22	1.12	1.94
Right-angle crashes	0.12	0.00	0.47	0.70	0.93
Nevada Ave. (2019-2023)					
Rear-end crashes	0.00	0.09	0.54	2.28	4.17
Right-angle crashes	0.00	0.21	1.05	2.52	6.30
Totals	**0.12**	**0.30**	**2.28**	**6.62**	**13.34**
Value of Crash	$13,200,000	$1,254,700	$246,900	$118,000	$5,300
Value of Crashes Prevented, Per Year	$1,540,000	$375,908	$562,504	$781,726	$70,708
Total Value, Per Year					$3,330,846
Life Cycle (Years)					10
Interest Rate					3.1%
Adjustment Factor (P/A, 5%, 10)					8.487
Total Project Safety Benefit					**$28,268,341**

Efficiency Benefit

To estimate benefits due to increased efficiency, delay reductions on the test corridors were obtained from simulation scenarios of the two test corridors using peak hour volumes. Delay reductions were calculated using the best-performing trajectory-based traffic control option tested in the simulation studies. The average amount of vehicle-hours per hour of delay was tabulated for each corridor/volume scenario as the average of five simulation iterations. These scenarios covered the peak hour scenario for a subset of the total number of intersections on each corridor. To scale the estimated delay reduction for the entire corridor targeted in later deployment activities, it was assumed that the delay reductions would be similar across the other intersections included in the corridor in later deployments.

The proposed control methods will operate at the intersections for not only the peak hours but for all times of day and all days of the week. To convert the estimated delay reductions to annualized values, several assumptions were required. First, it was assumed that a typical intersection would typically have peak periods and off-peak periods, with two peak hours per day, enabling a conversion from vehicle-hours per hour to total vehicle hours. Next, it was assumed that the amount of off-peak delay would be proportionate to the total peak delay, according to the distribution of urban area delay reported in the Texas Transportation Institute *Urban Mobility Report* (*3*). According to 2022 data, 39% of congestion occurred on surface streets during peak hours while 24% occurred on surface streets during off-peak hours (the remaining amount occurring on freeways). The ratio of 24:39 = 0.62 was used as an estimate of off-peak delay as a percentage of peak delay. Finally, to annualize these numbers, it was assumed that there would be 260 weekdays in the year and 105 weekend days, and that delay reductions on weekends would be equal to 50% of weekday delay reductions. This value was based on engineering judgment considering that traffic volumes are often lower on weekends, but weekend timing plans generally receive less attention. Monetary values of delay were obtained from the TTI *Urban Mobility Report* (*4*). The passenger value of time was $23.12/h and commercial vehicle operating cost was $64.68/h. An occupancy rate of 1.2 passengers per vehicle was assumed. Table 2 shows the calculation of the estimate. The estimated value of the efficiency benefit for the two corridors over a 10-year period was $10,683,260.

Table 2. Estimation of efficiency benefit.

Delay Reduction	Total Delay under Conventional Control (veh-h)	Total Delay under Trajectory-Based Control (veh-h)	Peak Hour Delay Reduction (veh-h)
Meridian Rd., peak hour	8.5	5.1	3.4
Nevada Ave., peak hour	26.9	22.6	4.3
Scale to Full Corridor Deployment	Percentage of intersections in corridor included in simulation models	Adjustment factor	Adjusted peak hour delay reduction (veh-h)
Meridian Rd.	67%	1.5	5.1
Nevada Ave.	13%	8.0	34.6
Scale to 24-hour operation	Estimated peak hour delay reduction (veh-h)	Estimated non-peak hour delay reduction (veh-h)	Total delay reduction, 24 hours (veh-h)
Meridian Rd.	10.2	6.3	16.5
Nevada Ave.	69.1	42.5	111.7
Annualized delay reduction	Estimated total delay reduction for weekdays (veh-h)	Estimated total delay reduction for weekends (veh-h)	Estimated total annual delay reduction (veh-h)
Meridian Rd.	4,284	865	5,149
Nevada Ave.	29,030	5,861	34,892
Total Annualized Delay Reduction (veh-h)			**40,041**
Percentage of Passenger Cars			90%
Passenger Car Occupancy			1.2
Value of Time Per Passenger Per Hour			$23.12
Percentage of Trucks			10%
Operating Cost for Trucks Per Hour			$64.68
Passenger Benefit, Per Year			$999,816
Truck Benefit, Per Year			$258,987
Total Benefit, Per Year			$1,258,803
Life Cycle (Years)			10
Interest Rate			3.1%
Adjustment Factor (P/A, 5%, 10)			8.487
Total Project Efficiency Benefit			**$10,683,260**

Total Benefit and Scaling to the System

The combined safety and efficiency benefits estimated over a 10-year period is $38,951,601. This estimate reflects the deployment of trajectory-based control at 46 intersections (six in the Meridian Rd. corridor and 40 in the Nevada Ave. corridor) within the scope of the deployment anticipated in Stage II. It should be noted, however, that the overall efforts anticipated by the City of Colorado Springs are not limited to these two corridors. In parallel with SMART Grant efforts, the City is pursuing deployment of trajectory-enabled detection systems and improvement of its control systems to integrate the data from these, with a goal of eventually outfitting a substantial portion of the approximately 600 intersections in the City and other communities in the region with the technology, which would lead to a much higher total benefit ultimately facilitated by efforts under the SMART Grant program.

References

1. Crash Modification Factors Clearinghouse. "Safety Effect of Dilemma-Zone Protection Using Actuated Advanced Warning Systems." https://cmfclearinghouse.fhwa.dot.gov/study_detail.php?stid=311

2. Hossain, M.R., M.-K. Kang, P. Biswas, N. Rahman, and M.M. Rahman. "Safety Evaluation of Dilemma Zone Protection System for Rural, High-Speed Signalized Intersections Using Empirical Bayes Method." Paper No. 25-05030, Transportation Research Board Annual Meeting, 2025.

3. USDOT. *Benefit-Cost Analysis Guidance for Discretionary Grant Programs.* US Department of Transportation, November 2024.

4. Glover, B.A. 2023 Urban Mobility Report, Appendix C: Value of Delay Time for Use in Mobility Monitoring Efforts. Texas Transportation Institute, February 2023.

A3 – Benefit Analysis Calculations

	Crash Count K	A	B	C	O	Years	Crash Rate K	A	B	C	O
Meridian											
Rear-End	0	0	3	15	26	**3**	0	0	1	5	8.666667
Broadside	1	0	4	6	8	**3**	0.333333	0	1.333333	2	2.666667
Nevada											
Rear-End	0	2	12	51	93	**5**	0	0.4	2.4	10.2	18.6
Broadside	0	3	15	36	90	**5**	0	0.6	3	7.2	18

Crash Modification Factors

Rear-End	0.776	0.564	0.988
Broadside (RLR)	0.65		

Source: Crash Modification Factors Clearinghouse. "Safety Effect of Dilemma-Zone Protection Using Actuated Advanced Warning Systems."
https://cmfclearinghouse.fhwa.dot.gov/study_detail.php?stid=311

Source: TRB Poster - Hossain, M.D. et al. "Safety Evaluation of Dilemma Zone Protection System for Rural, High-Speed Signalized Intersections Using Empirical Bayes Method."
Paper 25-05030

Note: 2nd paper focuses on RLR crashes

Estimated Prevented Crashes Per Category, per year

	K	A	B	C	O
Meridian					
Rear-End	0.00	0.00	0.22	1.12	1.94
Broadside	0.12	0.00	0.47	0.70	0.93
Nevada					
Rear-End	0.00	0.09	0.54	2.28	4.17
Broadside	0.00	0.21	1.05	2.52	6.30
Total, per year	0.12	0.30	2.28	6.62	13.34
Value of Crash (2023 dollars)	$13,200,000	$1,254,700	$246,900	$118,000	$5,300
Total Value, per year	$1,540,000	$375,908	$562,504	$781,726	$70,708
Total, per year	$3,330,846				
(excluding fatal)	$1,790,846				

Life cycle (years)	10
Interest rate	3.1%
adjustment factor (Present given .	8.486834559
Total Safety Benefit	**$28,268,340.75**
(excluding fatal)	$15,198,615.53

Safety Benefit	$28,268,341
Efficiency Benefit	$10,683,260
Total Benefit	**$38,951,601**

Table A-1: Value of Reduced Fatalities, Injuries, and Crashes

Recommended Monetized Value(s)

KABCO Level	Monetized Value (2023 $)
O – No Injury	$5,300
C – Possible Injury	$118,000
B – Non-incapacitating	$246,900
A – Incapacitating	$1,254,700
K – Killed	$13,200,000
U – Injured (Severity Unknown)	$229,800

Crash Type	Monetized Value (2023 $)
PDO Crash[1]	$9,500
Injury Crash[1]	$329,500
Fatal Crash[1]	$14,806,000

References and Notes

Treatment of the Economic Value of Preventing Fatalities and Injuries in Preparing Economic Analyses (2022)
https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis

The Economic and Societal Impact of Motor Vehicle Crashes, 2019 (revised February 2023), Page 46, Table 2-9, Incidence Summary, 2019"

Note: The KABCO level values shown result from multiplying the KABCO-level accident's associated MAIS-level probabilities by the recommended unit Value of Injuries for each MAIS level, and then summing the products. Crash data may not be presented on an annual

U.S. Department of Transportation

Benefit-Cost Analysis Guidance for Discretionary Grant Programs

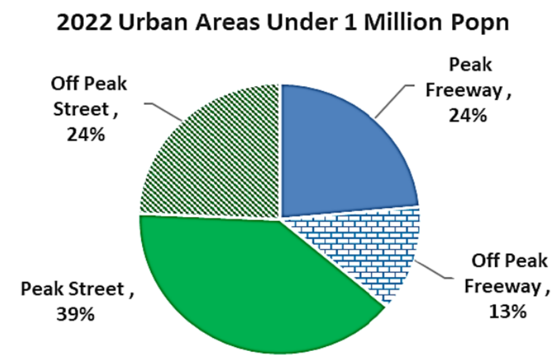
Office of the Secretary
U.S. Department of Transportation
November 2024

Total delay reduction (veh-h), per hour - coord vs. trajectory-based (lower total delay option)

	Conventional Control	Trajectory-Based Control	Delay Reduction	no. of intersections in simulation model	total intersections in corridor	% of intersections included in model	adj factor	adjusted delay reduction
Meridian (peak hour)	8.51	5.11	3.4	4	6	0.666666667	1.5	**5.1**
Nevada (peak hour)	26.94	22.62	4.32	5	40	0.125	8	**34.56**

Daily delay reduction (veh-h)

	Peak Hour Delay Reduction (assuming two peak hours per day)	Non-Peak hour Delay Reduction (assume ratio of off-peak vs peak street from TTI UMR)	Daily Total	Ratio:	0.615384615
Meridian	10.2	6.276923077	16.47692308		
Nevada	69.12	42.53538462	111.6553846		



The above is from the TTI urban mobility report for 2023 showing the breakdown of delays by facility and peak/off-peak condition

TTI UMR = Texas Transportation Institute Urban Mobility Report

Annual delay reduction (veh-h)	Weekdays	Weekends (assume 50% of weekday)	Weekend rate	Total
multiplier	260	105		
Meridian	4284	865.0384615	50%	5149.038
Nevada	29030.4	5861.907692	50%	34892.31

Total annualized delay reduction (veh-h)	40041.34615	
Percentage of passenger cars	90.0%	
Passenger car occupancy	1.2	
Value of time for passenger car (TTI UMR 2023)	$23.12	
Percentage of trucks	10.0%	
Operating cost for trucks (TTI UMR 2023)	$64.68	
Passenger benefit		$999,816.40
Truck benefit		$258,987.43
Total benefit (Year 1)		**$1,258,803.82**
Life cycle (years)		10
Interest rate		3%
Adjustment factor		8.486834559
Total Efficiency Benefit		**$10,683,259.79**

Meridian Rd

Intersection-Related Rear End Crashes (2021-2023)

Date	Time of Day	Severity	Year
2/26/2021	3:55 PM	Possible/Complaint of Injury (C)	2021
2/23/2021	12:09 PM	No Injury (PDO)	2021
3/2/2021	3:08 PM	No Injury (PDO)	2021
3/2/2021	3:50 PM	No Injury (PDO)	2021
3/30/2021	8:00 PM	Possible/Complaint of Injury (C)	2021
9/1/2021	9:35 AM	No Injury (PDO)	2021
10/4/2021	11:19 AM	No Injury (PDO)	2021
10/25/2021	7:00 AM	No Injury (PDO)	2021
12/14/2021	8:30 AM	Evident Non-Incapacitating (B)	2021
12/16/2021	3:36 PM	Possible/Complaint of Injury (C)	2021
1/29/2022	3:14 PM	Possible/Complaint of Injury (C)	2022
2/18/2022	8:37 PM	Possible/Complaint of Injury (C)	2022
3/31/2022	10:20 AM	No Injury (PDO)	2022
5/1/2022	2:18 PM	No Injury (PDO)	2022
5/10/2022	2:20 PM	Possible/Complaint of Injury (C)	2022
6/29/2022	4:20 PM	Possible/Complaint of Injury (C)	2022
7/19/2022	12:10 PM	Possible/Complaint of Injury (C)	2022
8/12/2022	4:10 PM	No Injury (PDO)	2022
8/25/2022	3:15 PM	Possible/Complaint of Injury (C)	2022
8/22/2022	6:54 AM	Possible/Complaint of Injury (C)	2022
9/2/2022	4:26 PM	No Injury (PDO)	2022
10/4/2022	12:45 PM	Possible/Complaint of Injury (C)	2022
10/10/2022	8:05 AM	No Injury (PDO)	2022
11/7/2022	8:35 AM	Evident Non-Incapacitating (B)	2022
12/19/2022	2:42 PM	No Injury (PDO)	2022
1/13/2023	2:55 PM	No Injury (PDO)	2023
1/24/2023	7:40 AM	Evident Non-Incapacitating (B)	2023
2/21/2023	7:15 AM	No Injury (PDO)	2023
3/10/2023	7:45 PM	No Injury (PDO)	2023
3/16/2023	10:55 AM	No Injury (PDO)	2023
3/19/2023	8:50 AM	No Injury (PDO)	2023
3/22/2023	10:47 AM	No Injury (PDO)	2023
3/31/2023	12:40 PM	Possible/Complaint of Injury (C)	2023
4/1/2023	9:00 PM	No Injury (PDO)	2023
4/11/2023	7:30 AM	No Injury (PDO)	2023
5/29/2023	1:25 PM	Possible/Complaint of Injury (C)	2023
6/9/2023	6:13 PM	No Injury (PDO)	2023
6/15/2023	7:50 AM	No Injury (PDO)	2023
7/15/2023	12:11 PM	No Injury (PDO)	2023
11/24/2023	10:05 AM	No Injury (PDO)	2023
12/10/2023	12:50 PM	Possible/Complaint of Injury (C)	2023
12/10/2023	3:00 PM	No Injury (PDO)	2023
12/15/2023	5:39 PM	Possible/Complaint of Injury (C)	2023
12/20/2023	5:50 PM	No Injury (PDO)	2023

Count of Date	Column Labels			
Row Labels	**Evident Non-Incapacitating (B)**	**No Injury (PDO)**	**Possible/Complaint of Injury (C)**	**Grand Total**
2021	1	6	3	10
2022	1	6	8	15
2023	1	14	4	19
Grand Total	**3**	**26**	**15**	**44**

Nevada Ave

Intersection-Related Rear End Crashes (2021-2023)

Date	Time of Day	Severity	Year
1/9/2019	1:50 PM	No Injury (PDO)	2019
1/24/2019	3:39 PM	No Injury (PDO)	2019
2/1/2019	3:30 PM	No Injury (PDO)	2019
2/7/2019	12:09 PM	No Injury (PDO)	2019
2/15/2019	1:30 PM	Possible/Complaint of Injury (C)	2019
2/20/2019	4:44 PM	No Injury (PDO)	2019
3/23/2019	11:35 AM	Evident Non-Incapacitating (B)	2019
5/14/2019	12:00 PM	No Injury (PDO)	2019
5/19/2019	12:23 AM	Evident, Incapacitating (A)	2019
5/23/2019	3:00 PM	Possible/Complaint of Injury (C)	2019
6/1/2019	8:13 AM	No Injury (PDO)	2019
6/3/2019	3:57 PM	No Injury (PDO)	2019
6/12/2019	1:15 PM	Evident Non-Incapacitating (B)	2019
6/13/2019	2:15 PM	Evident Non-Incapacitating (B)	2019
7/25/2019	3:00 PM	Possible/Complaint of Injury (C)	2019
8/27/2019	3:19 PM	Possible/Complaint of Injury (C)	2019
9/13/2019	2:06 AM	No Injury (PDO)	2019
9/21/2019	2:28 PM	No Injury (PDO)	2019
10/11/2019	2:40 PM	Possible/Complaint of Injury (C)	2019
10/23/2019	5:00 PM	No Injury (PDO)	2019
11/5/2019	12:38 PM	No Injury (PDO)	2019
11/5/2019	5:16 PM	No Injury (PDO)	2019
11/19/2019	1:20 PM	No Injury (PDO)	2019
12/6/2019	8:48 AM	Possible/Complaint of Injury (C)	2019
12/13/2019	1:30 PM	No Injury (PDO)	2019
12/21/2019	2:26 PM	Possible/Complaint of Injury (C)	2019
12/23/2019	1:34 PM	No Injury (PDO)	2019
1/15/2020	2:55 PM	No Injury (PDO)	2020
1/25/2020	12:33 PM	No Injury (PDO)	2020
2/2/2020	12:00 PM	No Injury (PDO)	2020
4/3/2020	11:55 AM	Evident Non-Incapacitating (B)	2020
4/14/2020	5:30 PM	No Injury (PDO)	2020
5/14/2020	4:11 PM	No Injury (PDO)	2020
6/12/2020	10:45 AM	No Injury (PDO)	2020
6/16/2020	10:00 AM	Possible/Complaint of Injury (C)	2020
7/8/2020	10:29 AM	No Injury (PDO)	2020
8/27/2020	6:21 PM	No Injury (PDO)	2020
8/28/2020	12:05 AM	No Injury (PDO)	2020
9/29/2020	12:48 PM	Possible/Complaint of Injury (C)	2020
10/4/2020	1:15 AM	Evident Non-Incapacitating (B)	2020
10/4/2020	1:15 AM	Evident Non-Incapacitating (B)	2020
10/17/2020	1:50 PM	No Injury (PDO)	2020
10/22/2020	10:35 AM	Possible/Complaint of Injury (C)	2020
11/13/2020	9:51 AM	Possible/Complaint of Injury (C)	2020
12/2/2020	12:12 PM	No Injury (PDO)	2020
12/3/2020	5:30 PM	No Injury (PDO)	2020
1/8/2021	4:25 PM	Possible/Complaint of Injury (C)	2021
1/9/2021	5:37 PM	No Injury (PDO)	2021
1/9/2021	6:02 PM	Evident Non-Incapacitating (B)	2021
2/2/2021	8:29 AM	No Injury (PDO)	2021
2/24/2021	7:40 PM	No Injury (PDO)	2021
3/20/2021	2:00 PM	No Injury (PDO)	2021
3/26/2021	9:08 AM	No Injury (PDO)	2021
4/6/2021	3:07 PM	No Injury (PDO)	2021

Count of Date	**Column Labels**				
Row Labels	**Evident Non-Incapacitating (B)**	**Evident, Incapacitating (A)**	**No Injury (PDO)**	**Possible/Complaint of Injury (C)**	**Grand Total**
2019	3	1	17	7	28
2020	3		12	4	19
2021	2		25	12	39
2022	1	1	15	14	31
2023	3		24	14	41
Grand Total	**12**	**2**	**93**	**51**	**158**

4/28/2021	4:42 PM	Possible/Complaint of Injury (C)	2021
6/8/2021	12:40 PM	Evident Non-Incapacitating (B)	2021
6/9/2021	12:04 PM	No Injury (PDO)	2021
6/5/2021	1:10 AM	No Injury (PDO)	2021
5/20/2021	8:30 AM	No Injury (PDO)	2021
3/21/2021	1:40 PM	No Injury (PDO)	2021
4/30/2021	4:28 PM	No Injury (PDO)	2021
5/7/2021	8:00 AM	Possible/Complaint of Injury (C)	2021
2/21/2021	10:04 PM	Possible/Complaint of Injury (C)	2021
6/23/2021	11:35 AM	No Injury (PDO)	2021
7/5/2021	7:55 AM	Possible/Complaint of Injury (C)	2021
7/9/2021	6:27 AM	No Injury (PDO)	2021
7/7/2021	8:45 AM	No Injury (PDO)	2021
7/20/2021	10:45 AM	No Injury (PDO)	2021
7/22/2021	2:45 AM	No Injury (PDO)	2021
8/17/2021	12:25 PM	No Injury (PDO)	2021
8/30/2021	7:46 AM	Possible/Complaint of Injury (C)	2021
9/3/2021	7:25 AM	Possible/Complaint of Injury (C)	2021
9/21/2021	4:53 AM	Possible/Complaint of Injury (C)	2021
9/21/2021	12:28 PM	No Injury (PDO)	2021
10/5/2021	1:15 AM	Possible/Complaint of Injury (C)	2021
9/28/2021	5:25 AM	No Injury (PDO)	2021
10/13/2021	7:47 AM	No Injury (PDO)	2021
10/11/2021	11:30 AM	Possible/Complaint of Injury (C)	2021
10/11/2021	11:30 AM	No Injury (PDO)	2021
10/27/2021	2:18 AM	No Injury (PDO)	2021
11/10/2021	4:45 AM	No Injury (PDO)	2021
6/23/2021	9:35 AM	Possible/Complaint of Injury (C)	2021
12/2/2021	2:40 AM	Possible/Complaint of Injury (C)	2021
12/18/2021	9:18 AM	No Injury (PDO)	2021
12/23/2021	11:17 AM	No Injury (PDO)	2021
2/23/2022	11:52 AM	No Injury (PDO)	2022
3/26/2022	1:15 AM	No Injury (PDO)	2022
3/30/2022	2:10 AM	No Injury (PDO)	2022
4/12/2022	11:01 AM	Possible/Complaint of Injury (C)	2022
4/8/2022	8:59 AM	Possible/Complaint of Injury (C)	2022
4/17/2022	10:12 AM	Possible/Complaint of Injury (C)	2022
4/29/2022	2:37 AM	Possible/Complaint of Injury (C)	2022
4/26/2022	1:02 AM	Evident, Incapacitating (A)	2022
4/25/2022	4:45 AM	No Injury (PDO)	2022
4/22/2022	6:06 AM	Possible/Complaint of Injury (C)	2022
5/5/2022	9:00 AM	No Injury (PDO)	2022
5/9/2022	4:45 AM	Possible/Complaint of Injury (C)	2022
5/24/2022	4:40 AM	No Injury (PDO)	2022
6/5/2022	2:26 AM	Possible/Complaint of Injury (C)	2022
5/27/2022	8:49 AM	No Injury (PDO)	2022
6/17/2022	3:20 AM	Possible/Complaint of Injury (C)	2022
6/21/2022	9:30 AM	Possible/Complaint of Injury (C)	2022
7/20/2022	7:19 AM	Possible/Complaint of Injury (C)	2022
7/27/2022	12:45 PM	Possible/Complaint of Injury (C)	2022
7/23/2022	5:14 AM	Evident Non-Incapacitating (B)	2022
8/4/2022	2:00 AM	No Injury (PDO)	2022
8/4/2022	8:35 AM	No Injury (PDO)	2022
8/15/2022	8:03 AM	Possible/Complaint of Injury (C)	2022
9/3/2022	12:37 PM	No Injury (PDO)	2022
9/9/2022	1:52 AM	No Injury (PDO)	2022
9/22/2022	12:29 PM	No Injury (PDO)	2022

10/1/2022	11:55 AM	Possible/Complaint of Injury (C)	2022
11/1/2022	10:21 AM	No Injury (PDO)	2022
12/14/2022	7:00 AM	Possible/Complaint of Injury (C)	2022
12/19/2022	5:30 AM	No Injury (PDO)	2022
12/24/2022	1:14 AM	No Injury (PDO)	2022
1/3/2023	11:00 AM	No Injury (PDO)	2023
1/15/2023	11:05 AM	No Injury (PDO)	2023
1/20/2023	8:59 AM	No Injury (PDO)	2023
1/23/2023	5:27 AM	No Injury (PDO)	2023
1/28/2023	2:25 AM	Evident Non-Incapacitating (B)	2023
3/8/2023	7:30 AM	No Injury (PDO)	2023
3/10/2023	9:57 AM	Possible/Complaint of Injury (C)	2023
3/14/2023	4:15 AM	No Injury (PDO)	2023
3/21/2023	9:56 AM	Possible/Complaint of Injury (C)	2023
4/7/2023	9:00 AM	No Injury (PDO)	2023
5/6/2023	10:43 AM	No Injury (PDO)	2023
6/5/2023	2:55 AM	Possible/Complaint of Injury (C)	2023
6/11/2023	10:15 AM	Evident Non-Incapacitating (B)	2023
6/15/2023	8:40 AM	No Injury (PDO)	2023
6/20/2023	1:00 AM	No Injury (PDO)	2023
6/27/2023	5:17 AM	Possible/Complaint of Injury (C)	2023
7/5/2023	11:02 AM	No Injury (PDO)	2023
7/9/2023	5:20 AM	No Injury (PDO)	2023
7/10/2023	11:00 AM	Possible/Complaint of Injury (C)	2023
7/21/2023	3:48 AM	No Injury (PDO)	2023
8/2/2023	2:30 AM	No Injury (PDO)	2023
8/5/2023	10:51 AM	No Injury (PDO)	2023
8/20/2023	4:26 AM	Possible/Complaint of Injury (C)	2023
9/19/2023	4:30 AM	No Injury (PDO)	2023
9/21/2023	6:05 AM	No Injury (PDO)	2023
9/22/2023	12:25 PM	No Injury (PDO)	2023
9/27/2023	5:15 AM	No Injury (PDO)	2023
10/11/2023	4:40 AM	No Injury (PDO)	2023
10/13/2023	1:55 AM	No Injury (PDO)	2023
10/17/2023	5:00 AM	Possible/Complaint of Injury (C)	2023
10/17/2023	8:30 AM	No Injury (PDO)	2023
10/24/2023	3:50 AM	Possible/Complaint of Injury (C)	2023
10/31/2023	2:30 AM	Evident Non-Incapacitating (B)	2023
11/5/2023	5:04 AM	Possible/Complaint of Injury (C)	2023
11/7/2023	10:16 AM	No Injury (PDO)	2023
11/23/2023	9:07 AM	Possible/Complaint of Injury (C)	2023
12/12/2023	4:55 AM	No Injury (PDO)	2023
12/27/2023	7:52 AM	Possible/Complaint of Injury (C)	2023
12/27/2023	7:52 AM	Possible/Complaint of Injury (C)	2023
2/15/2019	5:50 PM	No Injury (PDO)	2019
12/27/2023	7:52 AM	Possible/Complaint of Injury (C)	2023
12/27/2023	7:52 AM	Possible/Complaint of Injury (C)	2023

Meridian Rd

Intersection-Related Broadside Crashes (2021-2023)

Date	Time of Day	Severity	Year
4/19/2021	4:25 PM	Possible/Complaint of Injury (C)	2021
6/23/2021	10:59 AM	Evident Non-Incapacitating (B)	2021
1/24/2021	1:11 PM	Evident Non-Incapacitating (B)	2021
4/19/2021	4:25 PM	Possible/Complaint of Injury (C)	2021
6/29/2021	2:15 PM	Evident Non-Incapacitating (B)	2021
10/3/2021	12:20 PM	No Injury (PDO)	2021
1/16/2022	9:20 PM	Possible/Complaint of Injury (C)	2022
3/4/2022	3:50 PM	No Injury (PDO)	2022
3/17/2022	8:27 AM	No Injury (PDO)	2022
6/3/2022	1:48 PM	No Injury (PDO)	2022
5/29/2022	3:05 PM	Evident Non-Incapacitating (B)	2022
7/8/2022	9:50 PM	No Injury (PDO)	2022
12/12/2022	5:53 PM	No Injury (PDO)	2022
11/27/2022	1:25 PM	Possible/Complaint of Injury (C)	2022
5/3/2023	7:10 AM	Possible/Complaint of Injury (C)	2023
9/3/2023	7:16 PM	Possible/Complaint of Injury (C)	2023
10/27/2023	3:42 PM	No Injury (PDO)	2023
11/1/2023	10:28 AM	No Injury (PDO)	2023
11/17/2023	4:37 PM	Fatal (K)	2023

Count of Date	Column Labels				
Row Labels	Evident Non-Incapacitating (B)	Fatal (K)	No Injury (PDO)	Possible/Complaint of Injury (C)	Grand Total
2021	3		1	2	6
2022	1		5	2	8
2023		1	2	2	5
Grand Total	**4**	**1**	**8**	**6**	**19**

Nevada Ave

Intersection-Related Broadside Crashes (2021-2023)

Date	Time of Day	Severity	Year
1/15/2019	9:22 AM	No Injury (PDO)	2019
1/15/2019	10:05 AM	No Injury (PDO)	2019
2/11/2019	2:13 PM	No Injury (PDO)	2019
2/21/2019	11:28 AM	No Injury (PDO)	2019
2/27/2019	2:23 PM	No Injury (PDO)	2019
2/28/2019	9:45 AM	No Injury (PDO)	2019
4/9/2019	2:26 PM	Evident Non-Incapacitating (B)	2019
4/26/2019	6:35 PM	Possible/Complaint of Injury (C)	2019
4/28/2019	2:46 PM	Possible/Complaint of Injury (C)	2019
5/14/2019	2:47 PM	No Injury (PDO)	2019
6/18/2019	8:33 PM	Evident Non-Incapacitating (B)	2019
7/14/2019	2:57 AM	No Injury (PDO)	2019
7/21/2019	11:10 AM	No Injury (PDO)	2019
7/31/2019	1:05 PM	Possible/Complaint of Injury (C)	2019
8/17/2019	5:36 PM	No Injury (PDO)	2019
8/18/2019	1:38 PM	No Injury (PDO)	2019
8/27/2019	10:01 PM	No Injury (PDO)	2019
8/31/2019	5:38 PM	No Injury (PDO)	2019
10/9/2019	10:58 PM	Possible/Complaint of Injury (C)	2019
11/5/2019	6:46 PM	No Injury (PDO)	2019
11/16/201(	4:20 AM	No Injury (PDO)	2019
11/20/201(	2:52 PM	Evident Non-Incapacitating (B)	2019
12/3/2019	4:00 PM	No Injury (PDO)	2019
12/6/2019	2:27 PM	Possible/Complaint of Injury (C)	2019
12/9/2019	12:00 PM	No Injury (PDO)	2019
12/10/201(	3:58 PM	Evident Non-Incapacitating (B)	2019
12/21/201(	6:09 PM	Possible/Complaint of Injury (C)	2019
12/24/201(	12:22 AM	No Injury (PDO)	2019
1/5/2020	5:55 PM	No Injury (PDO)	2020
2/1/2020	6:35 PM	No Injury (PDO)	2020
2/1/2020	8:18 PM	No Injury (PDO)	2020
2/8/2020	6:21 AM	Possible/Complaint of Injury (C)	2020
2/12/2020	4:18 PM	No Injury (PDO)	2020
4/12/2020	4:05 PM	Possible/Complaint of Injury (C)	2020
5/1/2020	6:42 PM	No Injury (PDO)	2020
6/21/2020	5:11 AM	No Injury (PDO)	2020
7/2/2020	7:05 PM	No Injury (PDO)	2020
7/26/2020	12:28 PM	Possible/Complaint of Injury (C)	2020
8/8/2020	7:10 PM	Evident Non-Incapacitating (B)	2020
8/15/2020	11:30 AM	Possible/Complaint of Injury (C)	2020
8/24/2020	7:40 PM	No Injury (PDO)	2020
9/1/2020	10:02 AM	Possible/Complaint of Injury (C)	2020
10/17/202(	5:54 AM	No Injury (PDO)	2020

Count of Date	Column Labels				
Row Labels	Evident Non-Incapacitating (B)	Evident, Incapacitating (A)	No Injury (PDO)	Possible/Complaint of Injury (C)	Grand Total
2019	4		18	6	28
2020	3		10	9	22
2021	3		20	4	27
2022		1	27	11	39
2023	5	2	15	6	28
Grand Total	**15**	**3**	**90**	**36**	**144**

11/4/2020	10:45 AM	Evident Non-Incapacitating (B)	2020
11/14/202(	6:00 PM	Possible/Complaint of Injury (C)	2020
11/17/202(	12:06 PM	Possible/Complaint of Injury (C)	2020
11/22/202(	9:22 AM	Evident Non-Incapacitating (B)	2020
12/5/2020	7:39 PM	No Injury (PDO)	2020
12/14/202(	2:50 PM	Possible/Complaint of Injury (C)	2020
12/19/202(	8:50 AM	Possible/Complaint of Injury (C)	2020
1/8/2021	11:20 PM	Evident Non-Incapacitating (B)	2021
1/12/2021	4:25 PM	No Injury (PDO)	2021
1/13/2021	6:50 PM	No Injury (PDO)	2021
2/1/2021	6:45 PM	No Injury (PDO)	2021
2/12/2021	4:07 PM	No Injury (PDO)	2021
2/21/2021	9:44 AM	No Injury (PDO)	2021
2/19/2021	4:29 PM	Possible/Complaint of Injury (C)	2021
3/13/2021	11:49 AM	Possible/Complaint of Injury (C)	2021
4/19/2021	1:10 PM	No Injury (PDO)	2021
4/27/2021	6:40 PM	Possible/Complaint of Injury (C)	2021
4/28/2021	2:35 PM	No Injury (PDO)	2021
5/8/2021	8:18 AM	No Injury (PDO)	2021
7/7/2021	6:07 AM	No Injury (PDO)	2021
8/13/2021	8:16 AM	No Injury (PDO)	2021
8/30/2021	10:06 AM	No Injury (PDO)	2021
7/23/2021	8:00 AM	No Injury (PDO)	2021
9/7/2021	11:19 AM	No Injury (PDO)	2021
9/21/2021	1:37 AM	No Injury (PDO)	2021
9/19/2021	3:05 AM	No Injury (PDO)	2021
10/19/202	5:05 AM	Possible/Complaint of Injury (C)	2021
10/18/202	2:26 AM	No Injury (PDO)	2021
10/16/202	5:00 AM	No Injury (PDO)	2021
10/30/202	7:18 AM	No Injury (PDO)	2021
11/13/202	10:20 AM	No Injury (PDO)	2021
11/20/202	10:20 AM	Evident Non-Incapacitating (B)	2021
12/9/2021	2:56 AM	Evident Non-Incapacitating (B)	2021
12/18/202	12:54 PM	No Injury (PDO)	2021
1/8/2022	2:25 AM	No Injury (PDO)	2022
1/24/2022	9:42 AM	No Injury (PDO)	2022
1/24/2022	5:59 AM	No Injury (PDO)	2022
1/27/2022	9:50 AM	No Injury (PDO)	2022
1/7/2022	8:35 AM	Evident, Incapacitating (A)	2022
2/1/2022	12:43 PM	No Injury (PDO)	2022
2/10/2022	1:23 AM	No Injury (PDO)	2022
3/2/2022	8:13 AM	No Injury (PDO)	2022
2/5/2022	6:48 AM	Possible/Complaint of Injury (C)	2022
4/11/2022	11:07 AM	No Injury (PDO)	2022
4/16/2022	12:25 PM	No Injury (PDO)	2022
4/23/2022	2:31 AM	No Injury (PDO)	2022
4/30/2022	5:20 AM	No Injury (PDO)	2022

5/7/2022	8:12 AM	No Injury (PDO)	2022
5/12/2022	9:40 AM	Possible/Complaint of Injury (C)	2022
5/12/2022	7:43 AM	No Injury (PDO)	2022
5/17/2022	8:14 AM	Possible/Complaint of Injury (C)	2022
5/29/2022	8:25 AM	No Injury (PDO)	2022
5/28/2022	2:19 AM	Possible/Complaint of Injury (C)	2022
6/3/2022	2:40 AM	Possible/Complaint of Injury (C)	2022
6/15/2022	2:53 AM	No Injury (PDO)	2022
6/19/2022	10:59 AM	Possible/Complaint of Injury (C)	2022
6/15/2022	12:39 PM	No Injury (PDO)	2022
6/24/2022	4:45 AM	No Injury (PDO)	2022
6/27/2022	11:19 AM	Possible/Complaint of Injury (C)	2022
7/3/2022	2:52 AM	No Injury (PDO)	2022
8/8/2022	2:57 AM	No Injury (PDO)	2022
8/17/2022	7:00 AM	Possible/Complaint of Injury (C)	2022
9/21/2022	6:11 AM	Possible/Complaint of Injury (C)	2022
9/28/2022	11:51 AM	No Injury (PDO)	2022
10/6/2022	8:15 AM	No Injury (PDO)	2022
10/6/2022	4:25 AM	No Injury (PDO)	2022
10/13/2022	6:00 AM	No Injury (PDO)	2022
11/4/2022	11:35 AM	No Injury (PDO)	2022
11/5/2022	11:20 AM	No Injury (PDO)	2022
11/15/2022	9:20 AM	Possible/Complaint of Injury (C)	2022
11/6/2022	12:25 PM	No Injury (PDO)	2022
12/10/2022	8:15 AM	No Injury (PDO)	2022
12/16/2022	2:55 AM	Possible/Complaint of Injury (C)	2022
1/16/2023	12:13 PM	No Injury (PDO)	2023
1/17/2023	2:30 AM	Possible/Complaint of Injury (C)	2023
2/14/2023	10:12 AM	No Injury (PDO)	2023
4/3/2023	5:42 AM	No Injury (PDO)	2023
4/5/2023	5:37 AM	Evident Non-Incapacitating (B)	2023
4/28/2023	4:45 AM	No Injury (PDO)	2023
5/3/2023	9:37 AM	No Injury (PDO)	2023
5/9/2023	4:45 AM	Evident Non-Incapacitating (B)	2023
5/16/2023	2:52 AM	Possible/Complaint of Injury (C)	2023
5/16/2023	8:43 AM	Possible/Complaint of Injury (C)	2023
5/31/2023	8:37 AM	No Injury (PDO)	2023
6/2/2023	3:34 AM	Evident Non-Incapacitating (B)	2023
7/8/2023	4:59 AM	No Injury (PDO)	2023
7/14/2023	11:00 AM	Possible/Complaint of Injury (C)	2023
7/28/2023	9:57 AM	Evident, Incapacitating (A)	2023
8/2/2023	11:39 AM	No Injury (PDO)	2023
9/10/2023	1:31 AM	Possible/Complaint of Injury (C)	2023
9/11/2023	5:46 AM	No Injury (PDO)	2023
9/26/2023	8:25 AM	Evident Non-Incapacitating (B)	2023
9/28/2023	8:17 AM	No Injury (PDO)	2023
10/5/2023	2:54 AM	Possible/Complaint of Injury (C)	2023

10/13/2023	11:55 AM	No Injury (PDO)	2023
10/15/2023	4:01 AM	Evident Non-Incapacitating (B)	2023
10/24/2023	2:40 AM	No Injury (PDO)	2023
10/24/2023	7:55 AM	No Injury (PDO)	2023
10/31/2023	11:44 AM	No Injury (PDO)	2023
12/8/2023	11:26 AM	No Injury (PDO)	2023
12/17/2023	12:33 PM	Evident, Incapacitating (A)	2023

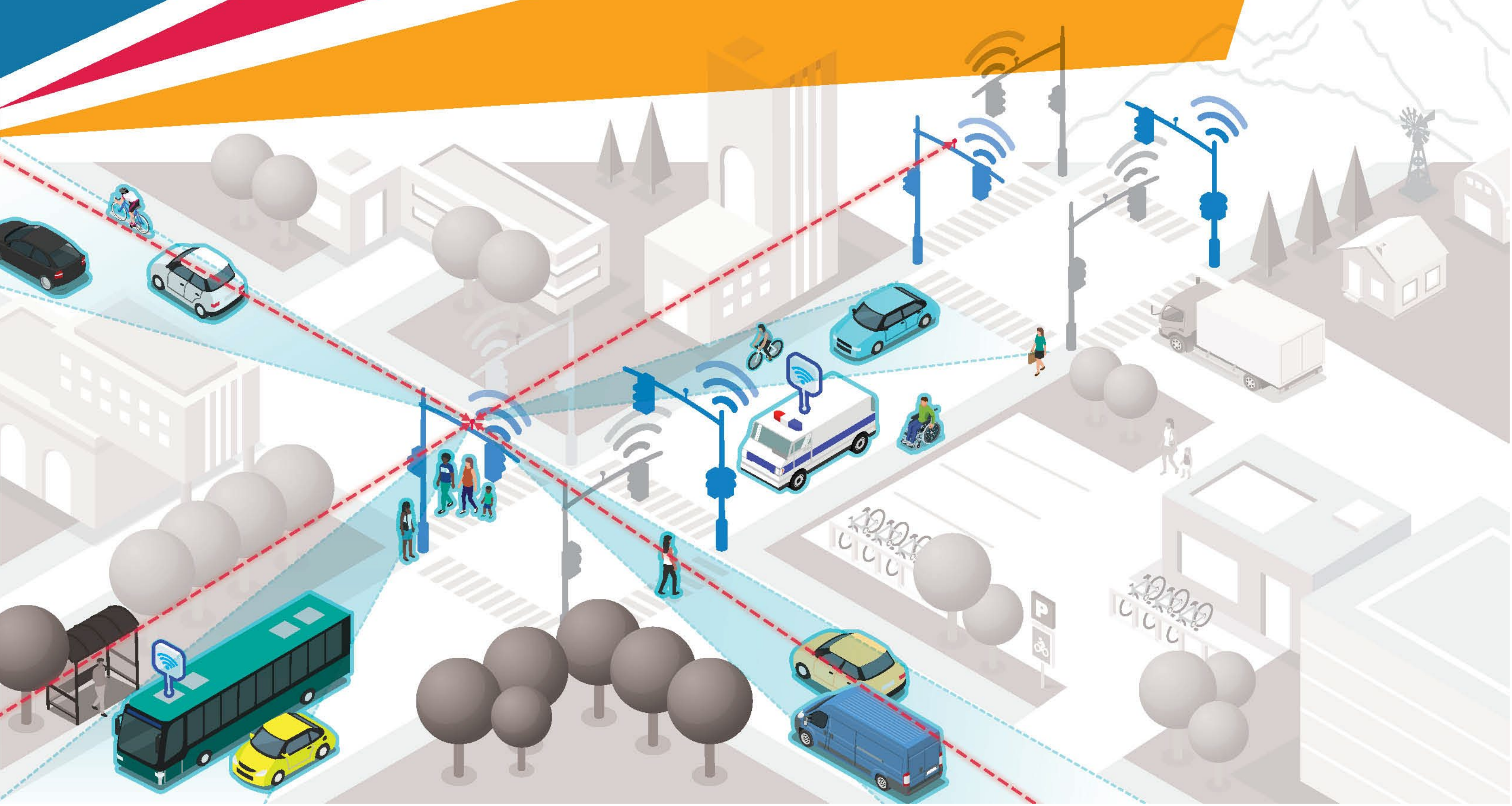
IMPLEMENTATION REPORT

Perception-Based Adaptive Traffic Management and Data Sharing

Appendix B – National Renewable Energy Laboratory

- B1 – Data Collection Summary
- B2 – A Framework for the Robust Deployment of Digital Infrastructure
- B3 – Institute of Electrical and Electronics Engineers (IEEE) Paper
- B4 – Transportation Research Board (TRB) Paper

COLORADO SPRINGS
OLYMPIC CITY USA



B1 – Data Collection Summary

MEMO

Date: Monday, February 24, 2025

To: Dan Sines and Zoami Calles-Rios Sosa, City of Colorado Springs

From: NREL, IPC Team – Stan Young, Faizan Mir, Rimple Sandhu, Qichao Wang, Todd Osborn

Subject: Summary and Key Takeaways from data collection for Strengthening Mobility and Revolutionizing Transportation (SMART) project with the city of Colorado Springs (CoCS)

This memorandum outlines the key takeaways and lessons learned during data collection at various traffic intersections in the city of Colorado Springs and its vicinity as part of the U.S. Department of Transportation (DOT) Strengthening Mobility and Revolutionizing Transportation (SMART) Project. The City of Colorado Springs and the National Renewable Energy Laboratory (NREL) collaborated to gather object-level trajectory data that reflected the movement of vehicles and vulnerable road users using multiple types of perception sensors. The data was collected in 2024 across multiple days and intersections in Colorado Springs by positioning NREL Infrastructure Perception and Control (IPC) mobile lab (IPCML) trailer at the intersection and utilizing sensor data from Colorado Springs based Radar sensors mounted on traffic poles. The state-of-the-art IPCML can deploy the latest generation of perception sensors at traffic intersections and capture real-time road user data. Multiple sensor modalities such as Radar, LiDAR and Cameras were deployed on the extendable masts of the IPC mobile lab to capture data in various sensor configurations and road settings to evaluate the perception sensor performance for roadside detection of vehicles and vulnerable road users.

Sensors included Econolite EVO RADAR units, Ouster OS1 LIDAR units, Cepton LiDAR units, Arecont Vision bullet cameras in combination with KAPSCH processing software and AXIS cameras with inbuilt object detection package. Outsight's SHIFT perception software was deployed to extract object-level data from point cloud data coming from the Ouster LIDAR units and the EVO radar object track data was access using the InnoSense API and stored on an edge compute device located inside the IPC mobile lab. In addition to perception sensors a test vehicle equipped with high accuracy RTK-GPS was also deployed to drive through the intersection multiples times and from multiple directions to record ground truth reference data for calibration and validation. The objective of the exercise was primarily to field test the various sensors in the mobile lab and installed on the traffic signal poles, and to assess this data could be calibrated, validated, fused, and integrated into a high-accruacy, low-latency digital twin of intersection movements.

Partnering with the city of Colorado Springs (CoCS), the IPC cooperative perception framework was tested and refined by collecting real-world dataset from multiple perception sensors at traffic intersections. The ongoing data collection efforts have highlighted several challenges and practical learning for real-world implementation of Infrastructure based Cooperative Perception and these key learnings have been documented in various research papers.

Results and take-aways from the Data Collection

Summary results / take-aways from the data collection are provided below. Detailed results from the various test dates are provided following for each data collection date.

1. **How many sensors do we need for full intersection perception coverage?**
   For a conventional four-way traffic intersection, two radar sensors at opposing ends of an intersection are the minimum number of sensors needed for full intersection perception coverage. However, this provides no overlapping field of view for robust or fail-safe coverage. Radar tends to be the most reliable technology as it is the least impacted by weather, light levels, and occlusion – and it has performed consistently with the lowest downtime in all the IPCML testing. Additionally, radar has the furthest range of these sensors and consistently provides reliable data. Camera and lidar sensors offer advantages that cannot be obtained exclusively using radar. Camera sensors are best at identifying environmental details such as light levels, object identification (distinguish between various vehicle classes and between vehicles and other road users), identify abnormal objects or obstacles. Lidar captures the most precise and high-frequency 3D data on moving objects, though range is limited compared to radar, it has good identification capabilities, though not as robust as cameras, and performs in low-lighting, though not as robust to inclement weather as radar. To create a robust perception system for intelligent transportation system, at least two sensor types are recommended. The maturity and reliability of radar technology indicates that they should be the primary sensor for providing both trajectory data of moving objects as distances sufficient for traffic control on a coordinated corridor, as well as provide inputs that are immune to all but the harshest of weather conditions. Radar with no overlapping field of view can be obtained with EVO with only two on opposite (diagonal) poles, with each radar provide data for two approaches and departures. Any redundancy and fail-safe would require additional units. Radars can be complemented by either lidars or cameras at an intersection. Lidars provide the highest spatial accuracy within 100 feet of the intersection, while cameras have the best identification capabilities. Cameras lead LiDARs in maturity and reliability, but are most subject to adverse weather conditions. LiDARs can identify objects based on high resolution 3D measurements, do not collect PII (as do cameras), and do not have a long track record of multi-year reliable performance. The EVO Radar is currently being upgraded to provide video as well as Radar (though video processing for trajectory and identification and other analytics are not planned for the initial release). Even so, video options combined with Radar appear the most viable near-term multi-sensor offering. Following figure 1(a) provides the Radar and Camera sensor configuration at one of the intersections and figure 1(b) provides Radar and Lidar sensor configuration at Nevada and Platte intersection in the city of Colorado Springs

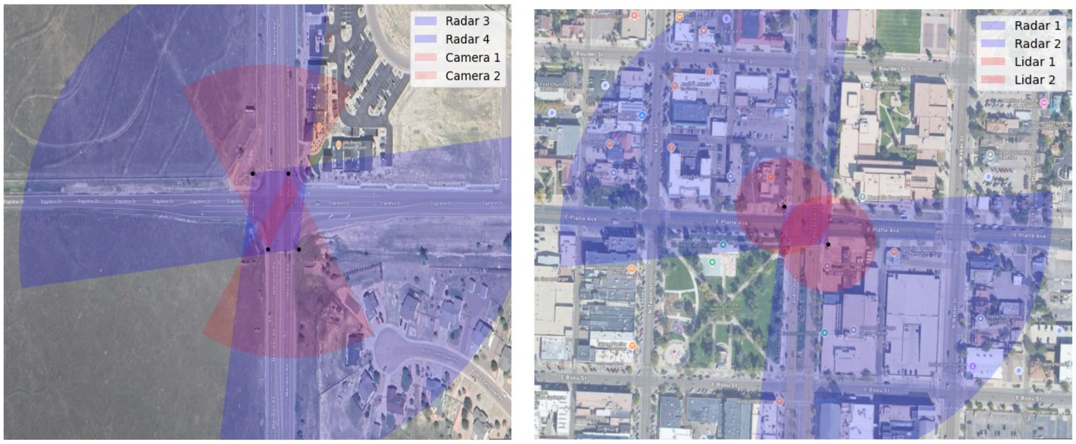


Figure 1: (a) Sensor Location and field-of-view at Meridian Rd & Stapleton Dr, Falcon CO with 2 Evo radar sensors and 2 Camera sensors. (b) Proposed sensor configuration at Nevada and Platte Ave, Colorado Springs, CO with 2 radar sensors and 2 Lidar sensors providing complete coverage of the intersection.

2. **Long term reliability?**
   Experience in field testing has shown that camera and radar sensors tend to have the best hardware reliability. The use of these sensors in field testing, both temporarily mounted and integrated into current infrastructure, has proven their reliability, while Lidar sensors tended to have the least reliable hardware. As new LiDARs are coming into the market at a faster rate it is difficult to gauge the long-term reliability of LiDAR sensors especially for the use by traffic departments which require operational lidars for at least 10 years to justify the high costs per intersection. The IPCML had an Ouster OS1 lidar failure during the field testing. Although the unit was replaced by manufacturer under warranty, this casts a doubt on the long term reliability of these sensors. This field is evolving quickly, and the technology is being commercialized primarily for automated vehicle applications, so although LiDARs (current generation) are not recommended at this time for production deployment (due in part to unproven reliability as well as cost), the technology should continue to be monitored, and newer generations tested.

3. **Accuracy and Latency?**
   Different sensors have varying levels of accuracy for different object class and range. Radar sensors offer the longest range, with field tests demonstrating superior detection capabilities at distances up to approximately 275–300 meters. However, they have shown limited accuracy in detecting vulnerable road users (VRUs). Lidar sensor accuracy is highly dependent on the density of the point cloud data. As distance increases, the point cloud becomes sparse, leading to a significant decline in lidar's detection and tracking performance. During field testing we observed superior VRU detection near the intersection from lidar. Camera detection accuracy largely depends on the deep learning algorithm used for object detection, as the quality of training images significantly impacts performance. Additionally, spatial accuracy is influenced by the quality of camera calibration. As objects move farther from the camera, spatial errors become more pronounced. In our testing, camera detection has been reliable up to a distance of 60-80 meters.

During field testing at intersections, lidar and camera sensors have demonstrated consistent latency performance. Lidar sensors reliably capture object track data at 10 Hz, while cameras, supported by a dedicated edge computer running sophisticated computer vision models, process data at 30 frames per second. In contrast, radar sensor sampling rates vary based on the number of sensors deployed. Adding more radar sensors to the same network may limit bandwidth, reducing the sampling rate. Our tests have shown radar sampling rates ranging from 2 to 10 Hz across different scenarios.

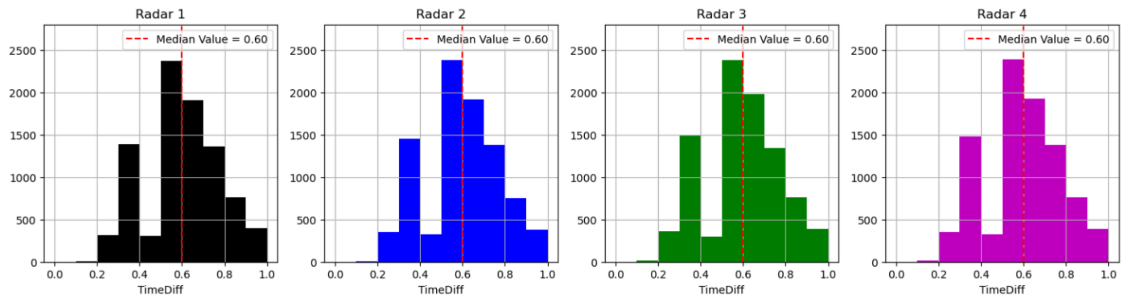


Figure 2: Radar sampling rate from data collection on Dec-20-2024 indicated lower sampling rate for Lidar due to the presence of camera which was recording video on the same network at 30fps

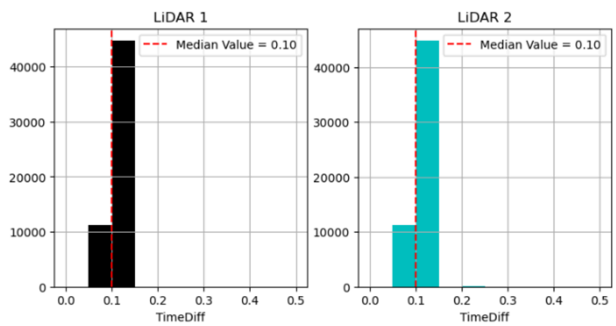


Figure 3 LiDAR sampling rate from Data collection on Dec-20-2024

4. **Adherence to given (current) standards, if any?**
   Currently, the sensor output data from roadside perception sensors doesn't adhere to a common data standard. Integrating data from multiple sensor types requires standardized formats to ensure interoperability between sensors models and vendors. NREL and CoCS have proposed a Standardized API data format which specifies the output data format from all perception sensors essential for track-data fusion ensuring system robustness and interoperability.

5. **Evaluate data retrieval process for all sensors?**
   Data captured from the IPC mobile lab mounted camera, radar, and lidar sensors were connected directly to computers in the mobile laboratory. Data was saved locally to these machines and could be retrieved and transferred to additional NREL research computers by members of the team. The data from infrastructure-based sensors was collected via wired network connections between the traffic cabinets at the intersections and the computers in the mobile laboratory. Each sensor had an edge computer which processed the raw point cloud data and generated a file with object tracks of the detections, however

each sensor setup process is different due to varying calibration techniques required for each sensor mode. The detections for Econolite EVO Radar sensors can be visualized and calibrated to a single coordinate frame using Econolite's proprietary Traffic Manager software package where the user manually aligns the two sensors together. Setup and data retrieval for Lidar sensors involved aligning the point clouds for the Lidar sensors together using Outsight SHIFT software and then defining a ground plane. Camera Calibration involves determining the camera intrinsic matrix which is function of the lens parameters such as focal length, optical center etc and finding the camera extrinsic matrix which define the camera orientation in real world coordinate frame, often performed by using a Checkered board. During this project NREL developed several calibration algorithms which simplified the sensor setup, calibration and data retrieval process. During the data collection from radar sensors NREL team captured data in local coordinate frame without having the need to use Traffic Manager software to manually align radar sensors together, similarly for lidar sensors each sensor was deployed to capture data in "standalone mode" (generate tracks in local sensor coordinate frame) eliminating the daunting process of manually aligning point clouds together. For camera NREL developed a camera calibration toolkit which calculate the camera extrinsic matrix utilizing the Lat/Long points in the camera frame. This calibration setup was handled by NREL fusion engine which uses a spatiotemporal matching algorithm to match object track from multiple sensors to find the common alignment between them. As with any multi sensors setup it is important to have all the sensors at a common time reference. To achieve this a local NTP server was setup which sends a time reference and clock drift information to each edge computer to synchronize the local clocks. Accurate time referencing is a critical issue for next generation infrastructure sensing. Current traffic cabinets may update time reference once per day or use power line (60 HZ) as a time reference. Such practices are not accurate enough for multiple sensor data fusion. Millisecond time reference and synchronization is critical for data fusion processes. At a minimum, a local NTP server connected to a common time reference that is updated using GPS based absolute time referencing (typically accurate to within one nanosecond) is recommended as minimum specification for any type of sensor deployment.

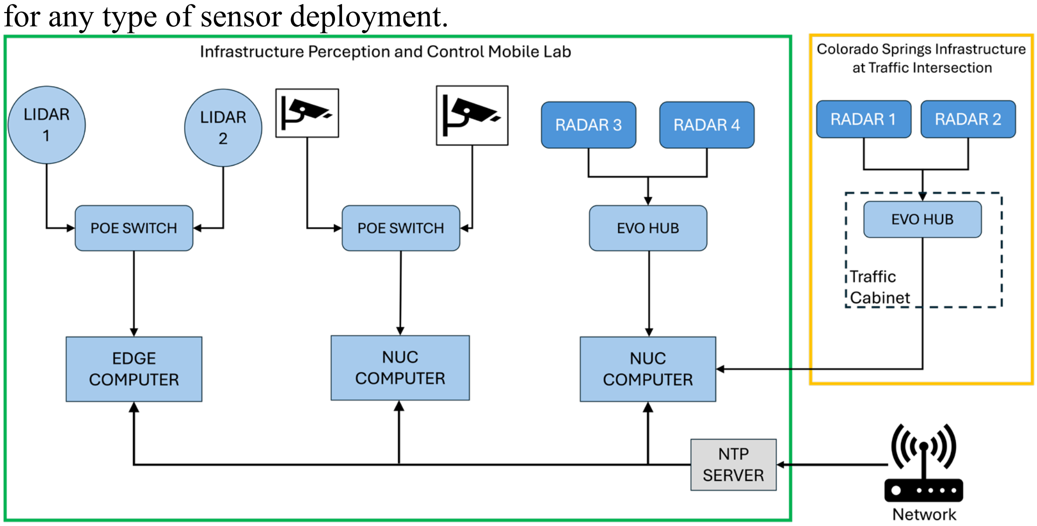


Figure 4: Sensor Schematic deployed at Traffic intersection utilizing IPC mobile lab and Pole Mounted sensors to retrieve object track data.

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6. **Feasibility and benefits / cost analysis?**

   Implementing additional sensors to improve perception at intersections is highly feasible. The infrastructure and processes to install these sensors are already in place and only require the additional upfront cost of the sensors and their maintenance for implementation. Camera and Radar sensors are already commonly used at intersections and with the latest generation of sensors able to interface with traffic controllers to actuate traffic lights using presence based (loop-emulation) logic. While camera sensors hardware is inexpensive, the software licenses to run proprietary object detection algorithms can contribute significantly to costs. These software licensing costs may be offset by utilizing open source algorithms like YOLO, as was demonstration during IPCML data collection. While roadside radar sensors are expensive, but they provide superior detection capability with significant improvement in range as compared to other sensors. The cost of these sensors can be offset by optimizing the deployment location such as placing these on diagonally opposite traffic pole to reduce the number of sensors required for complete coverage. Lidar is a rapidly improving technology that will likely also play a major role in the future of autonomous vehicles and smart-city infrastructure. However, the current price point of the technology, along with its issues with range and fragility, make it a less enticing deployment investment at the present time. While infrastructure-based lidar at intersections may not be a worthwhile investment currently, the rapidly evolving nature of this technology may make it a viable investment in the next several years.

   Additionally, technologies such as V2X communication and Connected Vehicle Data (CVD) can be easily integrated with current infrastructure. Such data is crucial for manageability of the advanced sensing. Each connected vehicle that transmits its time and location (typically derived from GPS coordinates) provides a calibration and validation opportunity on the entire system. It supplies a ‘heartbeat’ providing the infrastructure owner information on the health of the advanced sensors, and their fusion with each passing connected vehicle. This feedback loop is a must and critical for any deployment.

7. **Liabilities / mitigations?**

   There are potential privacy liabilities with the increased use of perception sensors, specifically cameras. To mitigate this liability, video footage would be processes through the object detection algorithm locally on each edge computer and converted into object tracks which would remove personally identifiable information, such as license plates or faces. Moreover, advanced federated learning algorithms can be employed to encode the object trajectories for all sensors providing an additional layer of security. This sensor will capture all movement – including movement that may be important for law enforcement such as speeding, crashes, and VRU incidents or persons of interest. Even if PII is eliminated, policies for sharing trajectory data need to be considered.

   As more applications use advanced sensor data, consideration concerning the ‘duty of care’ of these devices that would impact the liability on the use of the data they generate should be reviewed and policies established.

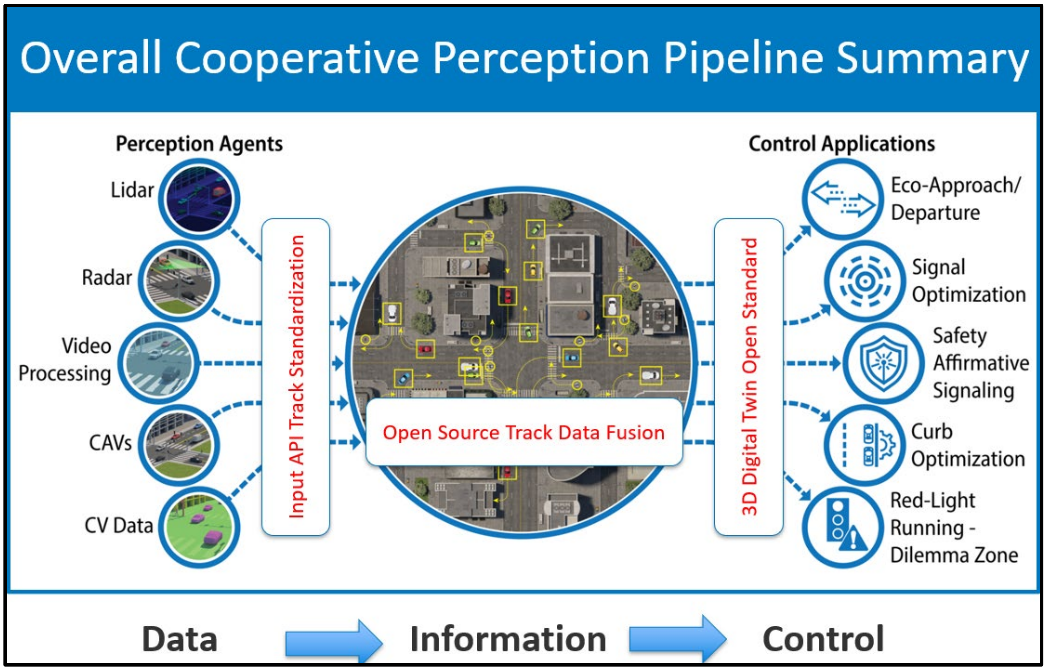
8. **Impact analysis & justification**

With roadways being the primary mode of travel for the population of the United States, improving their safety and efficiency benefits a vast number of people and saves money. Research conducted by the infrastructure perception control team at NREL into advanced sensing technologies for use at intersections and roadways will contribute to the development and advancement of our roadway infrastructure. Specifically, this research into advanced perception may reduce wait times at intersections, improve safety for pedestrians and vehicles, and enable the integration of new technologies, including autonomous vehicles, into our infrastructure. This investment in research and development has the potential to yield significant returns for the general population. This study examines the perception sensors in detail and presents the IPC framework which would help traffic departments across the United States to make informed decision regarding which perception technologies to employ for robust infrastructure side perception enhancing safety and efficiency for all road users.

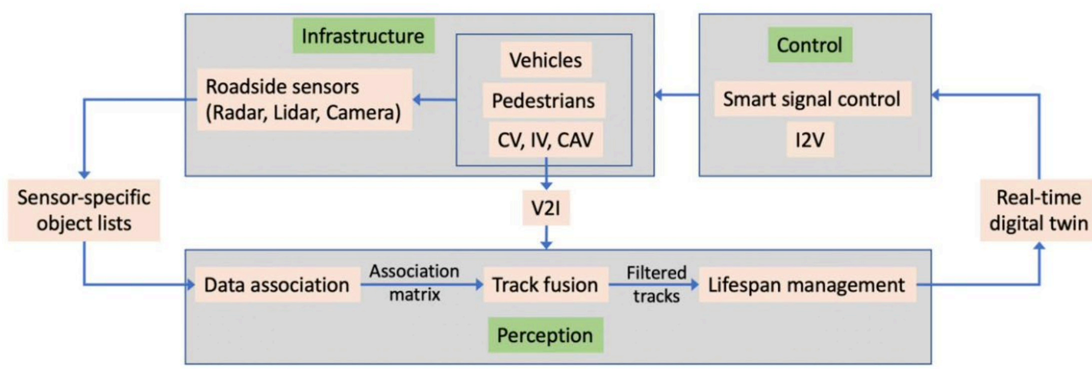
9. **Definition and architecture?**

The National Renewable Energy Laboratory (NREL) has pioneered an Infrastructure Perception and Control (IPC) framework to use advanced sensing technologies and computational methods to enhance safety, efficiency and sustainability of transportation infrastructure. The IPC framework utilizes real-time data from CVs, CAVs and infrastructure-based sensors (such as LiDAR, radar, and cameras) using a standardized API data input and output. This sensor data is fused by the "IPC Fusion Engine" which is an open-source track data fusion software, estimating and tracking the objects within the intersection enabling a robust digital twin. The IPC framework is critical to the transportation systems of the future because it allows for accurate traffic management, optimal signal control, and increased safety for vulnerable road users.

State estimation utilizing Bayesian filtering process is implemented to predict the state Probability Density Function (PDF) with the noisy sensor measurements and quantifying the uncertainty. A stochastic state-space model consisting of a motion model and a measurement model such as Constant Turn Rate Velocity (CTRV) model and Constant Turn Rate Acceleration (CTRA) which predict the physical movement of the object within a timestep while a measurement model which relates the object track information from the sensors to the state-space. Bayesian filtering techniques such as an Unscented Kalman Filter (UKF) is implemented to provide us a robust estimate of the state of each object.



With the state estimate of each object a sophisticated data association filter Nearest Neighbor Standard filter (NNSF) is implemented in this study which compares the probability density function of the predicted object state space motion model with the measurement model. Once the measurement data is associated with their individual tracks, an object lifespan manager is implemented to keep track of the new and existing objects within the field-of-view. The lifespan manager tells the filter to keep predicting the object until a measurement is received from the sensors and stops estimating the object after a certain threshold when no measurement is recorded.



10. Identify interoperability requirements and define integration requirements?

The current landscape of deploying and collecting infrastructure-based data from spatial sensors is dependent upon available equipment from industry vendors which often have limited end use capability with sensors of a different mode or different manufacturer. Often the base trajectory data is inaccessible in a well-defined application programming interface. Moreover, different sensors have different characteristics such as detection range, resolution, sampling rate, identification capabilities, and the varied data schemes to convey the object trajectory list. Often these sensors are configured to work in conjunction with other sensors of the same brand and type such as camera-camera, lidar-lidar and radar-radar. The NREL IPC framework proposes a standard or normalized data interfaces between the physical sensor output and the fusion engine so that the system can function agnostic to the sensor type, manufacturer, and/or model. Having a standardized data interface allows the city to procure the equipment on a specification-based approach from any manufacturer, and the proposed open-source multi-sensor track data fusion can work with any vendor's equipment rather having to develop custom data fusion for different sensor type. Additionally, the need for GPS time server needs to be integrated into the sensor system to allow for more accurate and consistent time keeping. Future intersection and infrastructure sensing is four-dimensional – three dimensions in space, and one in time.

11. Expected Real-Time performance of IPC fusion engine?

NREL is continuously optimizing the IPC Fusion Engine to improve its real-time performance by efficiently fusing detections from multiple sensors. Our initial results indicate that the IPC Fusion Engine is robust enough to run on an edge device while processing real-time streaming sensor data. The figure below illustrates the computation time and memory usage of various modules within the IPC Fusion Engine. In this test, we fused detections from two radar sensors deployed at the Palmer Park and Powers intersection in Colorado Springs, recorded on October 21, 2024. The fusion engine employs a discrete-time curvilinear constant turn rate and acceleration motion model to enhance vehicle motion prediction accuracy along with a Kalman smoother for robust state estimation of detected objects. The test involved processing approximately 1 hour 24 minutes and 15 seconds of recorded data, comprising of 215,052 detections, which the IPC fusion engine successfully fused in about 12 minutes. The fusion engine was run on a MacBook with an M2 processor, where memory usage peaked at approximately 3,564 MB, demonstrating that the fusion engine can run efficiently on an edge device. Furthermore, performance can be enhanced through multithreading, allowing better utilization of CPU cores by executing multiple tasks in parallel.

```
Kalman Filter:
KalmanFilter(nx=8, ny=6, dt=0.05, dt_tol=0.025, object_id=0)
Motion Model:
CA_RW(name='CA2D+RW2D', nx=8, xnames=['PositionX', 'SpeedX', 'AccnX', 'PositionY', 'SpeedY', 'AccnY', 'Width', 'Length'])
Observation Model:
LinearObservationModel(name=LinearObsModel(8/6), nx=8, xnames=PositionX,SpeedX,AccnX,PositionY,SpeedY,AccnY,Width,Length)
Memory Usage: 373.58 MB
Fusion: Fusing 215052 detections from sensors: Radar1,Radar2
Fusion-Run: 100%|████████████████████| 215052/215052 [07:39<00:00, 467.53it/s]
Memory Usage: 2314.16 MB
Memory Usage: 2314.16 MB
Fusion-Smoother: 100%|███████████████| 206902/206902 [00:41<00:00, 5001.74it/s]
Memory Usage: 2897.38 MB
Memory Usage: 2897.38 MB
Fusion-Gather: 100%|█████████████████| 206902/206902 [05:15<00:00, 656.15it/s]
Memory Usage: 3564.59 MB
Fused DataFrame:
                      TimeElapsed    Flag  PositionX  PositionX_Var    SpeedX  ...  YresNorm  NIS  NEES  LogLik  ObjectId
ObjectId TimeElapsed                                                           ...
0        31018794.1    31018794.0  Radar1  22.077518           16.0  0.872698  ...       NaN  NaN   NaN     NaN         0
1        31018794.1    31018794.0  Radar2 -67.202316           16.0  9.367956  ...       NaN  NaN   NaN     NaN         1
2        31018794.1    31018794.0  Radar2   8.602231           16.0 -0.112063  ...       NaN  NaN   NaN     NaN         2
3        31018794.1    31018794.0  Radar2   1.979012           16.0  0.000000  ...       NaN  NaN   NaN     NaN         3
4        31018794.1    31018794.0  Radar2  29.172421           16.0  4.769425  ...       NaN  NaN   NaN     NaN         4

[5 rows x 24 columns]
Memory usage increased by (Fusion Run): 1940.58 MB
Memory usage increased by (Smoother Run): 583.22 MB
Memory usage increased by (Gather Run): 667.22 MB
```

Papers Published:

1. Mir, Faizan, Stanley Young, Rimple Sandhu, and Qichao Wang. 2024. *Spatiotemporal Automatic Calibration of Infrastructure Lidar, Radar, and Camera with a Global Navigation Satellite System: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5400-89785. https://www.nrel.gov/docs/fy24osti/89785.pdf.
2. Mir, Faizan, Stanley Young, Rimple Sandhu, Qichao Wang, Charles Tripp, and Todd Osborn. 2024. *Infrastructure-Based Cooperative Perception at a Traffic Intersection: Overview and Challenges: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5400-92133. https://www.nrel.gov/docs/fy25osti/92133.pdf
3. Mir, F., Young, S., Sandhu, R., Wang, Q., Tripp, C., & Osborn, T. (2025). *Infrastructure-Based Cooperative Perception at a Traffic Intersection: Overview and Challenges.* National Renewable Energy Laboratory (NREL). https://www.nrel.gov/docs/fy25osti/91777.pdf
4. Young, S., Mir, F. Sines, D., Sosa, Z., Wang, Q., Sandhu, R., Tripp, C. & Osborn, T. *A Framework for the Robust Deployment of Digital Infrastructure.* IRF Global R2T Conference & Exhibition 2024. (in-press)
5. Mir, F., Sandhu, R., Young, S., Wang, Q., Tripp C & Osborn T. *The Sensor Dilemma in Intelligent Transportation Systems: Evaluating Radar, LiDAR, and Camera.* ASCE ICTD 2025 (in-press)
6. Mir, F., Young, S., Sandhu, R., Wang, Q. *A Robust Digital Twin Framework for Intelligent Transportation Systems.* 2025 IEEE 21st International Conference on Automation Science and Engineering (under preparation)

Data Repository:

- Multi-Sensor Object Tracking Data from Traffic Intersections in Colorado Springs, Colorado, USA
  doi: 10.17632/5vrf87rwb3.1

B2 – A Framework for the Robust Deployment of Digital Infrastructure

IRF R2T Conference & Exhibition
December 10 – 13, 2024
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Digital Infrastructure, Digital Twin, Intelligent Transportation Systems, Lidar, Radar, V2X communication

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ABSTRACT:

'Keeping your eyes on the road' has been a mantra for safe driving, and it is now becoming a mantra for digital infrastructure with respect to the application of advanced sensing to detect, process, and react to events and hazards on the roadway. Sensor data that measures the location and movement of all roadway users, whether from connected vehicles or roadside infrastructure, promises greater safety and efficiency. Research demonstrations have showed promise to enhance the safety of roadway users, including vulnerable roadway users such as pedestrians and bicyclists, increase efficiency of traffic signal operations, and reduce of energy and associated green-house gases. However, current deployment efforts lack a robust architecture for long-term, sustainable, and cost-effective application. The National Renewable Energy Laboratory in partnership with the City of Colorado Springs and other partners have formulated a framework for the robust deployment of digital infrastructure that leverages recent advancement in sensor technology and connected vehicles toward cost-effective deployment. The framework, referred to as infrastructure perception and control (IPC), seeks to normalize data interfaces from advanced sensors, fuses data from multiple sources and sensors, provide a continuous feedback loop for system health and calibration, and allow for continual technology refresh and maintenance while serving a host of productivity applications. This paper and subsequent presentation will cover the IPC framework, highlight progress toward these goals in the current initiative at Colorado Springs, and share continued challenges in harnessing modern sensor and communications toward scalable societal benefits.

A Framework for the Robust Deployment of Digital Infrastructure

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1 INTRODUCTION

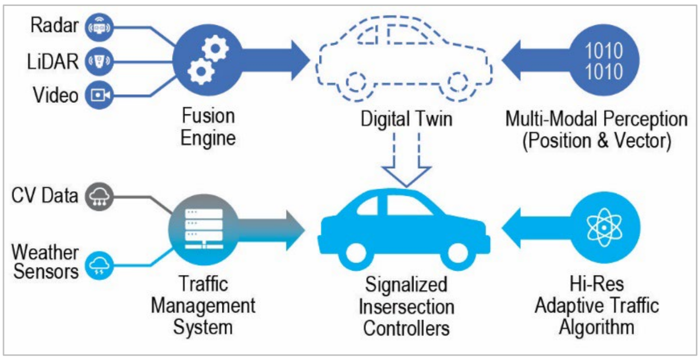
After receiving notification of acceptance of abstracts, authors wishing to see their work recognized in the official proceedings of the World Meeting & Exhibition must prepare a full-length paper of total length (inclusive of all text, tables, figures and references) of not more than **12 A4 size pages**. This document provides a set of instructions for preparing your paper and an example of the style you are required to use. Authors may use this document and follow the guidelines to adjust the format of their paper to the required form.

The paper will be expected to be a complete treatment and presentation, with all the usual elements of a self-contained scientific or technical paper. Contributions are accepted on the understanding that the paper is original and has not been published before. It should comply in structure and layout with the instructions given below. Papers are to be submitted electronically in Microsoft Word Document format.

Please note that the submitted papers will be reviewed for scientific/technical merit and checked for compliance with preparation instructions; authors may be required to re-submit amended papers following this process.

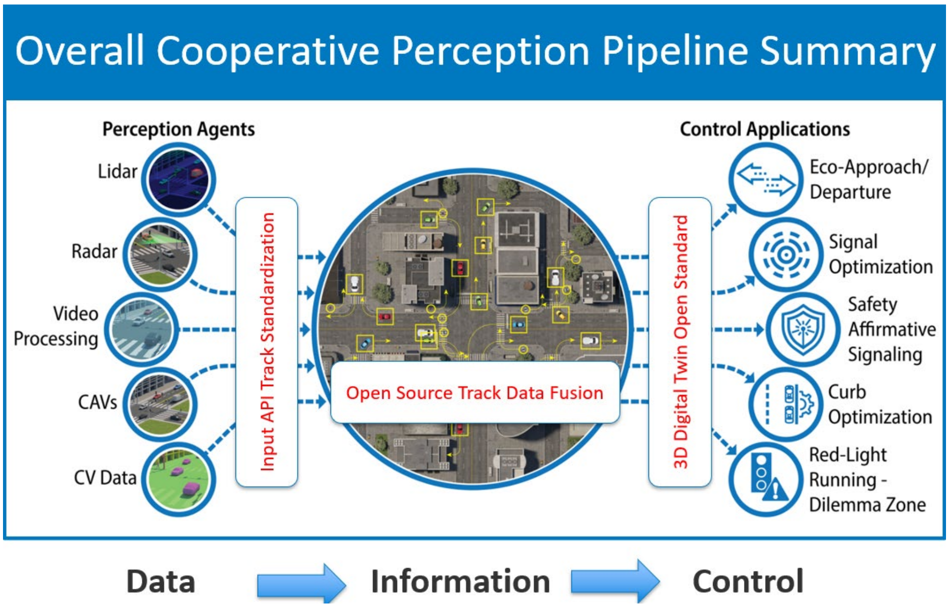
The City of Colorado Springs (COCS) was one of the first to incorporate vehicle trajectories for traffic control. Prior to the pandemic, they developed and successfully deployed a system that used vehicles trajectories, that is information on the location and speed of approaching vehicles to an intersection to eliminate dilemma zones and take advantage of natural breaks in traffic to allow for side street access to main line arterials. The system that utilizes data from radars to determine the time series location data of approaching traffic, referred to herein as vehicle trajectories. Although that generation of radars could not distinguish lanes, it could distinguish between multiple vehicles approaching the intersection at various distances and their corresponding speeds. With this information, computer logic was generated that searched for optimum time to transition from green to yellow, after a side-street call was initiated by an arriving vehicle. The success of this system, which was rolled out to approximately 200 intersections, revealed the potential of full spatial perception, and the corresponding travel time and safety efficiencies.

COCS is now pursuing its next-generation system that prioritizes safety, efficiency, and mobility for all road users through expanded perception capabilities and integration of multiple sensor inputs. In addition to the vehicle speed and distance perceived by first-generation radar technology, new radar, LiDAR, and video analytic technology allows sensors to perceive vehicles' precise lane position and position in the intersection (approaching, within, and departing); vehicle size and type; and non-motorized traffic. In contrast to connected vehicle data, this 'Perception-Based Adaptive Traffic Management', as coined by the COCS, perceives 100% of approaching vehicular traffic, as well as 100% of vulnerable roadway users such as pedestrians, bicyclists, scooters, wheelchair users. However, connected vehicle data plays a key role. The framework for the CoCS approached is summarizes in Figures X, below. Data from advanced sensors are fused into a comprehensive digital twin, which in turn feeds traffic control logic. Connected vehicles and weather information augment the data flows such that signalized intersections are optimally management for safety and throughput performance.



Concurrently the National Renewable Energy Laboratory developed the Infrastructure Perception and Control (IPC) concept, that harmonizes with the vision and approach by the CoCS. The IPC framework is illustration in Figure X+1. The individual perception agents are shown on the far right and encompass LiDAR, radar, and video processing, and is augmented with data from connected and automated vehicles (CAVs) and connected vehicle data (CV data). CV data refers to information on a vehicle's location and speeds (and perhaps other attributes) that are reported through vehicle telematics. CV data is typically highly detailed, but can be 30-60 seconds latent. All other data in the left hand side provide data in real-time with latencies in the millisecond range.

The center portion of Figure X+1 is a fusion engine that optimally combines data from multiple sensors to obtain the highest fidelity picture of the movement of road users (both vehicles and non-motorized) that can be derived from the sensor data with the resulting digital twin to enable a myriad of applications as shown to the far right. The digital twin is essentially and 'object list' generated and output in small time increments, such as every 10 to 100 milliseconds (100 to 10 times a second).



Although modern AI techniques are integrated into the processes, the core processing technology underpinning the data fusion engine is actually decades old, originating from target tracking technology from military applications. This techniques that discriminate data from different objects, and then optimally combines (in a statistical sense) are referred to as data aggregation and Bayesian filtering, commonly referred to as various flavors of Kalman filtering. A critical property of the track data fusion is the results of these statistical processes are not only a high fidelity digital operating picture of the theater, the output also contains estimate of the accuracy (or inaccuracy) of each object trajectory. Such information is critical to begin to push traffic perception to higher degrees of safety criticality. If traffic signals are altered as a result of the digital twin, inaccuracies at a minimum will cause inefficiency, and at a maximum present safety hazards.

The fusion engine not only constructs the highest fidelity digital twin using input data, it also monitors the relative agreement of all the sensors. The human body uses multiple sensor input to establish high confidence bearing and balance, namely your eyes and your inner ear. As long as motion you see with your eyes is in agreement with the 'accelerometer' of your inner ear, balance and bearing is maintained. If the information between your eyes and your inner ear are in disagreement, the body reacts with the phenomenon known as 'dizziness' – it is a signal to your brain that something is not right, and they you should brace yourself. Similarly, the concept of 'digital dizziness' is introduced through the data fusion process. As long as the data from multiple sensors in their fields of overlap are in agreement, system health is verified. If sensors provide conflicting data or incongruent data, the data fusion similarly reacts sending a 'digital dizziness' signal conveying that system health is compromised.

Connected vehicle (CV) data is critical with respect to system health monitoring. Although infrequent, CV data provides a statistically independent data to validate the system output. Information self-reported from the CV on its own position and speed (typically maintained through onboard GPS combined with an inertial navigation sub-system) provides opportunity to compare against the corresponding position of the vehicle as derived from fusion engine. The CV data can both contribute to the fusion engine, and act as a periodic independent validation instrument to continuously monitor system health. CV data can also be used to automate initial sensor spatial calibration, and periodically re-calibrate the infrastructure sensors.

Other aspects of the IPC framework are also critical – that of standardized data schemas for sensor inputs and standardize data schema for the digital twin. The former is critical for long term stability and maintainability of the system such as replacing a failed sensor in future years with the exact make and model is no longer in production. The latter is essential for economy of scale – that of using a single high-fidelity digital twin to drive a multitude of applications (only a few representative applications are shown in Figure X+1).

2 LITERATURE REVIEW

Almost 25% of all traffic fatalities and about half of all traffic injuries that occur in the US are cause at the traffic intersections (1). Because of this FHWA has prioritized national, state and local traffic safety and designated traffic intersections as focus area. Many of the inductive loop detectors that were once used to detect cars have been replaced by newer technologies such as video camera which are less expensive, easier to maintain, and offer reliable performance. The majority of these video camera are configured to identify cars with a certain zone such as left turn lane etc and transmit the controller a binary on/off signal similar to the inductive loop detectors. Due to the advancement in AI/ML and easily available computing resources, it has made it easier to train sophisticated deep learning models with a large dataset of images to improve the object detection and classification capabilities of video cameras (2-5). Despite all of the advancements in the object detection using video detection technologies, there are still some issues and drawbacks such as poor viewing angles, limited long range detection capability, significant decrease in detection accuracy in inclement weather and varying lighting conditions (6-9).

LiDAR and radar are two additional sensors that have been proposed as alternatives to video detection in order to address the difficulties in detecting and tracking vehicles at traffic intersections. In papers (10-13), roadside LiDAR were used for detection and tracking of cars and pedestrians at a traffic intersection. While roadside LiDAR offers a high resolution 3-dimensional information of the objects in the intersection due to its ability to capture dense point clouds of the objects and classify them as cars, trucks, cyclists and pedestrians, it has its own limitations such limited range of detections and the detection range and accuracy suffers in inclement weather conditions. In contrast to video detection and LiDAR, roadside radar has a lot of potential for capturing object data at the traffic intersection as it offers long range of detections (14-18). However, the roadside radar lacks the high-resolution information such as vehicle class, object size etc and detection of vulnerable road users (VRU) provided by the camera and LiDAR. The combination these perception sensors, however, creates a strong perception system that outperforms any one sensor alone and offers the best results in terms of resilience, accuracy, and detection range across a variety of environmental circumstances. Zimmer et al (19) proposed a multi-modal 3D object detection algorithm which uses multiple LiDAR for early-stage point cloud fusion and a combines camera using late-stage fusion. Sochaniwsky et al. (20) presented a real-time multi-object sensor fusion framework to integrate data from a camera and LiDAR and results shows that system performs better than a single sensor configuration. In (21)(22), a data fusion technique is presented, and experimental results demonstrate its ability to get precise roadside sensing information by fusing data from infrastructure-based camera and radar.

The above studies show why utilizing several sensors is preferable to use than a single mode of sensor. Recent developments in Vehicle-to-Everything (V2I) communication technology have demonstrated that roadside perception systems can enhance the real-time perception capacities of CVs and CAVs. Chen et al. (23) presented a preliminary assessment of a cooperative perception system using SAE Level 4 CAV and infrastructure-based LiDAR to communicate real-time messages through a Vehicle-to-Infrastructure (V2I) system. Field testing show that the CAV was able to identify the vulnerable road user (VRU) early with cooperative perception and plan its trajectory accordingly. Kim et al. (24) provided evidence of how vehicle-to-vehicle (V2V) cooperative perception can improve situational awareness and aid in better planning and decision-making by assessing scenarios and proactive and reactive lane changes for autonomous driving vehicles. At a roundabout in Ann Arbor, Michigan, USA, Zhang et al. (25) implemented a roadside perception system that combined detections from a thermal camera with a fisheye lens camera and showed how traffic volume monitoring and post-encroachment (PET) detection could be evaluated using the outputs of the fusion algorithm.

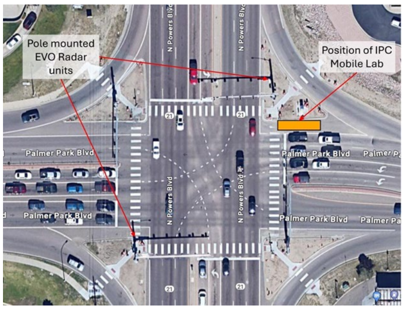
Although the aforementioned research studies demonstrate the efficacy of multi-sensor sensor fusion technologies in enhancing CV and CAV perception capabilities and identifying VRUs, none of them address the difficulties in implementing such a system at a traffic intersection. This study discusses the main difficulties encountered in implementing a cooperative perception system at a traffic crossroads and reports on a created framework for the same.

3 EXPERIMENTAL METHODS

NREL, in collaboration with COCS, and funded through a USDOT SMART grant, tested these concepts during the initial phase one of the grant. The concepts of the data fusion engine were tested with data gained from field data collection activities. Field data collection was enabled through use of the NREL IPC Mobile Laboratory, as picture in Figure X+2. The IPC Mobile Lab, as shown, has two extendable masts, with an instrument cluster mounted on each. Each instrument cluster consists of a radar, LiDAR, and video imaging (though only LiDAR and radar are shown in Figure X+2). The IPC Mobile can be towed to the intersection of interest, and multiple sensors of various types can be deployed quickly an safely, and data recorded for later processing, as well as processed in real time.

The data collection capabilities of the IPC Mobile Lab are complemented by permanently mounted sensor at select intersections in CoCS, namely new generation radars capable of long distance detection (roughly 800-900 feet). Radars are typically mounted two at each intersection on diagonally opposite signal support poles. Data from these permanent installations are combined with data from the mobile lab for sub-sequent processing.

This data collection methodology was exercised at various times within the CoCS, the with the most recent being at the intersection of Palmer and Power Blvd. Data from these exercises are used to illustrate the issues and insights on developing infrastructure perception as co-envisioned by project partners.



Commented [SY1]: Is this accurate Faizan?

Commented [FM2R1]: 800 - 900 feet and 110 degree field of view

This equipment is complemented by two GPS equipment suites such that two vehicles can traverse the theaters and provide a record of their location, heading and speed, simulating the information that could be obtained from connected vehicles. Higher accuracy is obtained through post-processing of the GPS data with information from a Real Time Kinematic (RTK) base station that is deployed at the time of testing/ data collection as shown in Figure X+T. The field data is post processed using a Post Processing Kinematic (PPK) software package to obtain highly accurate ground truth vehicle data from the GNSS receivers.

Figure X+T (a) Emlid RS+ base GNSS unit set up near the test site. (b) Test Vehicle driving through the intersection recording ground truth data while receiving differential correction through the base unit.

4 RESULTS AND DISCUSSION

Results are presented with respect to insights and lessons-learned from deploying multiple types of sensors, and then sub-sequent processing of the data toward a unified digital twin. Topics covered in this paper include the following (A) the need for auto-calibration for efficiency and maintainability, (B) time references compatible and accurate across all sensors, (C) the need for multiple sensor types for a comprehensive operating picture of all road users, (D) the critical input of periodic and independent probe data (as would be provided by connected vehicles data), (E) the need for backward compatibility of the digital twin, such that within 'digital dizziness' is detected, the system continues to operate in a fallback, fail-safe manner. Each of these are discussed with examples given from data collection exercises (where available) within the CoCS.

A. Auto-Calibration

Each sensor perceives the world from its own frame reference. For each sensor deployed in the theater, it measures the world in either a local 2-D coordinate frame (as is the case for video) or in a 3-D coordinate frame. The original of each respective coordinate frame is the sensor itself, and the length, width and depth to any object within each sensor's coordinate frame is based on the orientation of the sensors – that is the direction it is pointing, sometimes referred to as bearing, its angle of inclination, sometimes referred to as pitch, and whether it is tilted to the left or right, sometimes referred to as roll (most sensor are mounted such that roll is close to zero). The location and orientation of the sensor are critical information in order merge the data from each sensor into a common coordinate frame. The ability to quickly calibrate multiple sensors is essential. Initial practice for spatial sensors, such as a single radar for an approach, was to manually calibrate the device during installation. The technician would evaluate the response of the sensor to a known target, and then adjust parameters accordingly in a configuration file or screen. Such activity requires prolonged installation time, and possible additional exposure to traffic hazards as part of the calibration procedure.

The use of the IPC Mobile Lab, in which sensors are redeployed quickly accentuated the need for automate calibration procedures. In actual field operations sensors may be perturbed by weather, such as sever wind, or by contact with a vehicle. In either case, the initial calibration would not longer be accurate. Automated initial calibration is needed not only to save time (and corresponding exposure to traffic hazards and/or traffic disruption), but also to decreasing the specialty training of the personnel deploying and mounting sensors. Auto calibration would also allow small perturbations in the sensors location and orientation to be accounted for periodically. Namely, in combination with the output of the fusion engine, and periodic availability of CV data, auto-calibration can also detect and perturbation in a sensor mount and correct for them.

Figure X+3 depicts the data before and after calibration. On the left is data taken during a test at CoCS in which two LiDAR and two radars each record data in their own coordinate frames. On the right is the same data brought into agreement through appropriate transformations – as the result of auto-calibration routines.

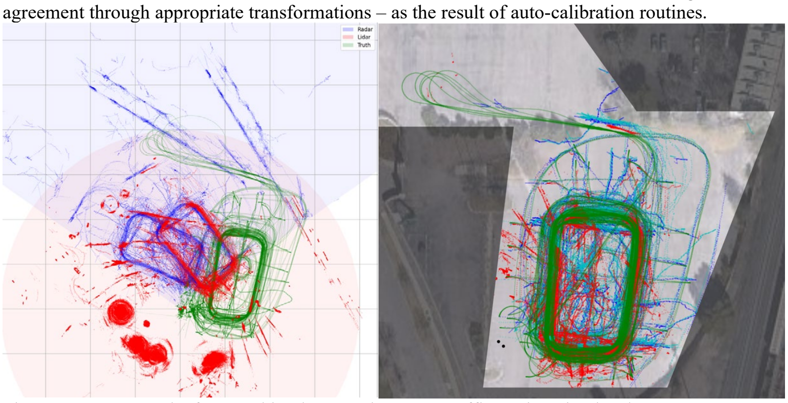


Figure X+3 Data take from parking lot near the CoCS traffic engineering headquarters

B. Time Referencing

Issues with obtaining and incorporating a highly accurate time reference are accentuated by the infrastructure deployments. Numerous systems depend on clock synchronizations, which can be achieved through the usage of Network Time Protocol (NTP), Precision Time Protocol (PTP), or Global Navigation Satellite System (GNSS) based time synchronization. In order to update the local sensor clock, NTP makes use of a data network to connect to an accurate time server and achieves an accuracy within a few milliseconds. GPS time offers an extremely precise time signal due to the presence of on-board atomic clocks. These clocks may be utilized to synchronize ground clocks by using the National Marine Electronics Association-0183 (NMEA) standard protocol to transmit accurate time reference to a GPS receiver which is accurate within a few nanoseconds of Coordinated Universal Time (UTC).

Accurate time referencing, that is timing errors less than 10 milliseconds ($1/100^{th}$ of a second) will keep position errors to a minimum (less than 1 foot). Current spatial sensors are targeted for application in which the sensor are integrated into a homogeneous, permanent mounted hardware product such as an automated/autonomous vehicle, and/or data would be access by a common computer and or data bus, such that the system processing clock could be used as a time reference, which in turn may rely on a network service for periodic updates. Infrastructure-based applications, on the other hand, might not have access to a dependable data network and are therefore more vulnerable to problems with clock drift and time referencing. In the data collection at CoCS, data was forwarded to local edge computing devices and/or laptops. Network connectivity was not guaranteed, so that accurate time reference was problematic. Figure X+4 shows the track of test vehicle before calibration as it makes a right hand turn in the intersection. The positional track shows the spatial registration of the test vehicle as capture by the radar and the GPS reciever, however Figure X+4(b) show the incorrect temporal registration between the Radar and GPS time. This time mismatch can be explained due to the absense of a NTP time reference for the Radar which led to the clock drift. This incorrect spatial and temporal relationship between the sensors will lead to inaccurate sensor calibration and data fusion.

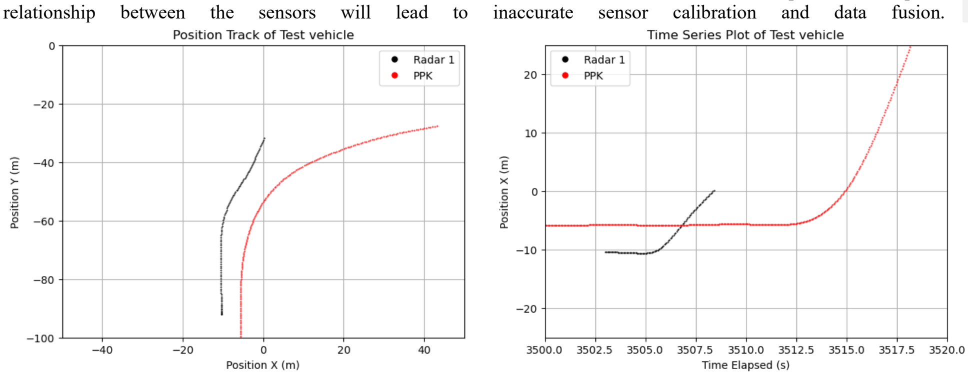
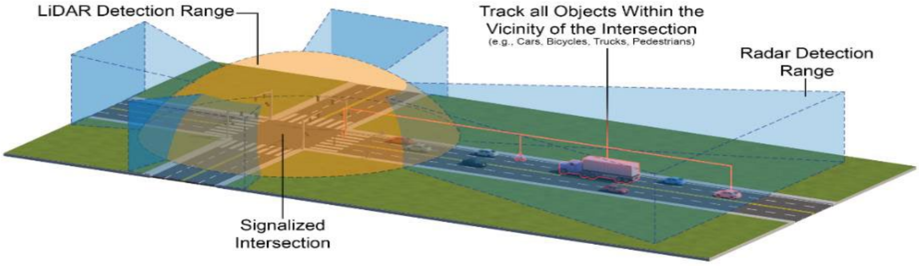


Figure X+4 Track of Test Vehicle before calibration making a right hand turn as captured by the GPS and Radar. (a) Positional Track of the test vehicle making a right turn at the intersection. (b) Time series plot showing the change in Position X of the test vehicle while making the turn as recorded by the GPS and Radar 1.

As a result, the NREL team highly recommends the incorporation of GPS into each sensor sub-system, or be able to subscribe to a common GPS data service that is NEMA compliant. Time derived from GPS based services is accurate to the level of micro-seconds (0.000010 seconds) where as timing services across the network are typically accurate in the millisecond range (0.001 seconds). GPS time reference is available without network connectivity, and also comes inherent with GPS positioning (latitude and longitude), in order to initialize calibration procedures.

C. Multi-types of sensors

Accuracy, reliability, and resiliency in sensor systems are obtained through multiple sensors and multiple sensor types. Figure X+4 illustrates how two sensor types complement each other. Radar technology typically can perceive inbound traffic at distances up to 1000 feet. Although distance and approach speed are highly accurate, vehicle size and identification of vehicle type are less accurate. Countering radars, LiDARs typically can perceive to distance of at most 300 feet consistently, but within that range (shown by the bubble in the Figure X+4) can capture size, shape, and type of vehicle moving object much more accurately than radar.



The bullets below draw out the relative strengths and weaknesses of the perception agents, and their ability to complement each other.

- Radar – one of the oldest spatial detection technologies. Even the latest generation which is capable of discerning lane as well as distance and speed accurately, is highly stable and dependable as it contains no moving parts. Working range of radar has been shown to consistently reach 900 to 1000 feet. Current radar can distinguish multiple vehicles on approach and is relatively low powered. Speed measurement and distance measurement radially from the radar head are highly accurate. The ability to perform object identification is least of all the main sensors.
- LiDAR – One of the newest spatial detection technologies. The LiDAR market has been somewhat chaotic, with considerable industry contraction to a few consolidated players. LiDAR equipment manufactures in general are evolving at a rapid pace with mergers and acquisitions, and bankruptcies. Long term durability remains a concern as the install base is small and young. A large portion of available LiDAR instruments are based on mechanically spinning hardware – which may wear out in time. LiDAR can distinguish and identify shapes accurately, and thus can provide vehicle class information. Range is limited to 300 feet, though most applications, the line of sight capable with LiDAR is 200 feet or less.
- Video image processing – One of the most rapidly evolving areas is video image processing, fueled by the AI trends of the last decade. Software needed to perform image recognition is beginning to be embedded with in the camera hardware, avoiding recurrently licensing fees if desired. Video image processing is unsurpassed with respect to object recognition and can even to classify additional attributes such as color or number of axles. Video has the added benefit of providing visual data to an operator when needed. Video is inherently 2D – providing primarily and image plane. Depth can be inferred from a ground plane, but otherwise an inherent 2D representation of the world. Range is similar to that of LiDAR, typically limited to 200 feet. Durability is expected to high, as base camera technology had been around for decades (in not a century).

Overall system accuracy and reliability is improved by various sensor types as described above.

D. Critical role of Connected Vehicle Data

Connected vehicle data, either in real-time or with minimal (30-60 latency) plays a critical role in IPC. In order to coverage of all road users, sensors along the roadside are absolutely essential, as connected vehicles are only small percentage of the traffic stream. However, the occasional connected vehicle data provides an opportunity test and verify system health. The self-reported position and travel time can be directly compared to that that of the digital twin, and assess relatively agreement. Without this independent source of information with known accuracy to world coordinate allows for precise troubleshooting. Although a system can (and should) assess the relative agreement between disparate sensor types, isolating the sensor that is not performing acceptably is harder to determine. Having a verifiable source of periodic and statistically independent trajectory data would provide the diagnostic capability for the system.

E. Backward compatibility and Fail Safe

Sensors, electronics and software can and do fail. It is not a question of if a system will fail, but when it will fail. Likewise, IPC frameworks need to be designed with fail-safe fallback capability. For intersection control, either the sensor of digital twin needs to provide the equivalent signals as conventional detection if a case 'digital dizziness' if flagged. This implies the ability to provide stop bar detection and approach detection in loop emulation mode. If the digital twin conveys that that the fused operating picture is of low confidence or accuracy, the system needs to provide traditional fall back parameters so that the system can continue to operate in a safe, though degraded state.

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See if you can add some data from recent data collection activities - particularly examples of fused data or calibration.

4 TABLES AND FIGURES

All diagrams, charts, maps, photographs etc., are to be referred to as figures. Within the text, refer to figures by the word Figure followed by the figure number e.g., Figure 1.

Use the same format for plain text in table and figure captions. Table and figure captions must be centered and separated from the plain text by 1 line space. Tables and figures must also be separated by 1 line space from both the plain text and the caption. Both tables and figures should be adjusted to "in-line text" format and must be formatted to sit horizontally centered (please see Table 1 and Figure 1).

Please Place figures and tables at the appropriate place in the text. Do not wrap the text around the figures or tables.

Figure 1. Assumed failure mode under a centrally loaded surface strip foundation on geogrid-reinforced soil.

Table 1. Probability of exceeding 25 mm settlement in the field

Predicted settlement (mm)	*PROBABILITY OF EXCEEDING 25 MM SETTLEMENT IN FIELD*		
	Terzaghi and Peck (1948, 1967)	Schmertmann et al. (1970)	Burland and Burbidge (1985)

1	0.00	0.00	0.00
5	0.00	0.00	0.03
10	0.00	0.02	0.15
15	0.09	0.13	0.25
20	0.20	0.20	0.34
25	0.26	0.27	0.42
30	0.31	0.32	0.49
35	0.35	0.37	0.55
40	0.387	0.42	0.61

5 FORMULAE

Mathematical and chemical formulae should be carefully typed using an equation-creating function. Equations should be intended 1 cm from left margin and numbered consecutively.

$$\eta = \frac{q}{p} \tag{1}$$

6 CONCLUSIONS

All findings, conclusions and recommendations. Recap the discussion above, but in a bulleted fashion

7 ACKNOWLEDGEMENTS

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By one or two authors quoted in the text: (Janbu 1963) or (Terzaghi & Peck 1948)

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- The title of the paper (using lower case letters and no inverted commas).
- The correct name of the book or journal in which the paper appears (spelled in full).
- The editor(s) of the book (if appropriate).
- The volume number(s) and page numbers (if appropriate).
- The publisher and place of publication (if appropriate).

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Hough, B.K. (1969). Basic Soils Engineering, Ronald Press, New York.

B3 – Institute of Electrical and Electronics Engineers (IEEE) Paper

Spatio-Temporal automatic calibration of Infrastructure lidar, radar and camera with GNSS

Faizan Mir[1], Stanley Young[1], Rimple Sandhu[2]

Abstract—Robust and accurate perception is important for modern intelligent transportation system (ITS), which use sensors of various modalities for data fusion to create a digital twin of the intersection. Sensor calibration is an important process which creates a unified coordinate frame for the sensor output data so that it can be used for data fusion. Classical approaches for sensor calibration are time consuming, require an overlapping field of view (FOV) for feature matching and not feasible for ITS application as they cause disruptions in the flow of traffic. In this paper, we present a spatiotemporal automatic calibration approach to calibrate multiple infrastructure Lidar, radar and cameras installed at a traffic intersection. The approach uses Global Navigation Satellite System (GNSS) positioning information shared by connected vehicles (CVs) and when the vehicle is detected by the sensor, we match the sensor detections with the GNSS coordinates. The proposed algorithm is evaluated with real -world dataset utilizing detections from two radars, cameras and Lidars with a test vehicle instrumented with a Post-Processing Kinematic (PPK) corrected Global Navigation Satellite System driving past the sensors installed at a four way traffic intersection. The experimental results show that proposed automatic calibration approach can achieve a spatial calibration error of less than 0.5m. The ability to rapidly calibrate sensors benefits not only for initial installations, but can also be used for system health monitoring, while utilizing available connected vehicle data to test the real-time sensor fidelity and operational status.

I. INTRODUCTION

Modern Intelligent Transportation Systems (ITS) employ multiple sensors to obtain a robust estimate of the perceived environment at a traffic intersection. This allows the system to balance the shortcomings of one sensor type with the advantages of another by utilizing sensors with different modalities. NREL's Infrastructure Perception and control concept proposed a cooperative perception engine which leverages data available from both infrastructure-based sensors (such as LiDAR, radar, and cameras) and cooperatively shared information from connected autonomous vehicles (CAVs) and connected vehicles (CVs) to support a

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wide variety of infrastructure applications such as trajectory based optimized signal control, eco-approach and departure, curbside management and safety-affirmative signaling [1][2]. In order to create a robust digital twin of the intersection, accurate spatial registration is required from these sensors for data fusion. The procedure of manually calibrating a sensor is costly and time-consuming. Automatic calibration is essential to manage the increasing number of sensors, particularly in multi-sensor systems. There are about 300,000 signalized intersections in the United States [3] and for a large scale deployment, manually calibrating each sensor at an intersection isn't feasible. Hence a robust system is required to calibrate these sensors. Classical methods for sensor calibration have been previously developed such as [4] for multiple laser scanners and [5] for a limited overlapping multi-camera setup which requires a calibration object be moved within the field of view (FOV) of the sensor. Therefore, during the calibration process, the route that is being observed must be blocked for a few hours. These techniques are ineffective as frequent road closures might negatively impact traffic flow as the calibration needs to be performed each time a sensor moves significantly, due to vibrations or changing weather conditions.

Multi-modal sensor calibration is a complex problem due to the different physical measuring conditions and the difficulty in obtaining corresponding features from different sensor modalities. Without a calibration object, an association problem must be solved on the basis of relative spatial and temporal alignment of cars in the intersection. In this paper we present a technique for multi-modal sensor calibration at a traffic intersection without an explicit use of calibration objects. Calibration is achieved by tracking the test vehicle instrumented with a Post-Processing Kinematic (PPK) corrected Global Navigation Satellite System (GNSS) within the sensor frame. The positional data from the GNSS equipped test vehicle are shared over to the infrastructure with V2I-setup. Most modern vehicles are equipped with a GPS although this positional data is not commonly available for use in the traffic infrastructure systems. However the approach in this work can be currently used by the city traffic departments for calibration and convenient for future adoption as vehicle geographic data becomes available for via V2I for traffic infrastructure systems from the CVs. To solve

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the problem of auto-calibration we used Rauch-TungStriebel smoother for the temporal alignment of sensors and solve an optimization problem to calculate the translation and rotational alignment of the sensors. We evaluate our approach on real-world data, utilizing detection from two radars, lidars and cameras installed at a four way traffic intersection in the city of Colorado Springs, Colorado, USA to show that it is able to achieve precise sensor calibration while utilizing detection from multiple sensor modes.

II. RELATED WORK

Sensor calibration has been extensively researched in both academia and industry. The goal of calibration, more especially extrinsic calibration, is to determine the spatiotemporal transformation that is, the relative rotation, translation, and system clock delay between two sensors. However the focus has been to calibrate homogeneous sensors (camera to camera, lidar to lidar) [6][7][8]. Most of the research on sensor calibration from different modalities has been done with a focus on Simultaneous Localization and Mapping (SLAM) [?] however these methodologies are not suitable for a ITS applications. Generally the sensor calibration can be classified into Target-based and target less methods. Target based approach require a calibration target such as a checkered board or a polygon board which can be accurately tracked within the sensor [9][10][11] and provides a reference for calibration. These methods can provide precise sensor calibration but can be hard to implement in a continuously moving traffic environment. On the contrary target-less methods don't rely on a calibration target and extract features from the environment and then apply feature matching to find the correspondences between the sensors [12] [13] [14]. However, using these approaches on a traffic intersection presents two common challenges: 1. Point clouds from road side point clouds are relatively sparse as sensors are mounted high up on the poles to get a better field of view of the intersection. 2. These approaches cannot be applied to sensors from different modalities such as radars which are commonly used for traffic applications lack descriptive visual features and output data in the form of detected objects.

Recently, these calibration ideas have recently been expanded to include different types of sensors and optimized for infrastructure based perception as well. Persiˇ c et al [15]´ designed a triangular retroreflector calibration target for a radar and a 3D lidar. The calibration method used two step optimization: using reprojection error optimization followed by field of view (FoV) optimization, leveraging radar crosssection (RCS) measurements. Ge et al. [13] presented a

targetless approach for calibration of RGBD camera and millimeter-wave radar which involved extracting geometric constraints to provide initial estimates of extrinsic parameters using simulated annealing and then using object velocity to fine tune the calibration. Domhof et al. [16] proposed a joint lidar, radar and camera calibration method by using

a specially designed calibration target that uses 4 circular holes on a planar object to represent a unique geometric 3D shape detected by all 3 sensors. Ren et al. [6] presented TrajMatch, a spatio-temporal calibration methodology for roadside LIDARs, which used a semantic matching feature and trajectory-level matching to calibrate the LIDARs. However the paper only addresses the calibration for LIDARs and doesn't include sensors of other modalities. In [17], an auto-calibration method for roadside radar and camera was presented by using Convolutional Neural Network (CNN) to estimate the rotational calibration between sensors. However, the paper only focuses on rotational calibration and cannot be employed on a conventional four way intersection.

A. Termporal Calibration

The time based calibration is usually required because of the different sampling frequencies of sensors. Researchers have presented various approaches for temporal alignment of asynchronous signals such GP regression [18] and data interpolation [19]. In [20], an alignment algorithm is proposed which takes the sensor with the highest sampling rate as the reference. In [21], a vehicle motion-fitting model was proposed for temporal alignment between a camera and a millimeter-wave radar.

B. Spatial Calibration

After establishing the temporal correspondence, the spaital alignment can be calculated analytically by using commonly employed point-set registration techniques such as Iterative Point Cloud (ICP) [22]. ICP algorithm works very well for SLAM applications where the pose between two transformations is small. For ITS application it does not provide reasonable results as it is heavily dependent on a good initial guess of the transformation.

III. CALIBRATION METHODOLOGY

In this section, the proposed auto-calibration algorithm is described. The problem formulation and required presumptions are first mentioned. Next, the calibration algorithm is explained in detail.

A. Problem Formulation

Consider a multi sensor (S_i) setup at an intersection with N sensors such that $S_i, i \in [1,N]$. We can define a set of 3D data points in world coordinates as $W = \{w_1, w_2, w_3, ... w_i\}$ and we can define a set of N sensors as $P_{S_N} = \{P_{S_1}, P_{S_2}, P_{S_3}, ... P_{S_N}\}$, where $P_{S_1} = \{p_1^1, p_2^1, p_3^1, ... p_i^1\}$ represents a set of 3D data points for 1st sensor. The points in the sensor and world coordinates have the same dimension and are given as:

$$p_{Ni} = [x_{Ni}, y_{iN}, t_{Ni}]^T, \; p_{Ni} \in R^3 \; w_i = [x_{wi}$$

$$, y_{iw}, t_{wi}]^T, \; w_i \in R^3$$

Therefore each point in the sensor coordinate frame can be mapped to a point in the world coordinate frame :

$$w_i = "R0_{S_{wi}} \quad T1_{S_{wi}}\#.p_{Ni} \tag{1}$$

$$| \quad \{_w z \quad \} \quad H_{Si}$$

where $R^w_{S_i}$ is the rotation matrix and $T^w_{S_i}$ is the translation matrix. For a point we can define the coordinate transform as:

$$\hat{p} = \begin{bmatrix} cos\theta & -sin\theta & 0 \\ sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} x \\ y \\ t \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \\ dt \end{bmatrix} \tag{2}$$

where θ is the angle between the two points, t_x and t_y are the translation in x and y and dt is the time offset.

B. Algorithm Overview

The sensor calibration framework is present in the Fig. 1. As soon as the object is in the field of view of the sensor it get detected, assigned an object id and classified into categories such as cars, trucks, bicycles, pedestrians etc., with its position and velocity information. The proposed framework takes the object trajectory information from multiple sensors and extracts features from the object list which are invariant to object rotation and transformation as the detection's are made by each sensor in their localized coordinate frame. As in case of any multi-sensor setup, each sensor has a different detection frequency and it is important to align these to a common time resolution to find the spatial alignment. Next we use a Rauch-Tung-Striebel (RTS) smoother for the temporal alignment of the selected object trajectory from the sensor and the PPK corrected GNSS equipped test vehicle. To increase tracking performance, the motion of the vehicles must be precisely represented with their dynamic behavior. Here we employ a constant velocity motion model to model the vehicle traveling through the intersection. The state vector for the constant velocity model is defined as: $\dot{x} = [p_x, p_y, v_x, v_y]^T$

where p_x, p_y represents the position in x and y direction respectively and v_x and v_y is the velocity in x and y direction respectively. The discrete time state-space form can be defined as:

$$x_k = A_k x_{k-1} + q_k \; y_k =$$

$Hx_k + r_k$ where $q_k \sim \mathrm{N}(0,Q_k)$; $T = t_k - t_{k-1}$;

$$A_k = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}; Q_k = \begin{bmatrix} \frac{\sigma_1^2 T^3}{3} & 0 & \frac{\sigma_1^2 T^2}{2} & 0 \\ 0 & \frac{\sigma_2^2 T^3}{3} & 0 & \frac{\sigma_2^2 T^2}{2} \\ \frac{\sigma_1^2 T^2}{2} & 0 & \sigma_1^2 T & 0 \\ 0 & \frac{\sigma_2^2 T^2}{2} & & \sigma_2^2 T \end{bmatrix}$$

0

The dicrete-time Kalman smoother, also known as RauchTung-Striebel smoother (RTS) is implemented to align the data from the sensors and the PPK-GNSS equipped test vehicle. The Kalman smoother involves a two step processa forward standard Kalman filer and a backward smoothing filter. The below equations (3)-(9) describe the Kalman Filter and smoother algorithm.

Kalman Filter ***Prediction***

$$x_{k+1|k} = F_k x_{k|k} \tag{3}$$

$$P_{k+1|k} = F_k P_k F_k^T + Q_k \tag{4}$$

Update

$$K_{k+1} = P_{k+1|k} H^T [H P_{k+1|k} H^T + R]^{-1} \tag{5}$$

$$x_{k+1|k+1} = x_{k+1|k} + K_{k+1}[y_{k+1} - H x_{k+1|k}] \tag{6}$$

$$P_{k+1|k+1} = P_{k+1|k} - K_{k+1}[R + H P_{k+1|k} H^T] K_{k+1}^T \tag{7}$$

where K is the Kalman gain and P is the error covariance matrix.

The smoother calculates the state posterior distribution $p(x_k \mid y_{k:k+N})$. The recursive equation for backward step are given as:

Kalman Smoother

$$x_{k|k+N} = x_{k|k} + C_k[x_{k+1|k+N} - x_{k+1|k}] \tag{8}$$

$$C_k = P_{k|k} F^T P_{k+1|k}^{-1} \tag{9}$$

where C_k is the smoother gain. Once we have the sensor points at the same time resolution as the GNSS positional data, we can match the position points from the trajectory at each time stamp to find the transformation which best fits the system until it reaches a threshold. The spatio-temporal problem can be setup as an optimization problem to minimize the matching error between the two sets of data points and is described as:

$$H^w_{S_i} = argmin \sum_i^P \left\| w_i - (R^w_{S_i} \times p_i^N + T^w_{S_i}) \right\| \tag{10}$$

We can use Singular Value Decomposition (SVD) [23] to calculate the rotational matrix R and transltion vector T.

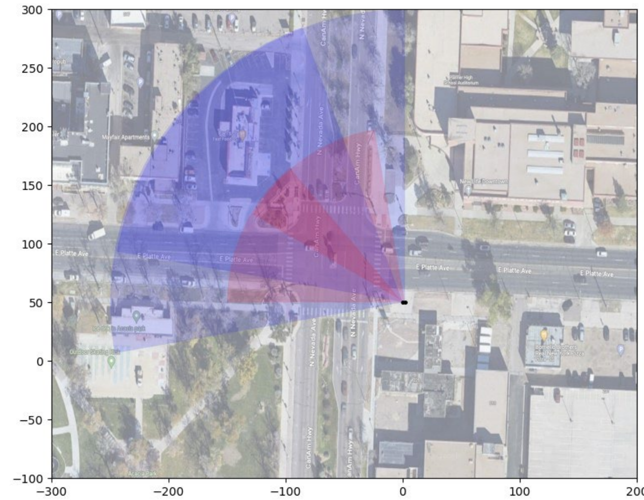
Fig. 2: Mounting location of the sensors with a statue in the center at the traffic intersection in the city of Colorado Springs, CO, USA.

IV. Evaluation and Results

A. Experimental Setup

The proposed calibration framework was evaluated at a four way traffic intersection in the city of Colorado Springs, Colorado USA. The intersection has a statue in the center which acts as a blind spot and the sensors loose track of the object when behind the statue and get detected again as they move out of it. The sensors were installed at a

corner of the intersection to track the cars in the intersection as well as the ones approaching from the North and West direction. Two Econolite EVO radars were setup with one of the radar directed towards the North-South Direction and the second was pointed towards East-West Figure 2. This ensured a full coverage of the intersection as well as the approaching vehicles shown in Figure 3. Each EVO radar has 110 degrees of field of view and about 250m of range and can classify cars, trucks and pedestrian. The sensor data was sent to a EVO Radar Hub for processing and recorded at a resolution of 10Hz. Two Axis cameras were also mounted to record the data at the intersection with each camera pointed in the same direction as the radar as shown in Figure 2. A deep learning model for object detection and classification developed by Kapsch was employed for



realtime classification of the objects (cars, trucks, pedestrians) inside and approaching the intersection using an edge device recording at a time resolution of 20Hz. A set of Ouster mechanical Lidars were also installed at the intersection. The Lidars were pointed towards the intersection to detect and classify objects from the 3D point cloud data. This setup containing 3 different modes of sensors with radar providing long range detection, camera detecting objects inside the intersection complimented by 3 dimensional information from the Lidar provides a robust image of the intersection which is essential for ITS applications and creating a digital twin.

A high accuracy Emlid Real-Time Kinematic (RTK) GNSS was mounted on the top of a test vehicle while a base unit was set up near the intersection for Post-Processing Kinematic correction of the geographic coordinates sent by the vehicle as it passed thought the intersection at a time resolution of 30Hz.

Fig. 3: The field of view of Radar (blue) and Camera (red) on the intersection with darker shade representing the overlap between sensors.

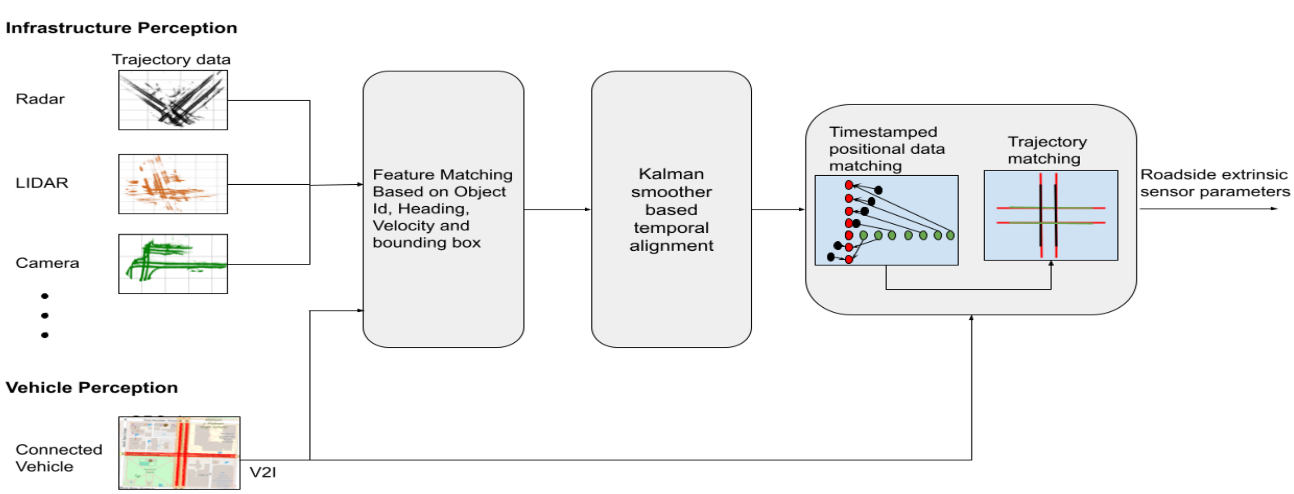


Fig. 1: The proposed spatio-temporal sensor auto-calibration framework.

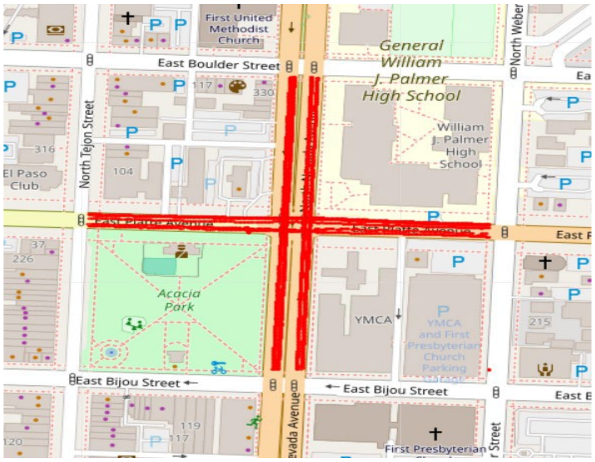
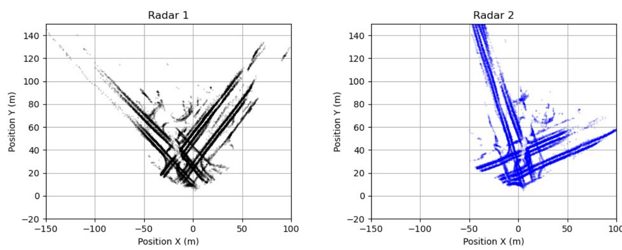
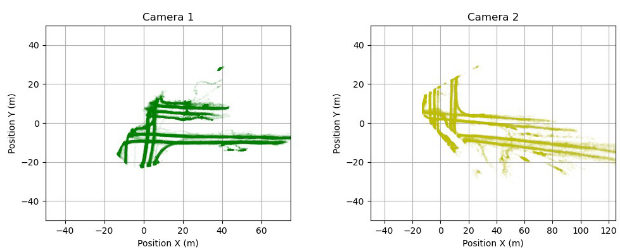


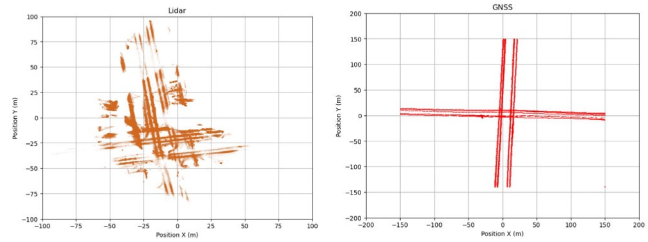
Fig. 4: The figure shows the PPK-GNSS tracks from the instrumented vehicle at the intersection.



(a) Radar 1 (b) Radar 2



(c) Camera 1 (d) Camera 2



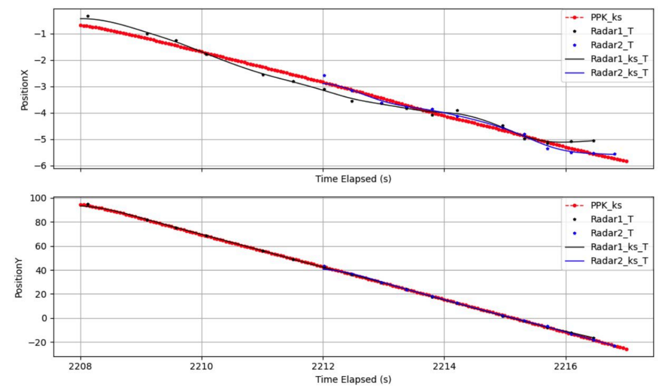
(e) Lidar (f) RTK-GNSS

Fig. 5: Vehicle and Pedestrian tracks detected by (a) Radar 1, (b) Radar 2, (c) Camera 1, (d) Camera 2, (b) Lidar and (f) tracks of test vehicle instrumented with RTK-GNSS passing through a four way intersection.

B. Results

As the test vehicle moves through the intersection it records its position in WGS-84 geodetic coordinates. First the geodetic latitude and longitude coordinates are transformed to Earth Centered, Earth Fixed (ECEF) coordinates and then transformed to East, North, Up (ENU) tangent plane in terms of x and y data points. With the GNSS positional data as our ground truth we are able to determine the timestamped detection from the sensor and apply the above discussed transformations to calibrate them. The vehicle and pedestrian tracks recorded for 2 hours and detected by the multi-sensor setup at the four way traffic intersection are shown in Figure 5. The tracks shown from each sensor are in their local coordinate frame.

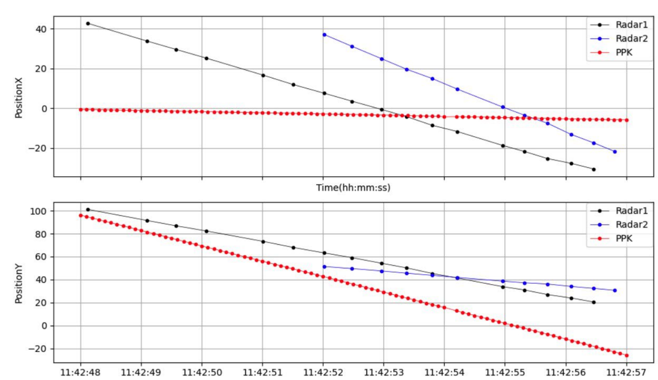
The positional track of the test vehicle as it passes through the intersection is shown in the figure 7. In (7a), the initial



(b) Positioning of the vehicle after transformation

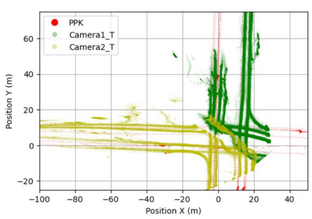
Fig. 6: Positional data of the vehicle (a) initial output, (b) final solution.

positional data of the test vehicle is shown as detected by radar 1 (black) and radar 2 (blue). After applying the proposed algorithm the positional data from the radar sensor is transformed into a common coordinate system. In (7b), the trajectory after applying a Kalman smoother is shown in black and blue for radar 1 and radar 2 respectively where as the data points represent the actual detection after transformation.

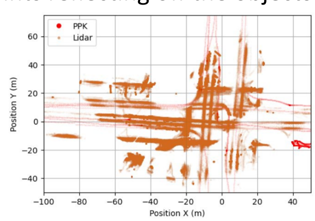


(a) Positioning of the vehicle in local sensor coordinate frame

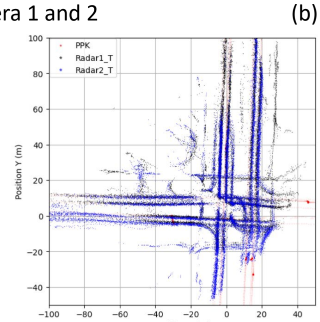
The vehicle and pedestrian tracks after calibrating the sensors using the proposed auto-calibration framework are shown in Figure 7. The detections from Radar 1 and 2 (Fig. 7c) have the least calibration error and are able to provide information about the vehicles approaching the traffic intersections as far as 100m. The detection from the cameras as shown in Figure (Fig. 7a) match with the GPS tracks however there are certain detections which don't match with the GPS tracks. This deviation can be explained by the following reasons: 1. The camera suffers with distortion and needs additional post processing to remove this distortion. 2. There is an error in the center point of the vehicle in the image plane. The camera uses a fixed vehicle center point based on bounding box dimension to determine the center point of the vehicle, however this method isn't consistent if the vehicle approaches the camera at various angles, hence causing the error in detection. Finally, for Lidar we have good matching results in the intersections as shown in Figure (Fig. 7b) however as we move away we start to observe the higher errors, this could be because the Lidar was pointed down towards to intersection to get more information and at the farther distances it had less points reflecting off the objects.



(a) Camera 1 and 2



(b) Lidar



(c) Radar 1 and 2

Fig. 7: Vehicle and Pedestrian tracks detected by (c) Camera 1 and 2, (a) Lidar and (b) Radar 1 and 2 transformed after using the proposed framework.

V. CONCLUSIONS

In this work, a automatic calibration method is presented for calibrating infrastructure based Radar, Lidar and cameras that use trajectory information provided by a GNSS equipped test vehicle to find the extrinsic calibration parameters for the sensors. By calibrating different types of sensors we are able to achieve a robust perception of the intersection. In future work, the algorithm should be further extended to perform system health monitoring and analyzing sensor fidelity in real-time at a traffic intersection.

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B4 – Transportation Research Board (TRB) Paper

Infrastructure-Based Cooperative Perception at a Traffic Intersection: Overview and Challenges

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ABSTRACT

Recent advancement in autonomous driving vehicles and V2X communication has attracted increasing attention towards Intelligent Transportation Systems to build a safe and reliable traffic intersection. However, most of the systems are still at the initial stages and require significant progress to become a reality. This paper presents an overview of NREL Infrastructure Perception and Control (IPC) framework which is an open-source track-data fusion engine which takes input from infrastructure-based perception sensors and cooperatively shared messages from Connected Autonomous Vehicles (CAVs) and Connected Vehicle (CVs) and the challenges associated with deploying such cooperative perception framework at a four-way traffic intersection in the city of Colorado Springs, CO, USA. The sensor data is collected by deploying two radars and two LiDAR sensors on the IPC mobile lab and two radars on diagonally opposite traffic poles at the proposed intersection. The sensor output results indicate the need for rapid sensor calibration to bring the collective perception to a common coordinate frame, the importance of time synchronization between the sensors in order to capture accurate spatial and temporal alignment of the objects, and the need for a health monitoring system with fail safe closed-loop detection model for real-time deployment.

Keywords: Cooperative Perception, intelligent transportation system, Digital-twin, radar, LiDAR, V2X communication.

INTRODUCTION

The automotive industry is undergoing a transformational change with the emergence of autonomous driving vehicles and connected vehicles. These vehicles promise to reform the way we travel by reducing congestion on roads, making roads safer and offering a mobility solution to people with limited mobility. The Society of Automotive Engineers (SAE) have developed a 6-level classification system to define the range of vehicle automation from no automation to full automation, which has also been adopted by U.S Department of Transportation. Automated vehicles, and automated mobility in general, are essential to creating a more equitable transportation system because they bridge the gaps in the country's transit network and provide economically disadvantaged communities and those unable to drive with a superior alternative to the vehicle ownership model.

Automated vehicles use embedded sensors to perceive the environment and localize the vehicle and the motion planner stack determines the travel path and driving actions (such as lane changes, acceleration, and braking) that are carried out by the control module. For perception and localization vehicles are equipped with multiple modes of sensors (e.g cameras, LiDAR, radar, etc) to perceive their surroundings. Although the sensors have significantly improved their range and detection accuracy; the capabilities of the vehicle-based sensors alone to recreate a holistic perception of the environment remain fundamentally impaired due to presence of obstacles in blind spots because of limited field of view and inclement weather conditions reducing the range and accuracy of these systems. Cooperative driving Automation (CDA) can help resolve some of these issues using V2X (Vehicle-to-Everything) communication to increase the perception capabilities of connected autonomous vehicles and connected vehicles and would help to accelerate deployment of driving automation (1) (2).

Infrastructure-based cooperative perception significantly enhances the CDA by providing connected vehicles with additional data about the driving environment, including data beyond the field of view (FoV) of the vehicle on-board sensors. This additional data from infrastructure-based perception sensors can help improve the detection accuracy of the vehicles, provide information about objects in the blind spots of the vehicle and increase their detection confidence. These infrastructure-based systems can also be used for Trajectory-based Optimal Signal Control (3), Eco-approach and Departure (4), Vulnerable Road User Protection (5) and many other related CDA application areas. For CDA applications to be effective, a strong infrastructure-based system is essential. The U.S. Department of Transportation recognized the need for robust infrastructure involvement and launched Cooperative Automation Research Mobility Applications (CARMA) Streets as part of its CARMA research and development program (6). The National Renewable Energy Lab (NREL) proposed an Infrastructure Perception and Control (IPC) framework which combines the data from both infrastructure-based sensors (LiDAR, radar, camera) and cooperative shared messaging from CAVs and CVs into a cooperative perception engine to perform track data fusion (7). The IPC fusion engine employs Bayesian filtering methods such as Extended Kalman Filter and Unscented Kalman Filter to provide the state estimate of a new or existing object detected from the sensors and data association algorithms for multi-object tracking in order to create a real-time digital twin of the traffic intersection.

This paper presents an overview of the concept and examines the challenges involved in implementing an infrastructure-based cooperative perception engine at a traffic intersection. In addition to outlining the physical components, this study also starts to address important data and communications challenges involved in a multi-sensor system. We present results of deploying the NREL IPC mobile trailer at a four-way traffic intersection in the city of Colorado Springs, Colorado, USA that employed multiple radar and lidar to capture the data. This study provides necessary practical learning for the CDA and traffic engineering communities for next-generation infrastructure based cooperative perception that promises improvements in signal control for optimized traffic flow among other applications, in addition to documenting finding for ongoing research and development efforts in other areas.

LITERATURE REVIEW

Intersections are responsible for almost half of all traffic injuries and around 25% of all traffic deaths that occur in the US each year (8). For this reason, FHWA has made traffic intersection a focus area and a national, state, and local traffic safety priority. In recent years many of the inductive loop detectors at traffic intersections have been replaced by video cameras and other technologies, which have low cost, easy to maintain and provide robust performance. Most of these video cameras are programmed to detect an object in a certain zone of the intersection and send the equivalent binary on/off signal to the traffic controller similar to older inductive loop technology. Due to improvements in object detection algorithms especially using deep learning approaches, these video detection methods are beginning to be used to detect and track moving objects on the road (9-12), beyond simple inductive loop emulation. Even with all the advancement in video detection technologies, there remains some challenges and disadvantages of the new technology such as low viewing angles, poor long range detection capability and poor detection ability in varying lighting and adverse weather conditions (13-16)

To overcome the challenges of video detection several other sensors such as LiDAR and radar have been presented as an alternative for detection and tracking of vehicle at a traffic intersection. In studies (17-20), algorithms were presented to use roadside LiDARs for detection and tracking of cars and pedestrians at traffic intersection. Although roadside LiDAR provides a high-resolution 3D information of objects within the intersection, it is not ideal for long-range detections and certain environmental conditions. In (21-25) roadside radar has been used to detect and classify objects at a traffic intersection which provides superior long-range detections as compared to camera and LiDAR. However, using these perception sensors in conjunction with each other allows for a robust perception system that performs better than an individual sensor and provides optimal performance in terms of detection range, accuracy and resilience in varying environmental conditions. Zimmer at al (26) proposed a multi-modal 3D object detection utilizing two roadside infrastructure LiDARs and cameras. The algorithm uses early-stage fusion of point-cloud level data from multiple LiDARs and combines the camera detection using late-stage fusion. The results indicate that multi-sensor fusion is able to achieve better results than using only camera input. In (27) (28), a fusion approach is presented which fuses data from infrastructure-based camera and radar, and experimental results show that it is able to acquire accurate roadside sensing information. Sochaniwsky et al (29) presented a real-time multi-object sensor fusion framework to combine data from a camera and LiDAR, and the test results indicate superior performance than a single sensor setup with a low runtime of 21.8 ms.

The above approaches indicate how a multi-sensor setup is more beneficial than using a single sensor. More recently with the advancement in Vehicle-to-Everything (V2I) communication technologies, roadside perception systems have been shown to improve the perception capabilities of CV and CAVs in real-time. Chen et al (30) presented a preliminary evaluation of a cooperative perception system by utilizing an infrastructure-based LiDAR and SAE Level 4 CAV to share real-time messages utilizing Vehicle-to-Infrastructure (V2I) system. Field tests demonstrate that with cooperative perception, the CAV was able to detect the vulnerable road user (VRU) earlier and plan a smoother vehicle trajectory while decreasing the acceleration. Kim et al (31) demonstrated how the vehicle-to-vehicle (V2V) cooperative perception can increase the situational awareness and contribute to a better decision making and planning by evaluating specific scenarios such as automated collision avoidance, lane-changing in reactive and proactive manners for an autonomous driving vehicle. Zhang et al. (32) implement a roadside perception system at a roundabout in Ann Arbor, Michigan, USA which fused detections from a fisheye lens camera and a thermal camera. The results demonstrated how the results from fusion algorithm could be used for traffic volume monitoring and Post-Encroachment (PET) Detection.

While the above studies present effectiveness of multi-sensor sensor fusion technologies in improving perception capability of CVs and CAVs and detecting VRUs, none of them present the challenges of deploying such a system at a traffic intersection. This paper reports on an established framework for cooperative perception while also discussing the key challenges faced in the deployment of such system at a traffic intersection.

IPC FRAMEWORK ARCHITECTURE

To create a safe and robust traffic intersection it is important to integrate data from sensors of various modalities as each sensor has different optimal range, resolution and accuracy. It is important to combine and fuse data from all these sensors to create a unified picture of the intersection which is safe and reliable enough to work in any environmental conditions. NREL Infrastructure Perception and Control (IPC) framework as shown in Figure 1 integrates perception data from sensors and cooperative shared information from CAVs and CVs to perform late-stage track data fusion and create a high accuracy digital twin of the intersection which has multiple control application potential such as eco-departure and approach, trajectory based signal optimization, safety affirmative signaling, curb management, red-light running detection, and dilemma zone detection and prevention.

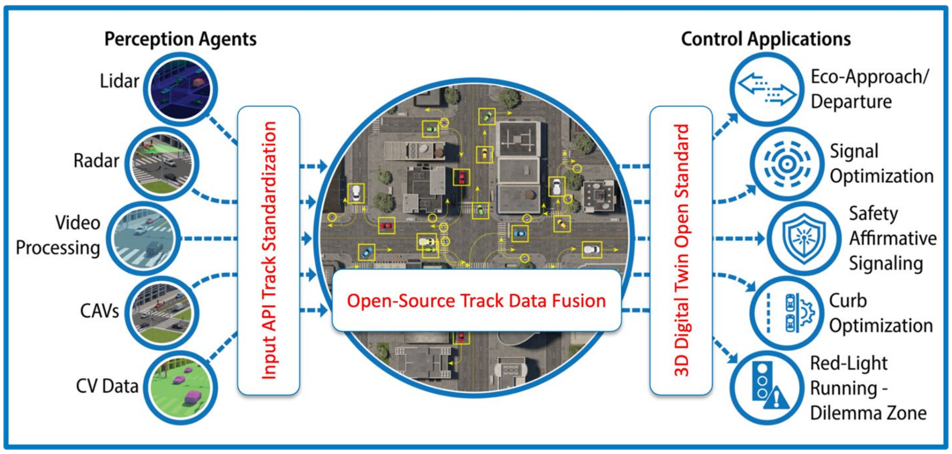

Figure 1 Infrastructure Perception and Control framework integrates perception data to perform track data fusion and create a digital twin of the intersection which has multiple control applications.

The current landscape of deploying and collecting infrastructure-based data from spatial sensors is dependent upon available equipment from industry vendors which often have limited end use capability with sensors of a different mode or different manufacturer. Often the base trajectory data is inaccessible in a well-defined application programming interface. Moreover, different sensors have different characteristics such as detection range, resolution, sampling rate and the varied data schemes to convey the object trajectory list. Often these sensors are configured to work in conjunction with other sensors of the same brand and type such as camera-camera, lidar-lidar and radar-radar. However, as there is no perfect sensor technology which can address all the challenges of perception within an intersection environment, data from multiple sensor types need to fused. The NREL IPC framework proposes a standard or normalized data interfaces between the physical sensor output and the fusion engine so that the system can function agnostic to the sensor type, manufacturer, and/or model. Having a standardized data interface allows the city to procure the equipment on a specification-based approach from any manufacturer, and the proposed open-source multi-sensor track data fusion can work with any vendor's equipment rather having to develop custom data fusion for different sensor type.

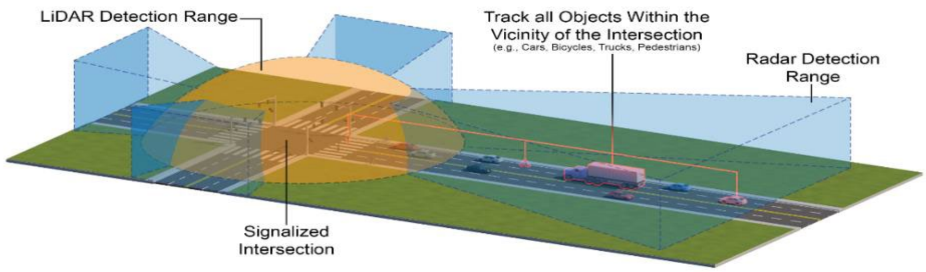

Figure 2 Multi-sensor perception setup with radar providing long range detection of vehicle approaching the intersection and LiDAR providing a high-resolution detection of the objects within the intersection.

Infrastructure-based sensors which are mounted on traffic poles at considerable height have an elevated view of the traffic intersection. To capture the objects approaching the intersection, a 3D radar is used to provide long range detection. While the resolution of 3D radars has increased over the years, it is still far behind that of LiDAR and video cameras. Therefore, it is difficult for radar to distinguish vulnerable road users (VRUs) when two or more are moving or standing close to each other. Using other sensors such as cameras and LiDARs which have high-resolution can provide better detection and identification accuracy of objects within the intersection. This includes enhanced classification accuracy of cars, trucks, cyclists and vulnerable road users. Figure 2 shows how a multi-modal sensor setup can be implemented at a signalized traffic intersection with radar providing long range detection and LiDAR providing 3D object detection of cars, bikes, trucks and pedestrians within the intersection.

METHODS

IPC Mobile Trailer

The Infrastructure Perception and Control (IPC) mobile laboratory is a state-of-the-art mobile laboratory with the ability to rapidly deploy multiple sensors and technologies at any traffic intersection and record data in real-time. Equipped with latest generation of perception sensors, the IPC mobile lab has two extendable masts as seen in Figure 3(a). These extendable masts allow the lab to deploy sensors at heights up to 30 feet simulating how these sensors would be mounted on traffic poles providing a comparable field of view. In this study, the IPC mobile laboratory was deployed at a four-way traffic intersection in the city of Colorado Springs, CO, USA. Two EVO radars were deployed, with one directed toward the North-West and the second pointed toward the South-West as shown in Figure 5(b). Each mast was mounted with an EVO radar and a 360-degree mechanically rotating LiDAR with each sensor sending object track data to edge compute devices located into the mobile laboratory. The masts were raised to a height of about 18 feet with EVO radars set at an elevation angle between 7-8 degrees and the LiDARs oriented to the intersection as shown in Figure 3(b).

Figure 3 (a) The IPC mobile trailer deployed at the intersection with radar and lidar mounted on each extendable mast. (b) The intersection as seen from the top of the IPC mobile trailer.

Test Site Description

The IPC mobile laboratory was positioned within the intersection in the zone as shown in Figure 4. In addition to the radar and LiDAR sensors mounted on the mast of the IPC trailer, two additional radars were mounted on the traffic poles diagonally as shown in Figure 4. These pole mounted radars were aligned to capture data in South-West and North-East directions as shown in Figure 5(a). This diagonal configuration of the sensors ensured full coverage of the intersection. Each radar has a 110° field-of-view (FoV) and about 250 m of range and can classify cars, trucks, and pedestrians. The data from the radar sensors mounted on the trailer and poles were sent to individual hubs mounted within the IPC trailer and traffic control cabinet respectively for processing, and the data from all four radars were recorded using a NUC computer located in the IPC mobile lab at a resolution of 10 Hz. Ouster 360 mechanical LiDARs mounted on the IPC trailer were setup to run in a standalone mode to detect and classify objects from the respective individual 3D point clouds, with data recording at a time resolution of 10 Hz. This data would be later processed and fused in the IPC fusion engine. This setup containing multiple modes of sensors—with radar providing long-range detection, and LiDAR providing 3D information within the intersection provides a robust image of the intersection essential to enable cooperative perception and creating a functional digital twin.

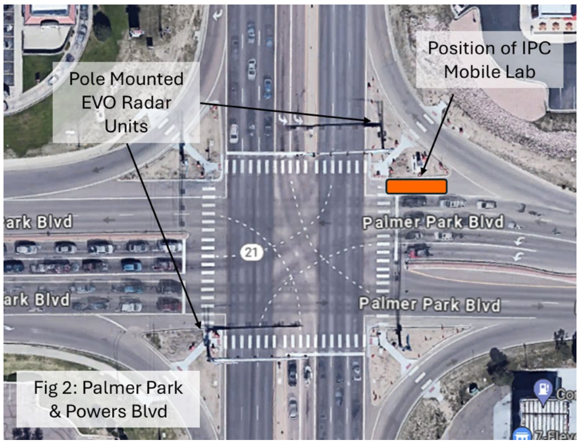

Figure 4 Show the test site with the location of the sensors used to capture data within the intersection.

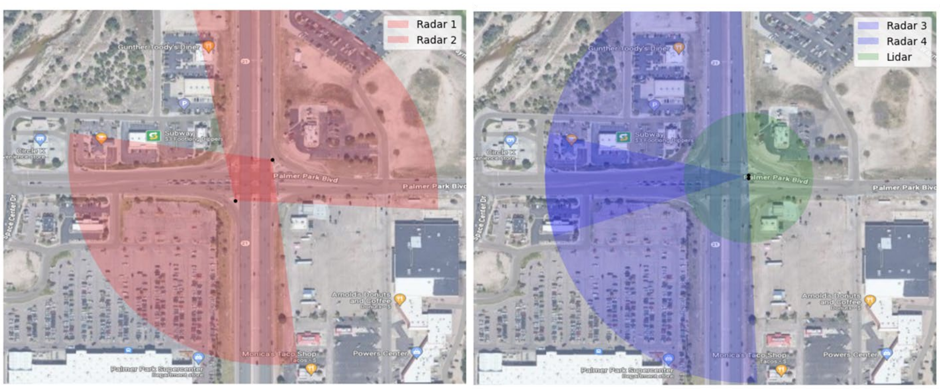

Figure 5 Shows the Field of View of the deployed sensors at the intersection with the darker shades representing the overlap between the sensors. (a) Radar 1 and Radar 2 (red) mounted on opposite traffic poles of the intersection providing full coverage of the intersection (b) Radar 3 and Radar 4 (blue) and 2 Lidars (green) deployed on IPC mobile trailer.

Test Vehicle

A test vehicle equipped with a high accuracy Emlid post-processing kinematic (PPK) GPS was used to simulate connected vehicles within the intersection and was used to collect ground truth GPS data for calibration of the system. A GPS receiver mounted on top of the vehicle collected GPS trace data from the roving vehicle. Differential correction was obtained from a public base unit located about 11 miles east of the test site. The differential correction data was used to improve the accuracy of the GPS location of the roving vehicle. The vehicle tracks from the roving GPS-instrumented vehicle provided the essential ground truth data required for sensor calibration and monitoring. The GPS collected data at a time resolution of 30 Hz. Figure 6 shows the GPS tracks of the test vehicle as it drove through the intersection.

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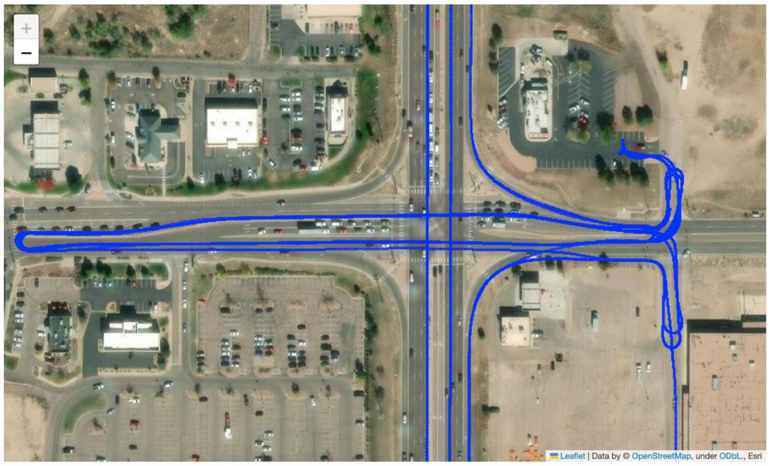

Figure 6 GPS traces from the test vehicle after differential correction from a public base.

RESULTS AND DISCUSSION

In this section we present the results and the challenges that need to be addressed for the IPC open framework track data fusion to output the fused trajectory from the sensor data. It is important to have a common coordinate frame for the sensor data and having correct temporal alignment for data fusion to function properly. The sections below explain the importance of these and how these issues were resolved within the framework of the data collection exercise. We also discuss the need of a health monitoring system which can determine any issues with the data collection equipment and fusion process and switch the traffic signal system into a fail-safe mode to avoid any potential failures.

Sensor Calibration

To create a robust digital twin of the traffic intersection, accurate spatial registration is required from the sensors for data fusion. Manual sensor calibration is an expensive and time-consuming process which can expose workers to hazardous conditions, particularly in high-traffic intersections. To handle the growing number of sensors, especially in multi-sensor systems, automatic calibration is crucial. In the US, there are approximately 300,000 signalized intersections. It is time and resource intensive to manually calibrate every sensor at each intersection for a large-scale deployment. Therefore, in order to calibrate these sensors, a reliable automatic calibration method is needed. Classical calibration methods have been previously developed that require a calibration object such as a checkered board or other readily recognized vehicle to be deployed and detected by the sensor. However, implementing such manual calibration procedures is disruptive at a traffic intersection as frequent road closures negatively impact the flow of traffic. Calibration would need to be performed every time the sensor moves which can be caused from excessive structure vibration, contact with an object, or inclement weather (particularly high winds).

Sensor calibration methods for perception sensors has been previously studied especially for SLAM and robotics applications. Such methods generally use an iterative closest point (ICP) algorithm (33) and its various implementations (34-37) to solve the problem of sensor calibration. These algorithms perform well when the initial pose between sensors is small but perform poorly in cases where the sensor pose is large as it is heavily dependent on a good initial guess of the absolute sensor position and orientation. To resolve this bottleneck for the IPC framework, we employ Global Navigation Satellite System (GNSS) trace of vehicles travelling through the intersection to calibrate the sensors both initially and in an ongoing basis. As CAVs and CVs travel through the traffic intersection, they would share their spatial information to the intersection-based road side unit (RSU) via V2I messaging. This information

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Commented [FM3R2]: It is used to describe the alignment between sensors can be used by the IPC framework to calibrate the sensors and evaluate the sensor fidelity in real time. Mir et al (38) demonstrated this concept by deploying a test vehicle equipped by a PPK GNSS unit at the subject intersection. The vehicle was driven through the intersection multiple times and from multiple approaches. The position data from the vehicle was associated with the corresponding traces from the infrastructure sensors in order to calibrate them appropriately, that is to obtain the absolute position and orientation of each sensor to a degree of accuracy to enable high fidelity sensor fusion. This process was tested and affirmed for LiDAR, radar and camera sensors.

For a sensor capturing data at an intersection, a ground plane is determined to reduce the dimensionality from a 3D problem into a 2D transformation by omitting the height of vehicles. Now the problem is reduced to translation and rotation with the ground plane as z=0 representing the road surface. The detection points in world coordinates (w_i) and sensor coordinates (s_i) are given as in **Equation (1)**

$$s_i = [x_i^s, y_i^s]^T, \quad s_i \in R^2 \qquad (1)$$
$$w_i = [x_i^w, y_i^w]^T, \quad w_i \in R^2$$

For every point we define the coordinate transformation as given by the **Equation (2)**

$$w_i = \underbrace{\begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix}}_{R} \times \begin{bmatrix} x_i^s \\ y_i^s \end{bmatrix} + \underbrace{\begin{bmatrix} t_x \\ t_y \end{bmatrix}}_{T} \qquad (2)$$

where R and T represent rotation and translation matrices respectively.

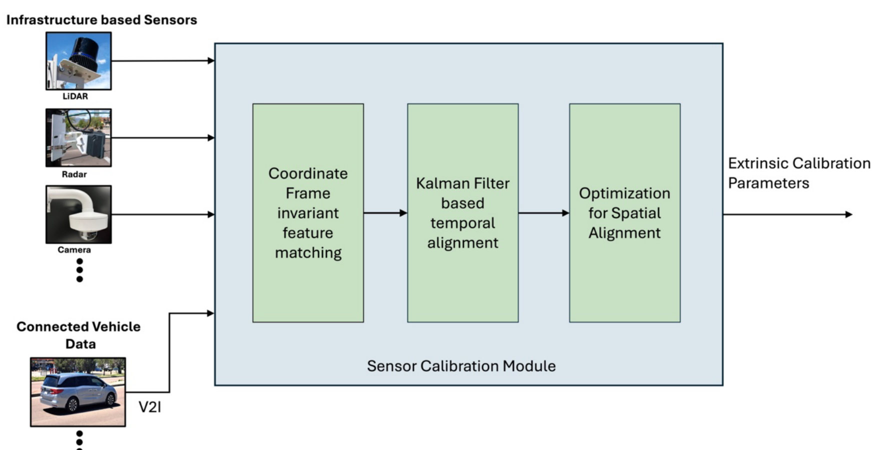

Figure 7 Sensor autocalibration framework which use GNSS trace from connected vehicles to calibrate infrastructure-based perception sensors.

Figure 7 presents a sensor calibration framework which can be used to calibrate infrastructure sensors with CV and CAVs data. The framework employs a Kalman filter for time alignment and takes object trajectory information from sensors to extract features from the object list which are invariant to transformation and then matches it to spatial and temporal information shared by a connected vehicle to achieve precise calibration. Figures 8 and 9 show the output positional data from EVO radars and LiDARs used in this study. Even though the Radar 1 and Radar 2 were mounted diagonally on the traffic

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poles providing a complete view of the intersection, the output data is in local sensor coordinate frame which needs to be transformed to a common frame of reference for data fusion.

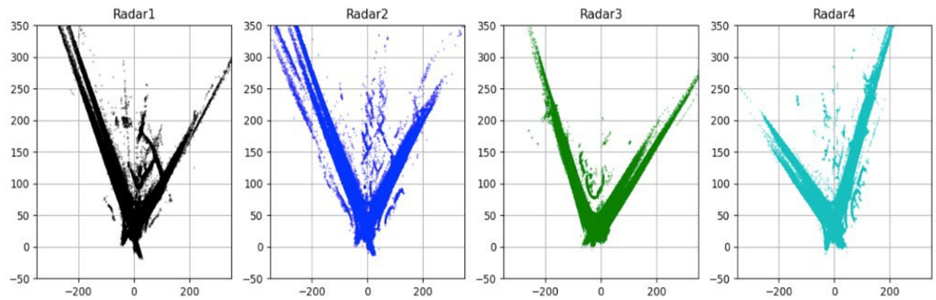

Figure 8 The positional output from EVO radar for an hour of recording is displayed, with Radar1 and Radar 2 mounted on traffic pole while Radar 3 and Radar 4 mounted on IPC mobile lab.

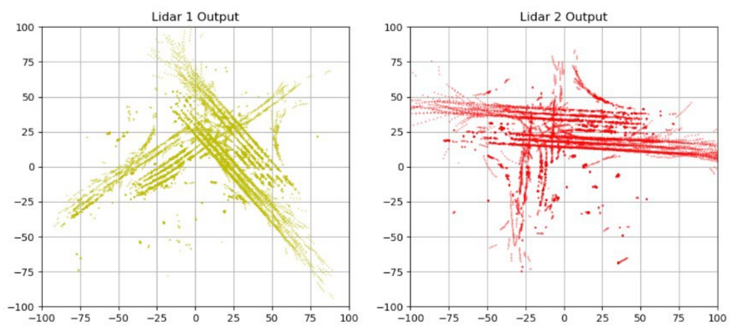

Figure 9 The positional output from LiDAR mounted on IPC mobile lab in local sensor coordinate frame.

Clock Synchronization

For systems with several sensors, time synchronization is essential. Time drift occurs when the reference clocks from multiple sensors start to deviate from a common reference due to the lack of periodic synchronization. Variations in the oscillator frequency of clocks leads to inaccuracies in each sensor time reference. These variations can be caused by various factors such as clock inaccuracies, temperature variations, power supply fluctuations and hardware inconsistencies. Many systems rely on clock synchronizations either use Network Time Protocol (NTP), Precision Time Protocol (PTP) or Global Navigation Satellite System (GNSS) based time synchronization. NTP uses a data network to access an accurate time server to make adjustments to the local sensor clock. NTP can achieve accuracy within a few milliseconds. PTP is based on IEEE 1588 standard using a master-slave hierarchy to synchronize the system clocks to the master clock. PTP can achieve sub-microsecond synchronization. GPS time provides highly accurate time signal due to the presence of atomic clocks on satellites which are highly accurate and stable and can be used to synchronize ground system clocks using National Marine Electronics Association-0183 (NMEA) standard protocol send to a GPS receiver. GPS time is typically accurate to within nanoseconds of Universal Time Coordinated (UTC). Due to the distributed nature of sensor within infrastructure applications, sometimes bridging across multiple miles, and the uncertainty of availability of reliable data network, the authors advocated for GPS referenced sensor data as a the most robust time reference for the IPC framework.

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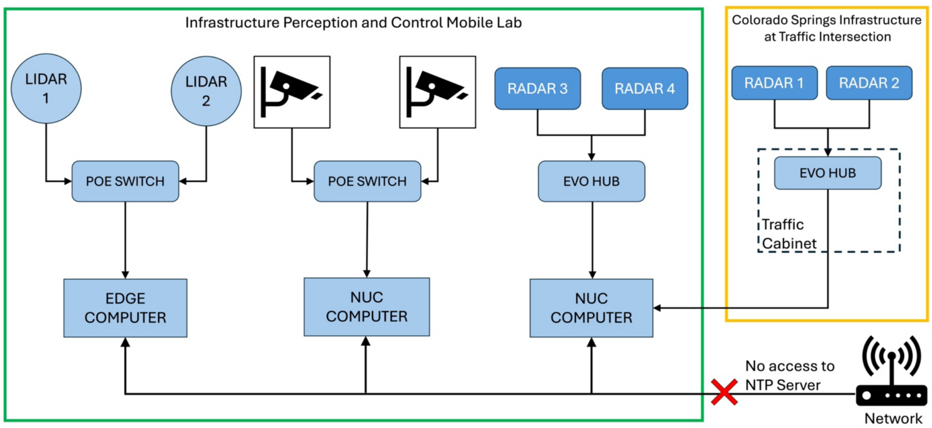

Figure 10 Schematic for a multi-sensor perception setup, where the sensor captures the data and sends it to an edge compute device for classification and processing and converts the information into an object list containing detection information such as Object ID, Object Class, Position, Speed etc.

Sensor fusion which integrates data from multiple sensors to achieve better accuracy and reliability than could be obtained from any single sensor alone heavily relies on precise temporal alignment of data from each sensor. Time misalignments cause corresponding spatial misalignments, ultimately degrading accuracy of the system. Accurate spatial sensing from multiple sensors requires four-dimensional calibration – three spatial dimensions and time. Time referencing or time synchronization is more difficult in infrastructure contexts than in vehicle environments. In vehicle environments, the sensors are connected to a common vehicle data network, which in turn provides a common time reference. In an infrastructure environment, this assumptions of a common network, or overall internet connectivity across all sensors is often not the case.

Many perception sensors (radar, LiDAR, imaging) are design to utilized Network Time Protocol to address the issue of an accurate time reference and to adjust for any local clock drift. However, infrastructure-based application may not have access to a reliable data network and hence are more subject to both to time initialization and clock drift issues. Sensor calibration described relies on precise temporal alignment. If sensors have errors with respect to time, the spatial mapping also becomes inaccurate, leading to incorrect calibration.

One solution to non-networked sensors is to periodically connect them to a common edge compute device on a network so they can synchronize the system clocks using NTP and capture accurate spatio-temporal relationships from the sensors. However, this is not feasible for large scale deployment at intersections as the associated costs would be very high. This would also potentially expose the system to other failure modes as loss of internet connectivity as well as cybersecurity concerns. Additionally, the system will rely on connected vehicle information for periodic re-calibration and health monitoring of the system. Accurate clock synchronization from CVs (which are not on the local network) is critical. See the next section for further discussion.

The preferred method to address this issue would be to use an embedded GPS receiver in the sensors so their clocks can be periodically synchronized using a GPS signal. This would result in a minimal increase in cost for the sensors but provide a stable and dependable global time reference. Additionally having a GPS module would also be useful to provide an initial location for sensor spatial calibration, as the sensors can be located within the intersection within a couple of meters of accuracy.

GPS is also useful for sensor fault monitoring as traffic engineers can easily geo-locate any faulty sensor from the GPS coordinates.

System Health Monitoring

In modern intelligent transportation systems (ITS), which incorporate multiple perception sensors such as camera, radars and LiDARs at the traffic intersection it is imperative to employ a robust system for health monitoring to ensure these systems are functioning correctly at all times. This is important to assure the reliable operation of all the components of a cooperative perception system from sensor detection to objects track fusion and to ensure the reliability and accuracy of the data used for making decisions at the traffic controller and various downstream application. Efficient traffic management depends on the system's capacity to operate continuously, and failsafe procedures make sure that backup systems can take over in the event of a malfunction, ensuring uninterrupted system performance.

Video cameras currently used for traditional vehicle detection at intersection run 24 hours a day and can sometimes malfunction. When malfunctions are detected, the traffic signal resorts to a fail-safe operation mode in which it sequences green light phases to the side street on a pre-timed based to ensure access and safe operation. Fault detection with traditional sensors has been well established, however within a multi-sensor framework relying on data fusion continuously monitoring all sensors, their calibration and accuracy is more complex. Figure 11 shows a schematic for the deployment of IPC fusion engine with trajectory-based signal timing control sent to the controller. The system employs loop detection as a failure mode if the fusion engine seems to be working incorrectly due to faulty sensor data. Note that the loop detection can also be loop detection emulation from one or more of the modern sensors deployed (radar, lidar, or video).

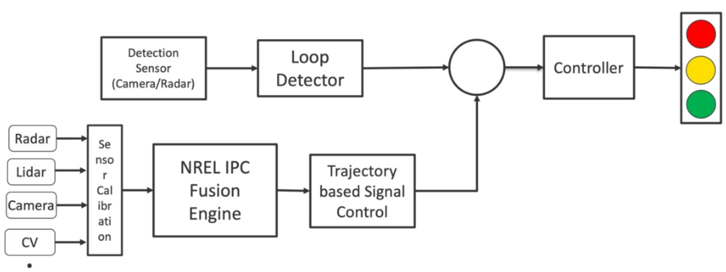

Figure 11 Real-time deployment of IPC fusion engine framework for trajectory based optimal signal control with a loop detection as a fail-safe mode.

For the sensors to continue collecting reliable and accurate data, real-time sensor fidelity monitoring is crucial. Furthermore, real time sensor fidelity monitoring would allow enable the system to adapt to changing environmental conditions such as lighting and precipitation and prompt the necessary compensatory algorithms in IPC fusion engine to account for increased uncertainty in the data captured by that sensor. This ensures the cooperative track data fusion form the IPC fusion engine is robust under various conditions, a crucial attribute of traffic management systems. Real-time data driven decision making for adjusting traffic signal timings can reduce traffic congestion and enhance overall traffic efficiency. Cross comparing the data from multiple sensors within their overlap regions to check for consistency and identify any discrepancies is one method to monitor system health and assess accuracy. Sensor fidelity can also be checked by comparing the spatio-temporal data of CVs or CAVs as they pass through the sensor field-of-view. This also provides a global time and geo-spatial alignment check critical for calibration. Additionally artificial intelligence and machine learning methods can assist. By looking at the historical data from the sensors, machine learning models such as autoencoder to efficiently compress the input data (encodes) and then reconstruct the original input while measuring the reconstruction error. Isolation Forest techniques, an ensemble method, can be similarly employed that uses binary trees to detect sensor anomalies. These models can be trained to identify typical sensor behavior and identify variations that might point to fidelity problems.

CONCLUSIONS

This paper reports an overview of IPC cooperative perception framework, the implementation of such systems and the challenges associated with the deployment. The findings were derived from field deployment of the IPC mobile lab and infrastructure radar mounted on the traffic pole at operational intersections in the city of Colorado Springs, CO, USA. Experimental results show the need for an auto calibration algorithm to bring the sensor output data to a common coordinate frame and the need for robust clock synchronization to register correct spatial and temporal data from the sensors, which is necessary for data fusion. GPS synchronization is highly recommended for infrastructure-based applications where connectivity to NTP servers can be problematic and a source of failure as well as the need for time synchronization with CVs. The work also expands on the requirement for a system health monitoring system to validate the overall system accuracy and monitor sensor fidelity in real-time. Whenever the system detects a fault, the sensor suite will need to fall back on loop emulation mode to allow for graceful system degradation.

Several future works are planned to be carried out to evaluate the performance of the IPC fusion engine by deploying various sensor configurations, evaluating the performance of the algorithm in various road settings such as rural, urban and highway. Also utilizing various sensor types and different manufacturers will evaluate the robustness of the proposed track-fusion framework and the associated data schemas. Testing the proposed cooperative perception engine in varying environmental conditions is also in the pipeline. In order to evaluate the capabilities of information sharing from infrastructure sensors via I2V communication, we will also deploy roadside units and an onboard unit in the test vehicle in future studies to facilitate real-time implementation. Lastly, in order to evaluate the framework to perform various downstream control applications such as trajectory based optimal signal control at a traffic intersection, the digital twin output will be configured to feed various downstream applications.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: S.Young, Q.Wang, R.Sandhu, C. Tripp; data collection: F.Mir, S.Young, Q.Wang, R.Sandhu, T.Osborn; analysis and interpretation of results: F.Mir, R.Sandhu; draft manuscript preparation: F.Mir, S.Young. All authors reviewed the results and approved the final version of the manuscript.

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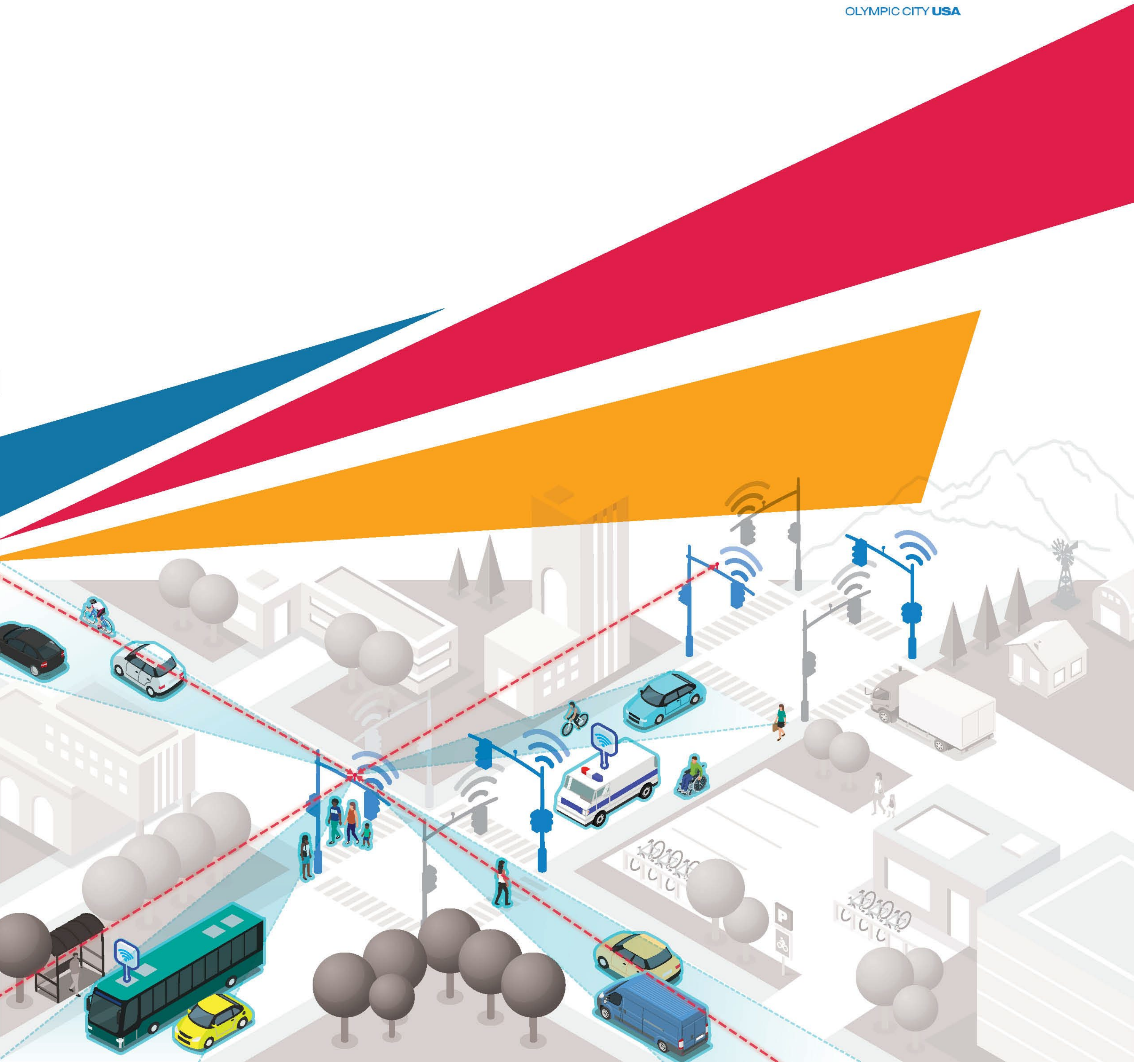
IMPLEMENTATION REPORT

Perception-Based Adaptive Traffic Management and Data Sharing

Appendix C – University of Alabama: Connected Vehicles

COLORADO SPRINGS
OLYMPIC CITY USA



Definition and Architecture

Connected vehicle information is shared to, from, and between many different locations or endpoints in a traffic network. These endpoints can be infrastructure components such as traffic signals, dynamic message signs, etc., or traveler based such as vehicles, drivers, bicyclists, etc. For the infrastructure-based locations, a radio in the form of a roadside unit (RSU) is used to interface with various components that generate data and/or information to share to travelers. For traveler-based endpoints, radios in the form of on-board units (OBUs) are able to transmit and receive data and often integrate into some sort of human machine interface (HMI) for humans to use. The general layout and architecture are shown in Exhibit 1. In this particular architecture, a variety of communication methods and technologies are used. Data paths are shown without direct indication of specific applications or use cases.

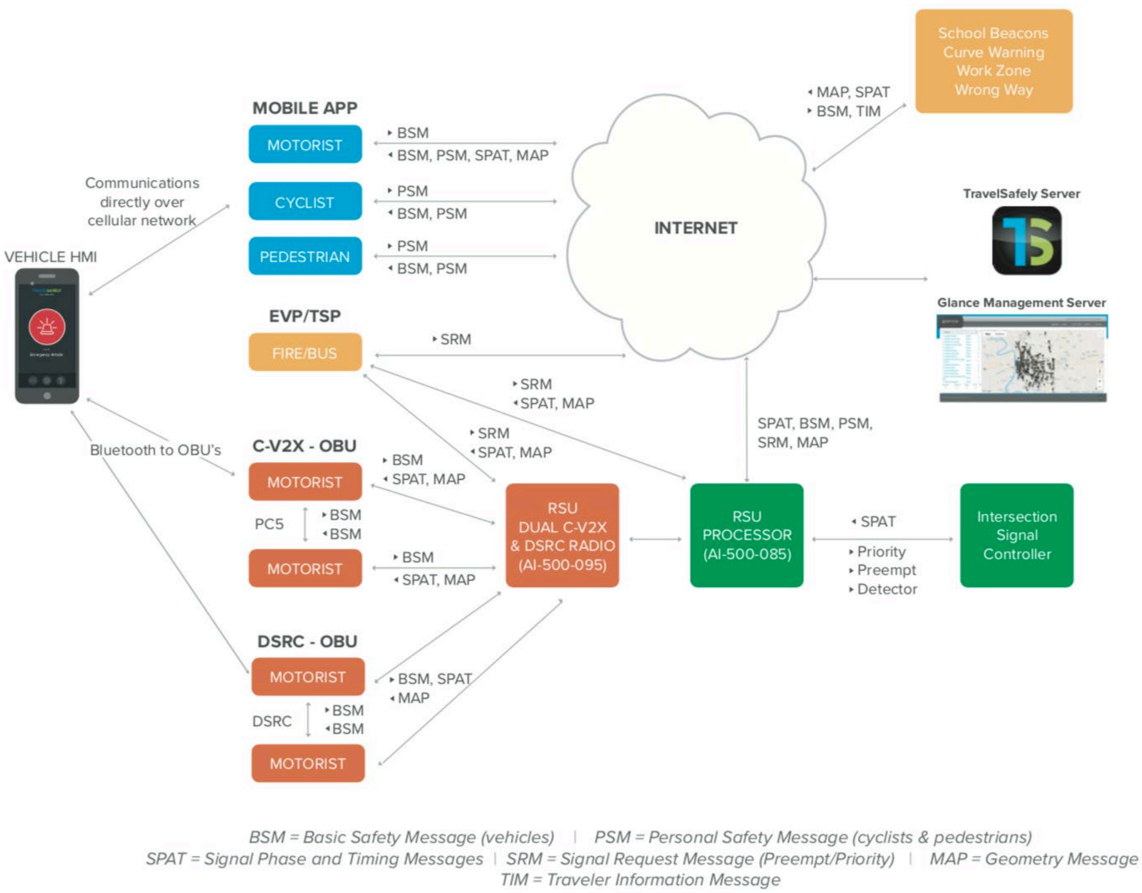


Exhibit 1. Architecture of connected vehicle platform

Communications

Historically, dedicated short-range communications (DSRC) radios were used to share information from vehicle-to-vehicle (V2V), from vehicle-to-infrastructure (V2I), and broadly vehicle-to-everything (V2X). The DSRC radios utilized 75 MHz on the 5.9 GHz band as allocated in the late 1990s by the Federal Communications Commission (FCC). The protocol was based on IEEE 802.11p.

In late 2020, the DSRC bandwidth was reduced to 30 MHz and newer cellular vehicle-to-everything (C-V2X) largely replaced DSRC as the FCC ceased issuing licenses for the original DSRC spectrum. With C-V2X, there are two major ways on how vehicle communications with cellular radio hardware are conducted: (1) direct communications known as PC5 which does not require a cellular network and (2) network communications known as Uu which does use existing cellular networks [1].

Exhibit 2 shows a variety of connected vehicle hardware. The RSUs are usually small radios with varying levels of computing capability. They will often have global positioning (GPS) capabilities to determine position, speed, heading, and other information. An optional HMI can be used to relay information to drivers or travelers. Often, these HMIs are tablets connected with WiFi or Bluetooth in exploratory systems. In the future, modern vehicles with dedicated HMIs for infotainment and other uses may be used in conjunction with C-V2X technology.

Exhibit 2. Connected vehicle hardware including DSRC OBU and HMI (Left), C-V2X OBU and HMI (Middle), and C-V2N (Uu) HMIs (Right)

Message Types

Sharing information in a connected vehicle environment usually utilizes a number of standard messages, including the following messages pertinent to this project [2]:

1. **Signal Phase and Timing (SPaT)** – These messages are based on information from traffic signal controllers using National Transportation Communications for Intelligent Transportation System Protocol (NTCIP) standard 1202 and Society of Automotive Engineers (SAE) J2735. These standards set up the sharing of basic traffic signal status and information.
2. **Basic Safety Message (BSM)** – These messages are usually shared from a vehicle or traveler and include information such as speed, position, and heading.
3. **Personal Safety Message (PSM)** – Similar to a BSM, this location, speed, and heading information is for vulnerable road users such as bicyclists and pedestrians.
4. **Map data (MAP)** – This information is usually shared from RSUs so that pertinent SPaT data can be filtered based on a vehicle or traveler's circumstances and interests.

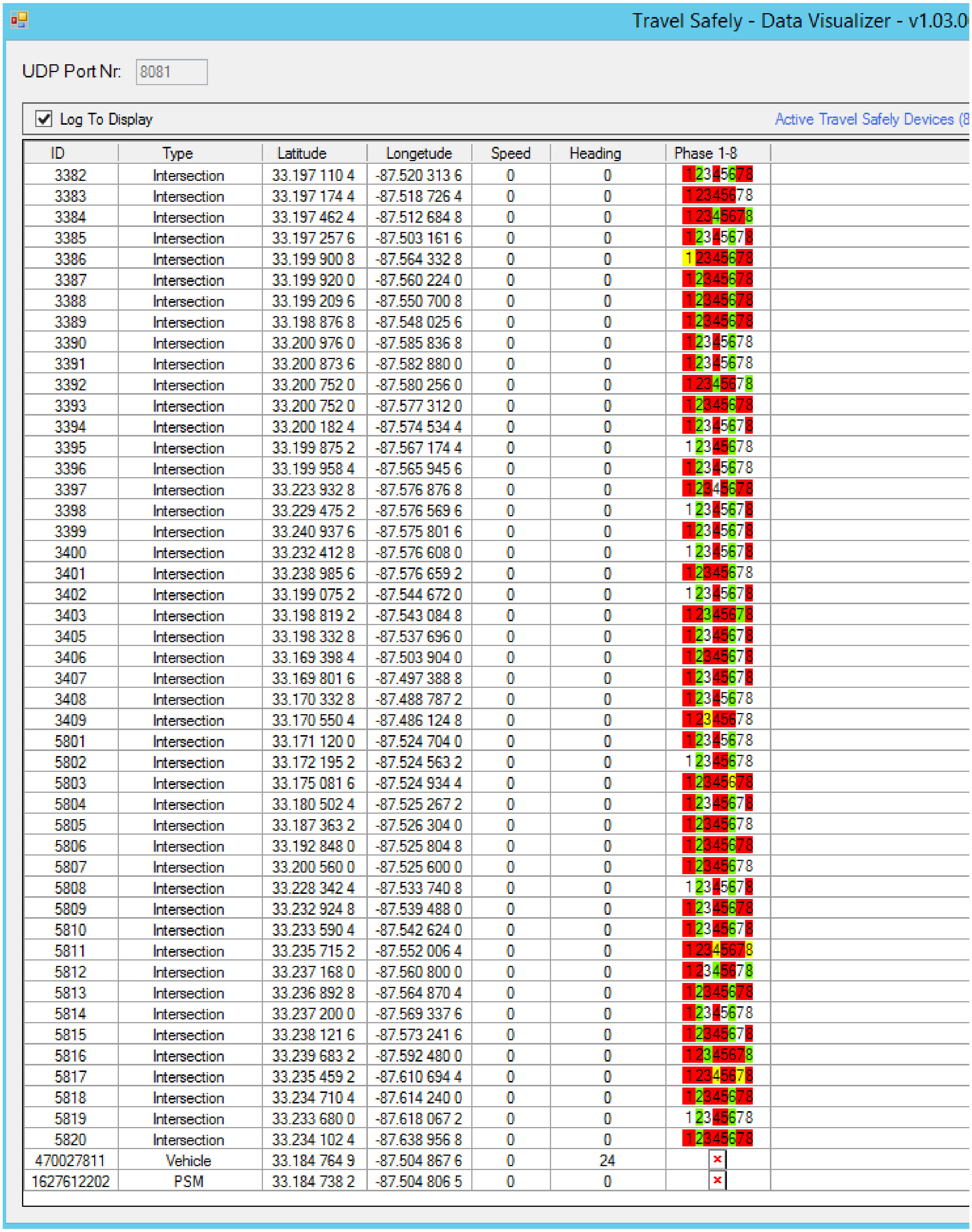
The message definitions (data frames and data elements) for all sixteen messages are covered in SAE J2735 [3] and further address in SAE J2945 [4].

Message Sharing

The system deployed in this project utilizes three main modes of communication as shown in Exhibit 1. While DSRC is shown, the currently used modes include the mobile app over C-V2N (Uu), C-V2X (PC5), and EVP/TSP (900 MHz). The system is able to take whichever message arrives first. The C-V2N is event-based with typical BSM sharing at once per second but may utilize slower rates when stopped. The C-V2X data operates at ten times a second, but the GPS refresh rate is once per second. The specific application (e.g. SPaT sharing, platooning, preempt/priority, etc.) is important when considering the appropriate communication method. In slower applications, using all available modes is advantageous to ensure redundant communications.

Data Retrieval Process for Connected Vehicles

Data from each of the different sources and communications can vary. With the C-V2N, a central server handles communication between devices and the messages can be shared through a content delivery network. Exhibit 3 shows a front-end application for examining C-V2N data in real time. This particular feed is updated once per second. The exhibit shows information mostly for SPaT data at dozens of intersections but has two lines at the bottom showing BSM and PSM messages. For this project, the data was logged and stored in a SQL database hosted at the University of Alabama. The data feed contains data for all Alabama OBUs and RSUs, and for test OBUs and RSUs in Colorado Springs, Colorado and Des Moines, Iowa. Exhibit 4 shows a one-minute extract of the data collected from a drive in Colorado Springs. The points have been plotted on a KML as shown in Exhibit 5. Record ID 2629 or Trackpoint #7 is highlighted in the table and shown on the map, respectively. Used in real time, this information can be used and included in trajectory-based control algorithms.


Travel Safely - Data Visualizer - v1.03.0

UDP Port Nr: 8081

Log To Display

Active Travel Safely Devices (8

ID	Type	Latitude	Longetude	Speed	Heading	Phase 1-8
3382	Intersection	33.197 110 4	-87.520 313 6	0	0	12345678
3383	Intersection	33.197 174 4	-87.518 726 4	0	0	12345678
3384	Intersection	33.197 462 4	-87.512 684 8	0	0	12345678
3385	Intersection	33.197 257 6	-87.503 161 6	0	0	12345678
3386	Intersection	33.199 900 8	-87.564 332 8	0	0	12345678
3387	Intersection	33.199 920 0	-87.560 224 0	0	0	12345678
3388	Intersection	33.199 209 6	-87.550 700 8	0	0	12345678
3389	Intersection	33.198 876 8	-87.548 025 6	0	0	12345678
3390	Intersection	33.200 976 0	-87.585 836 8	0	0	12345678
3391	Intersection	33.200 873 6	-87.582 880 0	0	0	12345678
3392	Intersection	33.200 752 0	-87.580 256 0	0	0	12345678
3393	Intersection	33.200 752 0	-87.577 312 0	0	0	12345678
3394	Intersection	33.200 182 4	-87.574 534 4	0	0	12345678
3395	Intersection	33.199 875 2	-87.567 174 4	0	0	12345678
3396	Intersection	33.199 958 4	-87.565 945 6	0	0	12345678
3397	Intersection	33.223 932 8	-87.576 876 8	0	0	12345678
3398	Intersection	33.229 475 2	-87.576 569 6	0	0	12345678
3399	Intersection	33.240 937 6	-87.575 801 6	0	0	12345678
3400	Intersection	33.232 412 8	-87.576 608 0	0	0	12345678
3401	Intersection	33.238 985 6	-87.576 659 2	0	0	12345678
3402	Intersection	33.199 075 2	-87.544 672 0	0	0	12345678
3403	Intersection	33.198 819 2	-87.543 084 8	0	0	12345678
3405	Intersection	33.198 332 8	-87.537 696 0	0	0	12345678
3406	Intersection	33.169 398 4	-87.503 904 0	0	0	12345678
3407	Intersection	33.169 801 6	-87.497 388 8	0	0	12345678
3408	Intersection	33.170 332 8	-87.488 787 2	0	0	12345678
3409	Intersection	33.170 550 4	-87.486 124 8	0	0	12345678
5801	Intersection	33.171 120 0	-87.524 704 0	0	0	12345678
5802	Intersection	33.172 195 2	-87.524 563 2	0	0	12345678
5803	Intersection	33.175 081 6	-87.524 934 4	0	0	12345678
5804	Intersection	33.180 502 4	-87.525 267 2	0	0	12345678
5805	Intersection	33.187 363 2	-87.526 304 0	0	0	12345678
5806	Intersection	33.192 848 0	-87.525 804 8	0	0	12345678
5807	Intersection	33.200 560 0	-87.525 600 0	0	0	12345678
5808	Intersection	33.228 342 4	-87.533 740 8	0	0	12345678
5809	Intersection	33.232 924 8	-87.539 488 0	0	0	12345678
5810	Intersection	33.233 590 4	-87.542 624 0	0	0	12345678
5811	Intersection	33.235 715 2	-87.552 006 4	0	0	12345678
5812	Intersection	33.237 168 0	-87.560 800 0	0	0	12345678
5813	Intersection	33.236 892 8	-87.564 870 4	0	0	12345678
5814	Intersection	33.237 200 0	-87.569 337 6	0	0	12345678
5815	Intersection	33.238 121 6	-87.573 241 6	0	0	12345678
5816	Intersection	33.239 683 2	-87.592 480 0	0	0	12345678
5817	Intersection	33.235 459 2	-87.610 694 4	0	0	12345678
5818	Intersection	33.234 710 4	-87.614 240 0	0	0	12345678
5819	Intersection	33.233 680 0	-87.618 067 2	0	0	12345678
5820	Intersection	33.234 102 4	-87.638 956 8	0	0	12345678
470027811	Vehicle	33.184 764 9	-87.504 867 6	0	24	
1627612202	PSM	33.184 738 2	-87.504 806 5	0	0	

Exhibit 3. Traffic Safety Data Visualizer for C-V2N Uu Data (note the last two rows for BSM and PSM)

Exhibit 4. One minute of sample data from Colorado Springs

Id	DeviceId	Timestamp	Latitude	Longitude	Speed	Elevation	Speed	Heading
2623	494844272	2024-09-02 17:36:00	38.8310383	-104.8343053	19.20	18330	690	184
2624	494844272	2024-09-02 17:36:01	38.8311483	-104.8342396	18.84	18340	677	192
2625	494844272	2024-09-02 17:36:02	38.8312516	-104.8341726	18.15	18340	652	192
2626	494844272	2024-09-02 17:36:03	38.8313589	-104.8341006	18.54	18340	666	192
2627	494844272	2024-09-02 17:36:05	38.8315737	-104.8339459	18.90	18330	679	240
2628	494844272	2024-09-02 17:36:08	38.8317846	-104.8337793	18.70	18330	672	256
2629	494844272	2024-09-02 17:36:09	38.8318835	-104.8336956	18.20	18330	654	280
2630	494844272	2024-09-02 17:36:10	38.8319758	-104.8336121	17.67	18330	635	280
2631	494844272	2024-09-02 17:36:11	38.8320663	-104.8335279	17.37	18330	624	288
2632	494844272	2024-09-02 17:36:12	38.8321557	-104.8334419	17.26	18340	620	304
2633	494844272	2024-09-02 17:36:13	38.8322414	-104.8333524	17.12	18340	615	304
2634	494844272	2024-09-02 17:36:14	38.8323242	-104.8332618	16.92	18330	608	312
2635	494844272	2024-09-02 17:36:15	38.8324078	-104.8331709	16.92	18330	608	320
2636	494844272	2024-09-02 17:36:16	38.8324948	-104.8330759	17.62	18330	633	320
2638	494844272	2024-09-02 17:36:19	38.8327425	-104.8327854	16.92	18330	608	336
2639	494844272	2024-09-02 17:36:20	38.8328227	-104.8326893	17.23	18330	619	336
2640	494844272	2024-09-02 17:36:21	38.8329061	-104.8325906	17.56	18330	631	336
2641	494844272	2024-09-02 17:36:22	38.832987	-104.8324919	17.06	18320	613	344
2642	494844272	2024-09-02 17:36:24	38.8331424	-104.8323085	15.98	18320	574	336
2643	494844272	2024-09-02 17:36:27	38.8333452	-104.8320744	13.78	18320	495	320
2644	494844272	2024-09-02 17:36:28	38.8334124	-104.8319987	13.64	18320	490	320
2645	494844272	2024-09-02 17:36:29	38.8334768	-104.8319284	13.25	18310	476	320
2646	494844272	2024-09-02 17:36:30	38.8335375	-104.8318647	12.72	18310	457	320
2647	494844272	2024-09-02 17:36:31	38.8336006	-104.8318026	12.39	18310	445	304
2648	494844272	2024-09-02 17:36:32	38.8336663	-104.831738	12.86	18310	462	304
2649	494844272	2024-09-02 17:36:33	38.8337318	-104.8316742	12.83	18300	461	296
2650	494844272	2024-09-02 17:36:34	38.8337974	-104.8316052	12.80	18300	460	280
2651	494844272	2024-09-02 17:36:37	38.8340046	-104.8314176	13.36	18290	480	264
2652	494844272	2024-09-02 17:36:38	38.8340781	-104.8313562	13.55	18290	487	264
2653	494844272	2024-09-02 17:36:39	38.8341456	-104.831299	12.66	18290	455	256
2654	494844272	2024-09-02 17:36:40	38.834211	-104.8312465	11.77	18290	423	248
2655	494844272	2024-09-02 17:36:41	38.8342714	-104.8311975	10.80	18290	388	232
2656	494844272	2024-09-02 17:36:42	38.8343259	-104.8311509	10.41	18290	374	256
2657	494844272	2024-09-02 17:36:43	38.834385	-104.8311058	10.58	18300	380	248
2658	494844272	2024-09-02 17:36:44	38.8344633	-104.8310512	12.16	18300	437	240
2659	494844272	2024-09-02 17:36:45	38.8345459	-104.8309979	13.25	18300	476	224
2660	494844272	2024-09-02 17:36:47	38.8347169	-104.8308948	14.50	18300	521	208
2661	494844272	2024-09-02 17:36:48	38.8347997	-104.8308438	14.53	18290	522	184
2662	494844272	2024-09-02 17:36:49	38.8348847	-104.8307945	14.53	18290	522	184
2663	494844272	2024-09-02 17:36:50	38.8349679	-104.8307473	14.47	18300	520	176
2664	494844272	2024-09-02 17:36:51	38.8350562	-104.8306987	14.92	18300	536	176
2665	494844272	2024-09-02 17:36:52	38.8351465	-104.8306518	14.86	18300	534	160
2666	494844272	2024-09-02 17:36:54	38.8354033	-104.8305309	13.69	18290	492	152
2667	494844272	2024-09-02 17:36:55	38.8354869	-104.8304967	13.58	18290	488	136
2668	494844272	2024-09-02 17:36:56	38.8355745	-104.8304617	14.08	18290	506	136
2669	494844272	2024-09-02 17:36:57	38.8356661	-104.8304294	14.50	18300	521	120
2670	494844272	2024-09-02 17:36:58	38.8357639	-104.8303978	15.34	18290	551	104
2671	494844272	2024-09-02 17:36:59	38.8358641	-104.83037	15.45	18290	555	104

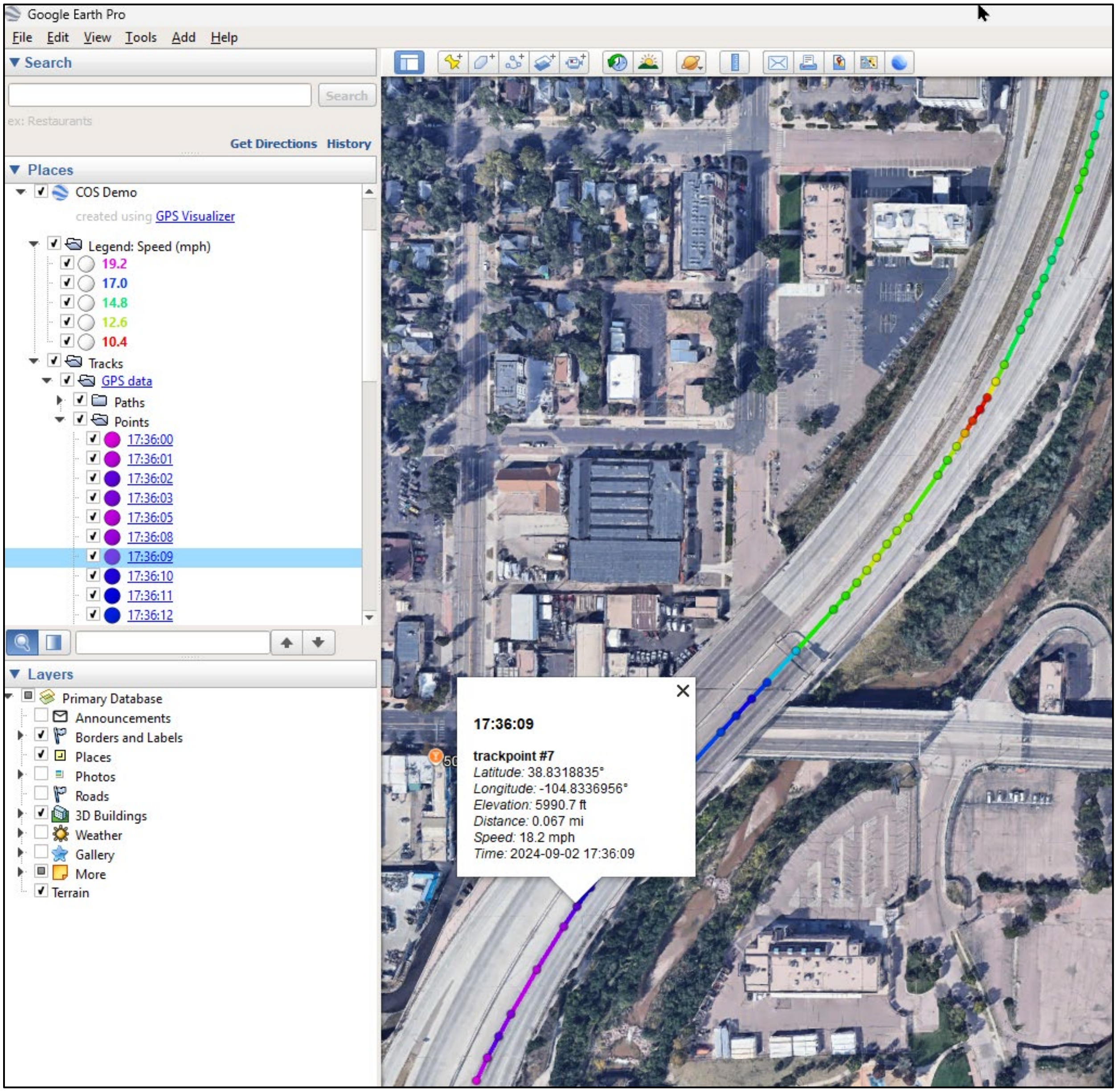


Exhibit 5. Colorize KML file of the sample data

Collection of the C-V2X data is a bit more involved. With the Applied Information Model 065 C-V2X OBUs, a raw stream of BSMs is generated ten times a second. Also, the RSUs broadcast SPaT information ten times a second. With MAP messages, messages can be selectively used as appropriate depending on the direction, speed, lane, and other parameters. A sample communication record of MAP messages from the RSU to the OBU is shown in Exhibit 6. The very right-most column shows the separation distance (used to verify the correct intersection). A map of a C-V2X drive around the UA campus is shown in Exhibit 7. There are large gaps in the data on the south edge and east edge of the circuits when the test OBU is out of the range of any C-V2X RSU.

Exhibit 6. C-V2X MAP data received ten times a second (noting separation in the last column)

Time	Latitude	Longitude	Altitude (ft)	Heading	Speed (mph)	Radio	TX/RX	Message Type	Transmitted Latitude	Transmitted Longitude	Separation (ft)
2024-10-30 15:06:07	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:08	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:09	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:09	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:09	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:09	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:09	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:09	33.211957	-87.530043	285.36	338	34.18	C-V2X	RX	MAP	33.21437	-87.531392	971
2024-10-30 15:06:09	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:09	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:09	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:09	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:10	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:11	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:11	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:11	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:11	33.212215	-87.530169	285.36	337	34.80	C-V2X	RX	MAP	33.21437	-87.531392	870
2024-10-30 15:06:11	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:11	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:11	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:11	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:11	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:11	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:12	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:12	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:12	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:12	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818
2024-10-30 15:06:12	33.212345	-87.530235	285.36	337	34.18	C-V2X	RX	MAP	33.21437	-87.531392	818

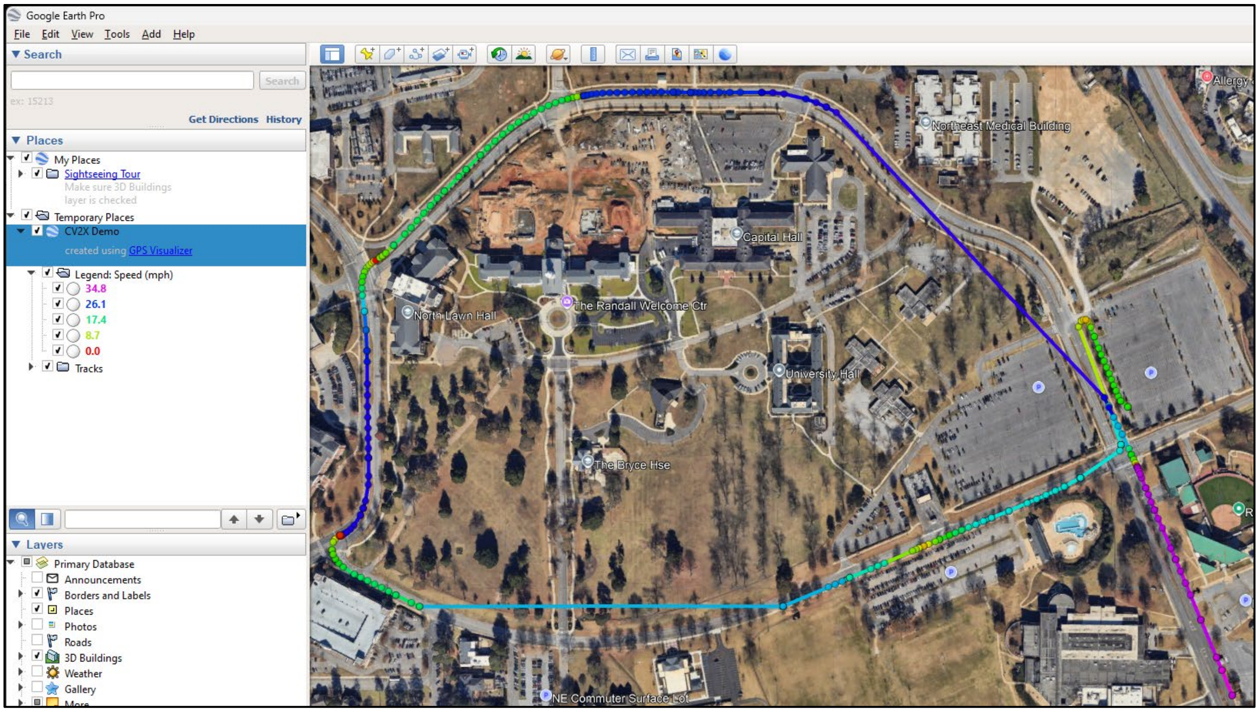


Exhibit 7. C-V2X Demo drive (note the large gaps when the vehicle is outside of the broadcast radius of the C-V2X RSUs)

The data shown in Exhibit 6 was collected from a manually-enabled logging system on the 065 OBU. To collect the actual stream from the OBU to the RSU, V2XHub should be used to have the RSU forward SPaT, MAP, and received BSMs to another interface for data collection. For this project, only the C-V2N data was collected and stored in a SQL database (as previously shown in Exhibit 4).

With any of these systems, there is potential for disruptions in communications or interference, and certainly cybersecurity issues. With the C-V2N, security for the radios is handled through a central system from a vendor. For open C-V2X, more complex certificate management and authenticating systems are required. These are very complex and outside of the scope of focusing on the traffic problems at hand for this project. However, all data available to the research team and traffic team is anonymous and cycled on periodic intervals. This type of partnership is key for working with both traditional traffic teams and modern cyber security teams.

Finally, for this SMART grant project, other sensors can be used to generate virtual BSMs from non-connected vehicles. For example, object tracking detection systems and sensors such as cameras, radars, and LiDARs can be used to collect speed, heading, and location for moving objects within varying distances of the intersections. These feeds can provide lists of tracked objects and be used in various controller algorithms (just as proposed in this project). Fusing these different object lists, whether directly from connected vehicle radios or through passive infrastructure sensing, needs to take place to remove duplicate objects. This will be future research.

Long Term Reliability

All of these systems and hardware have long term reliability and usability considerations. The research team has found that a managed central system with support for updates and security is very desirable. However, more open radios may be more desirable for wider deployments without recurring costs. All C-V2N and C-V2X radios have cellular coverage (on top of fiber network connectivity) so that the hardware can handle Uu communications and provide software and security updates. Furthermore, additional radios can be installed for some level of future proofing. Indeed, the radios used in this project were upgraded from 3G cellular to 4G cellular and were upgraded from DSRC to C-V2X. The vendor used in this project (Applied Information) manages more than 40,000 of these radios across the country as shown in their 24/7 monitoring dashboard presented as Exhibit 8.

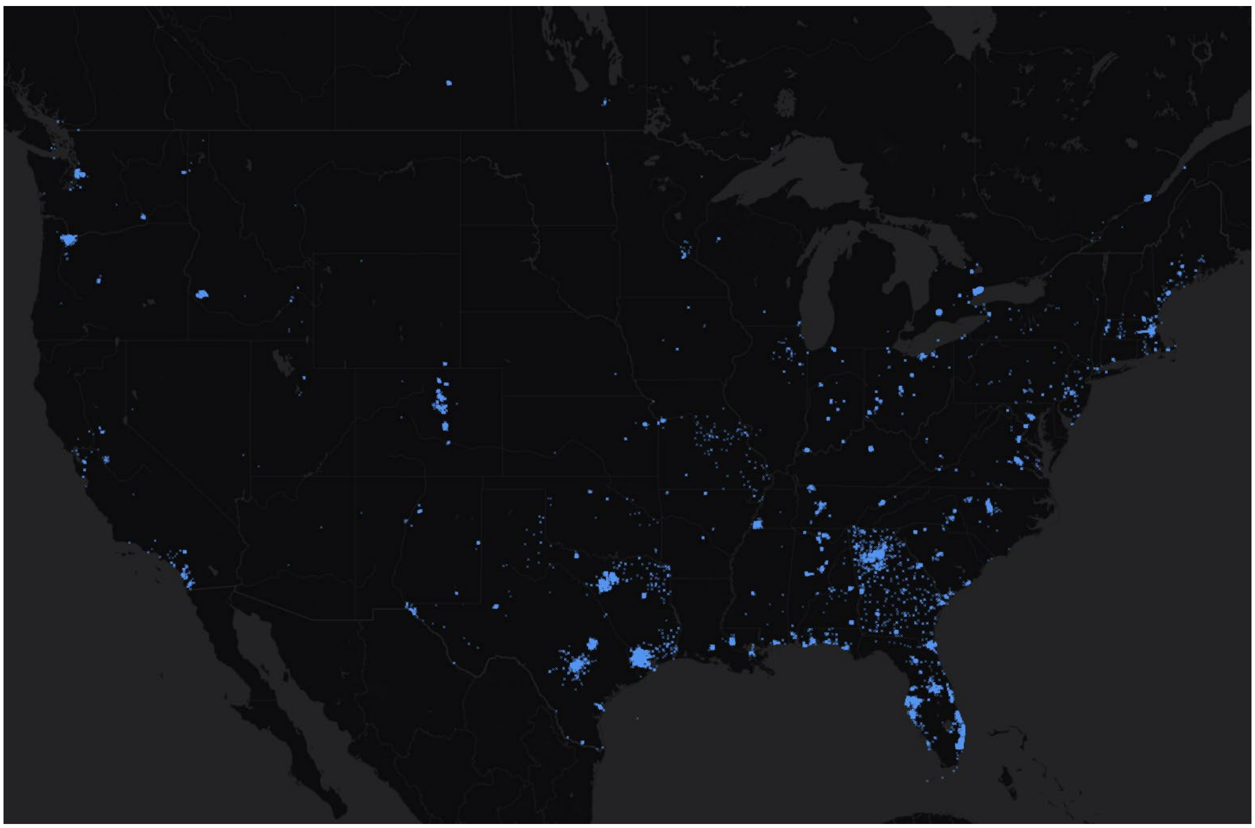


Exhibit 8. Map of Applied Information's 40,000 devices monitored 24/7 (as of 20241211)

Accuracy and Latency

As hardware and technology evolve, latency and accuracy have continuously improved. Positional accuracy is currently based on GPS technology. Dual GPS technology has brought positional accuracy down to 2 centimeters in some instances, and differential GPS can provide accuracy even down to 1 CM. The communication latency can vary widely depending on the technology. Early on, C-V2N (Uu) testing was around 400 ms and now, with 5G, is down to about 120 ms. C-V2X (and historically DSRC) usually aims for 20 ms of latency. Depending on the application, different latencies will be required and should be carefully considered.

Adherence to Standards

There are many standards in the connected vehicle world. While the scope of this project was pilot testing with hardware and software, here are several of the standards (compiled with AI/ML):

1. IEEE Standards
    a. IEEE 802.11p (WAVE) – A variant of Wi-Fi tailored for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, enabling low-latency, short-range data exchange in vehicular environments.
    b. IEEE 1609 (WAVE Architecture) – A family of standards defining the architecture, communication protocols, and security services for Wireless Access in Vehicular Environments (WAVE). Key Subparts:
        i. 1609.2: Security and credential management.
        ii. 1609.3: Networking services for data exchange.
        iii. 1609.4: Multi-channel operations for efficient spectrum use.
2. SAE Standards
    a. SAE J2735 (Message Dictionary) – Defines the structure and content of messages used in V2X communications, including Basic Safety Messages (BSM), SPaT, MAP, and TIM.
    b. SAE J2945 (Performance Guidelines) – Specifies performance requirements for V2X systems to ensure reliable, timely, and interoperable communication. Subparts:
        i. J2945/0: Overview and foundational guidance for V2X systems.
        ii. J2945/1: Requirements for BSM applications, focusing on V2V safety communications.
        iii. J2945/2: Guidelines for V2I safety applications, including SPaT and MAP data.
        iv. J2945/3: Requirements for V2P (Vehicle-to-Pedestrian) communication.
        v. J2945/4: Requirements for V2N (Vehicle-to-Network) communication.
3. 3GPP Standards
    a. 3GPP Release 14 (C-V2X PC5 Interface) – Introduced cellular V2X, enabling direct communication (V2V, V2I, V2P) without the need for a cellular network.
    b. 3GPP Release 15 (5G NR for V2X) – Expands C-V2X capabilities with 5G New Radio (NR), enhancing range, latency, and reliability for future mobility applications.
    c. 3GPP Release 16 (Advanced V2X) – Introduces advanced features for autonomous driving, including precise positioning and network slicing for prioritizing safety-critical data.
4. ISO Standards
    a. ISO 21217 (ITS Station Reference Architecture) – Defines the architecture of an Intelligent Transport System (ITS) station for seamless communication across different transport modes.
    b. ISO 19091 (V2I Communication) – Provides guidance for traffic signal applications in V2I communications, focusing on SPaT and MAP data exchange.

    c. ISO 26262 (Functional Safety) – Addresses functional safety requirements for electrical and electronic systems in vehicles, relevant for V2X-enabled autonomous features.
5. NHTSA Guidelines
    a. FMVSS 150 (Proposed Rule) – A proposed U.S. regulation to mandate V2V communication capability in new vehicles, focusing on interoperability and safety messaging.
6. IETF Standards
    a. RFC 8964 (IPv6 over IEEE 802.11-OCB) – Specifies how IPv6 packets are transmitted over IEEE 802.11 outside the context of a basic service set (OCB), supporting V2X communications.
7. NEMA (National Electrical Manufacturers Association) Standards
    a. NEMA TS 2 (Traffic Controller Assemblies) – Defines requirements for traffic signal controller hardware to ensure compatibility with advanced traffic management systems, including V2X applications.
    b. NEMA TS 8 (Cyber and Physical Security for Traffic Management Systems) – Provides guidelines for securing traffic management infrastructure, including V2X systems, against cyber and physical threats.
    c. NEMA ATC (Advanced Transportation Controller) – Specifies requirements for traffic controllers to support advanced applications like adaptive signal control and connected vehicle integration.
8. NTCIP (National Transportation Communications for ITS Protocol) Standards
    a. NTCIP 1202 (Traffic Signal Controller Objects) – Defines data objects for managing traffic signal controllers, enabling integration with connected vehicle systems.
    b. NTCIP 1209 (Data Collection Objects) – Provides data standards for traffic sensors and systems that collect vehicle data, ensuring compatibility with V2X systems.
    c. NTCIP 1213 (Electrical and Lighting Management) – Focuses on managing electrical and lighting systems within the ITS ecosystem, including those related to V2X roadside units.
    d. NTCIP 1218 (Roadside Units for V2X) – Specifies requirements for V2X roadside equipment, including communication with vehicles and infrastructure.
    e. NTCIP 1102/1103 (Base Standards for Communications Protocols) – Provides foundational standards for data exchange in ITS systems, ensuring interoperability across various connected vehicle components.
9. ITE (Institute of Transportation Engineers) Standards
    a. ITE ATC 5201 (Advanced Transportation Controller) – Sets specifications for advanced controllers that support connected vehicle technologies and adaptive traffic management.
    b. ITE SPaT Challenge Standards – Includes implementation guidelines for deploying Signal Phase and Timing (SPaT) data across traffic signals in connected environments.
10. Other Notable Standards and Guidelines
    a. ASTM E2213 (Standard Specification for DSRC) – Focuses on physical and data link layers for DSRC communication, a precursor to more modern C-V2X standards.

b. IEEE 1512 (Incident Management) – Defines standards for incident management messages in transportation systems, relevant for V2X-enabled hazard notifications.
c. CAMP (Crash Avoidance Metrics Partnership) Guidelines – Provides performance requirements and best practices for implementing V2V and V2I systems.
d. APTA V2X Standards (Transit) – Developed by the American Public Transportation Association, these standards focus on V2X applications for transit systems, such as transit signal priority.
e. ITE/ITS America Connected Intersections (CI) Guidelines – Aims to standardize the deployment of connected intersection technology, focusing on SPaT, MAP, and V2X communication requirements.

These standards represent many thousands of pages of standards. It is important for traffic personnel to partner with their radio vendors and manufacturers to ensure that standards adherence is met, both at present and into the future with updates.

Feasibility and Benefits/Costs Analysis

The costs of connected vehicles can range from hundreds of dollars to thousands of dollars. Currently, C-V2X RSUs and OBUs range from $1,500 to $3,000. With more advanced managed devices with cellular modems and data coverage and multiple radios, prices of $5,000 to $10,000 are more typical. The benefits from these deployments will vary tremendously based upon the applications, the extent of any existing or baseline conditions (relative to improvements), and the volume of vehicles or travelers over various durations or timeframes during which benefits are accrued. Also, ongoing licensing and costs/maintenance for the radio equipment may be challenges to consider.

Liabilities / Mitigations

The most important aspect against liabilities is to ensure proper baseline traffic signal operation. In the event of a radio failure, properly designed signal timings and detection systems should maintain adequate operations. For security liabilities, traffic personnel should work carefully with their communications teams, information technology teams, and any third parties such as security certificate authorizers or radio management vendors. There are emerging roles for connected vehicle deployments that will need to be integrated into traditional Department of Transportation (DOT) structures in the future. Also, insurance requirements for liabilities (e.g. cyber security insurance) should be carefully considered by offices of technology and legal teams.

Impact Analysis & Justification

When a sufficient number of vehicles are able to share and receive information (or have virtual BSMs place on their behalf), traffic signal operations will have drastic changes from traditional zone-based detection with call and extend. The sharing of information will lead to safety impacts (e.g., reduction in accidents), efficiency improvements (e.g., reduced queuing and delays), and changes in environmental outcomes (e.g., greenhouse gas reduction). With regard to this project, trajectory-based control algorithms can be enabled and enhanced. Priority operations can also be conducted with extended information such as plow up/down for plow vehicles, occupancies for buses, and other prioritized vehicle classes and/or operations.

Interoperability Requirements and Integration Requirements

With connected vehicle solutions, there are advantages and disadvantages to going with open hardware/software or a semi- or fully-proprietary platform. With all of the standards previously listed, it is important that all hardware be designed, built, and maintained with current standards. Open hardware/software places those burdens on the traffic system operator. With a semi- or fully-proprietary system, much of this can be handled by the vendor or manufacturer (albeit for some sort of fee). However, both platforms and all solutions ideally should be able to share information. Usually, this is much more achievable with open hardware/software standards. Semi-proprietary systems may be able to include open hardware/software but still provide additional software, security, and, in instances, hardware updates.

Shared Resources and Evaluation of Capacity/Bandwidth and Upgrades

Often today, edge computing is discussed in traffic signal environments. Small roadside computers (perhaps multiple of them) may exist in the cabinet. Some of these edge compute nodes allow for different software to be implemented. In this project, V2XHub was deployed on relatively inexpensive Raspberry Pi devices. In theory, this software could be deployed on other edge devices such as a traffic signal controller (or secondary process card in the controller), advanced detection computers with extra capacity, or other small computing platforms.

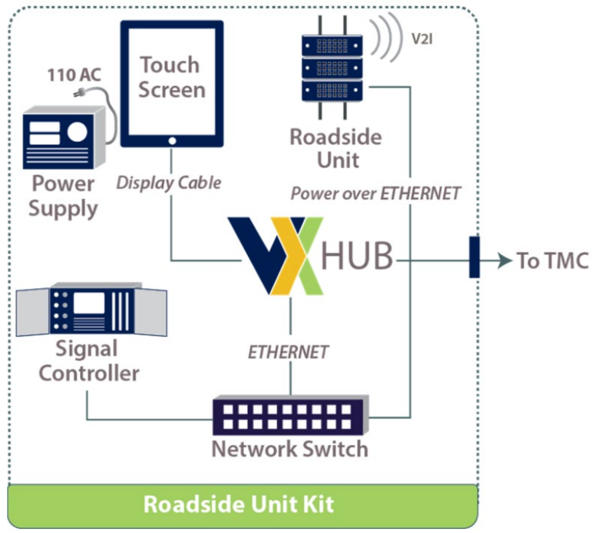
With the low penetration rate of connected vehicles, capacity and bandwidth were not considered in this phase of work. With higher penetration rates in the future, this should be carefully considered and examined.

Finally, communications upgrades at intersections may be helpful for reliability, capacity, and bandwidth. Fiber communications, 16-port switches with POE, and edge computing devices may benefit certain applications in the traffic signal cabinet. Some of these could be consolidated or shared depending on load and capacity.

Open source

Data Retrieval Process for Connected Vehicles

The data retrieval process for connected vehicles involves seamless communication between vehicles and infrastructure through Vehicle-to-Infrastructure (V2I) technology. In this project, it is managed using V2XHub, a middleware platform that facilitates communication between RSUs and central systems. The system is designed to collect, process, and transmit data from vehicles to infrastructure and vice versa. The data is transmitted as messages. RSUs serve as the primary collection points, which then forward the data to V2XHub for further processing.



The RSU is a central component in your system, responsible for collecting data from connected vehicles and forwarding it to the V2XHub using SNMP configurations. The Raspberry Pi is hosting the V2XHub which processes the data from RSU. The ethernet connections show the connectivity between devices including RSU, V2XHub and the signal controller. Here the Traffic management center is the real-time monitoring system that handles the data.

The various sensors and devices work together to facilitate data retrieval:

1. RSUs: These collect BSMs, including details such as speed, direction, and location, from connected vehicles.
2. V2XHub: A middleware platform that processes data from RSUs and sends it to applications like traffic management systems.
3. Onboard Units (OBUs): Installed in vehicles, they broadcast and receive V2X messages.

RSUs are configured to forward BSMs to your V2XHub setup via specific SNMP commands and these SNMP commands are used to define the destination IP, port, and protocol for message forwarding.

The RSU gathers data from OBUs which broadcast the messages so using SNMP commands RSU's are configured to forward the messages to the IP address and port of the Raspberry Pi where V2X-Hub is deployed. The steps are as follows:

1. Configured network settings to connect the Raspberry Pi to campus network with a static IP.
2. Installed SSH for remote access and tools like Putty and WinSCP for file management
3. Cloned the V2X Hub repository from GitHub and unpacked the source code
4. Installed Docker and Docker Compose on the Raspberry Pi.
5. Built and deployed the V2X Hub application using:
6. sudo docker-compose up -d

7. Verified the application was running by accessing the V2X Hub GUI at https://10.XXX.YY.ZZ:19760.
8. sudo docker ps
9. Access using http://10.XXX.YY.ZZZ/admin/admin.html
10. Configure the Plugin with correct IP address and port Configured the Message Receiver Plugin to: Listen on IP: 10.XXX.YY.ZZZ and Port: 26789.
11. Locate the Message Receiver Plugin in the plugin manager.
12. Click Enable to activate it.
13. Start the Plugin
14. Verify that the plugin's status turns green or active.
15. Use sudo apt-get install snmp-mibs-downloader and placed NTCIP1218-v01 in the correct MIB directory which configure RSU Forwarding by setting Set destination IP, port, and protocol using snmpset. Used snmpwalk to verify BSM messages.

The commands to forward messages are as follows:

```
snmpset -v 2c -c private 10.XXX.YY.ZZZ \
NTCIP1218-v01::rsuReceivedMsgPsid.1 x "00000020" \
NTCIP1218-v01::rsuReceivedMsgDestIpAddr.1 s "10.XXX.YY.WWW" \
NTCIP1218-v01::rsuReceivedMsgDestPort.1 = 26789\
NTCIP1218-v01::rsuReceivedMsgProtocol.1 = 2 \
NTCIP1218-v01::rsuReceivedMsgRssi.1 = -60 \
NTCIP1218-v01::rsuReceivedMsgInterval.1 = 1 \
NTCIP1218-v01::rsuReceivedMsgDeliveryStart.1 x "07e10a0717220000" \
NTCIP1218-v01::rsuReceivedMsgDeliveryStop.1 x "07e80a0717220000" \
NTCIP1218-v01::rsuReceivedMsgSecure.1 = 1 \
NTCIP1218-v01::rsuReceivedMsgAuthMsgInterval.1 = 1 \
NTCIP1218-v01::rsuReceivedMsgStatus.1 = 4
```

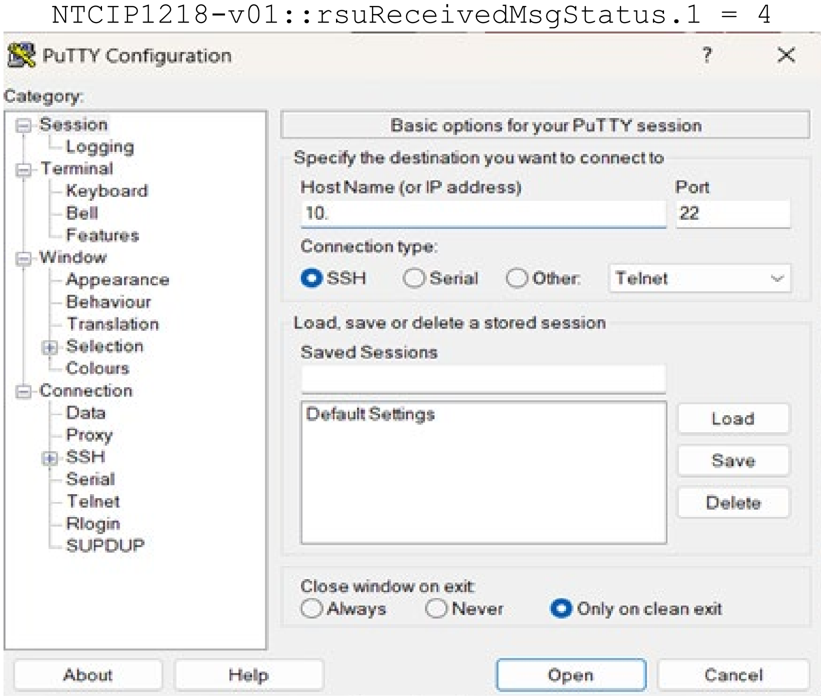


Exhibit 9. Connection to the RPi using PUTTY

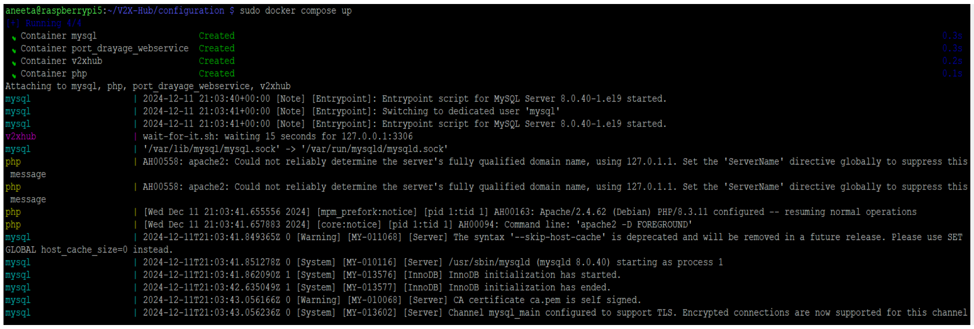


Exhibit 10. Using the docker to run the application

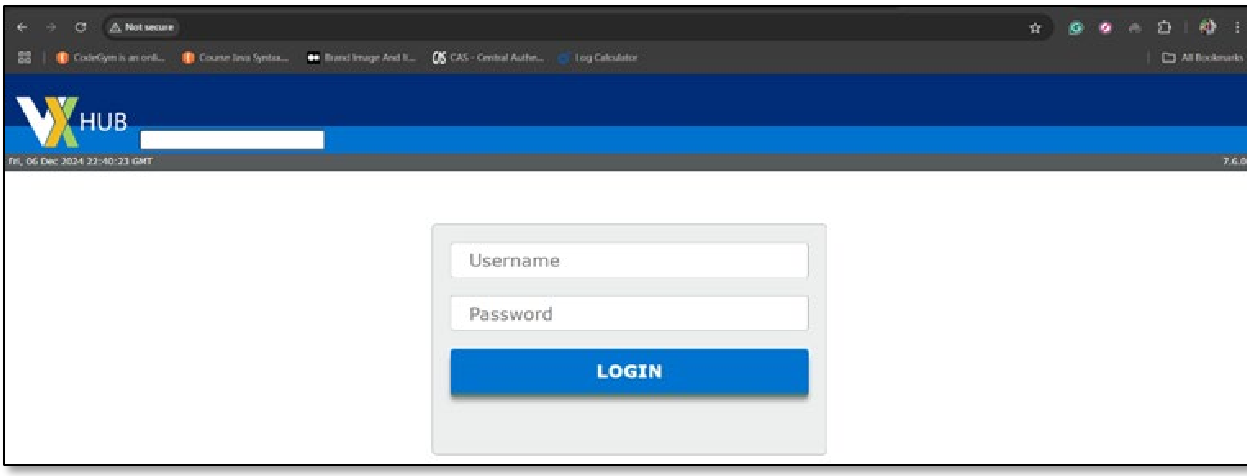


Exhibit 11. Application accessible at the required IP address and port of Rpi

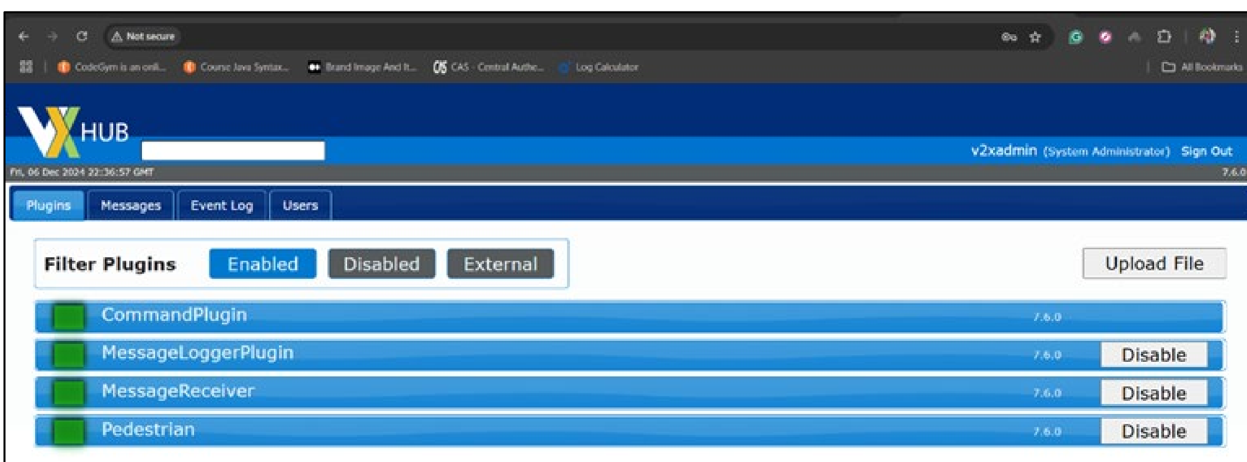
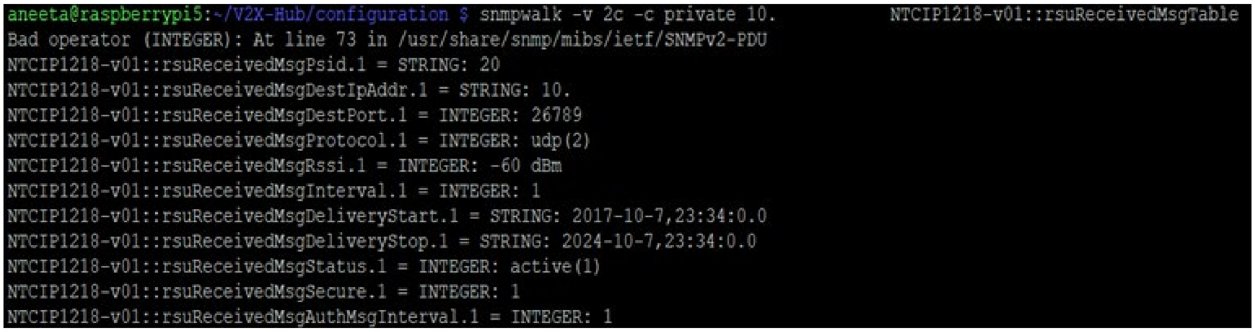
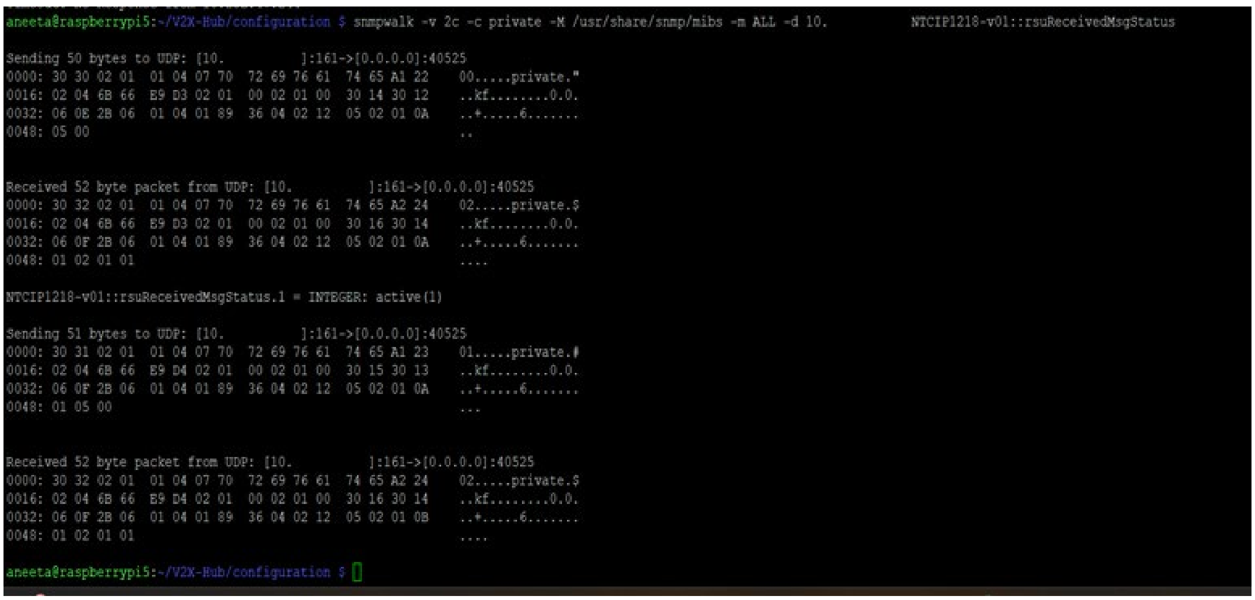


Exhibit 12. Enabling the required plugins to receive the messages



```
aneeta@raspberrypi5:~/V2X-Hub/configuration $ snmpwalk -v 2c -c private 10.          NTCIP1218-v01::rsuReceivedMsgTable
Bad operator (INTEGER): At line 73 in /usr/share/snmp/mibs/ietf/SNMPv2-PDU
NTCIP1218-v01::rsuReceivedMsgPsid.1 = STRING: 20
NTCIP1218-v01::rsuReceivedMsgDestIpAddr.1 = STRING: 10.
NTCIP1218-v01::rsuReceivedMsgDestPort.1 = INTEGER: 26789
NTCIP1218-v01::rsuReceivedMsgProtocol.1 = INTEGER: udp(2)
NTCIP1218-v01::rsuReceivedMsgRssi.1 = INTEGER: -60 dBm
NTCIP1218-v01::rsuReceivedMsgInterval.1 = INTEGER: 1
NTCIP1218-v01::rsuReceivedMsgDeliveryStart.1 = STRING: 2017-10-7,23:34:0.0
NTCIP1218-v01::rsuReceivedMsgDeliveryStop.1 = STRING: 2024-10-7,23:34:0.0
NTCIP1218-v01::rsuReceivedMsgStatus.1 = INTEGER: active(1)
NTCIP1218-v01::rsuReceivedMsgSecure.1 = INTEGER: 1
NTCIP1218-v01::rsuReceivedMsgAuthMsgInterval.1 = INTEGER: 1
```

Exhibit 13. Using SNMP, the values are set to the corresponding RSU to make sure that we are forwarding the messages.



```
aneeta@raspberrypi5:~/V2X-Hub/configuration $ snmpwalk -v 2c -c private -M /usr/share/snmp/mibs -m ALL -d 10.          NTCIP1218-v01::rsuReceivedMsgStatus

Sending 50 bytes to UDP: [10.          ]:161->[0.0.0.0]:40525
0000: 30 30 02 01  01 04 07 70  72 69 76 61  74 65 A1 22    00.....private."
0016: 02 04 6B 66  E9 D3 02 01  00 02 01 00  30 14 30 12    ..kf........0.0.
0032: 06 0E 2B 06  01 04 01 89  36 04 02 12  05 02 01 0A    ..+.....6.......
0048: 05 00                                                 ..


Received 52 byte packet from UDP: [10.          ]:161->[0.0.0.0]:40525
0000: 30 32 02 01  01 04 07 70  72 69 76 61  74 65 A2 24    02.....private.$
0016: 02 04 6B 66  E9 D3 02 01  00 02 01 00  30 16 30 14    ..kf........0.0.
0032: 06 0F 2B 06  01 04 01 89  36 04 02 12  05 02 01 0A    ..+.....6.......
0048: 01 02 01 01                                           ....

NTCIP1218-v01::rsuReceivedMsgStatus.1 = INTEGER: active(1)

Sending 51 bytes to UDP: [10.          ]:161->[0.0.0.0]:40525
0000: 30 31 02 01  01 04 07 70  72 69 76 61  74 65 A1 23    01.....private.#
0016: 02 04 6B 66  E9 D4 02 01  00 02 01 00  30 15 30 13    ..kf........0.0.
0032: 06 0F 2B 06  01 04 01 89  36 04 02 12  05 02 01 0A    ..+.....6.......
0048: 01 05 00                                              ...


Received 52 byte packet from UDP: [10.          ]:161->[0.0.0.0]:40525
0000: 30 32 02 01  01 04 07 70  72 69 76 61  74 65 A2 24    02.....private.$
0016: 02 04 6B 66  E9 D4 02 01  00 02 01 00  30 16 30 14    ..kf........0.0.
0032: 06 0F 2B 06  01 04 01 89  36 04 02 12  05 02 01 0B    ..+.....6.......
0048: 01 02 01 01                                           ....

aneeta@raspberrypi5:~/V2X-Hub/configuration $
```

Exhibit 14. Logs of messages being transmitted between RSU and RPi

References

[1] 5GAA, "C-V2X Explained," 2024. [Online]. Available: https://5gaa.org/c-v2x-explained/. [Accessed 11 December 2024].

[2] U.S Department of Transportation Federal Highway Administration, "FHWA-HRT-22-047: VEHICLE-TO-EVERYTHING (V2X) HUB: Open-Source Connected Vehicle (CV) Software," Office of Safety and Operations Research and Development, 2022. [Online]. Available: https://www.fhwa.dot.gov/publications/research/operations/22047/22047.pdf. [Accessed 11 December 2024].

[3] Society of Automotive Engineers, "J2735: Dedicated Short Range Communications (DSRC) Messages Set Dictionary," SAE, Warrendale, 2016.

[4] Society of Automotive Engineers, "J2945/0: Dedicated Short Range Communication (DSRC) Performance Requirements," SAE, Warrendale, 2016.

Appendix A – Connected Vehicle Standards Notes

Overview of V2X Communication standards

1

Introduction to V2X

- Define Vehicle-to-Everything (V2X) communication, highlighting its role in enabling vehicles to communicate with each other (V2V), pedestrians (V2P), infrastructure (V2I), and more.

2

SAE J2945 Series

- A set of standards governing the performance, security, and interoperability of V2X communication systems.
- Ensures V2X technologies function effectively in real-world applications, improving safety and traffic efficiency.
- Includes standards for V2V (J2945/1), V2P (J2945/2), V2I (J2945/3), V2B (J2945/4), and security (J2945/9).

3

SAE J2945/1 - V2V Communication

- Sets minimum performance requirements for Vehicle-to-Vehicle (V2V) communication systems.
- Enables real-time data exchange between vehicles, including speed, position, and direction.
- Enhances road safety by supporting collision avoidance and cooperative driving.

4

SAE J2945/2 - V2P Communication

- Defines performance requirements for Vehicle-to-Pedestrian (V2P) communication.
- Facilitates communication between vehicles and pedestrian devices for timely alerts and warnings.
- Aims to reduce accidents involving pedestrians by enabling proactive safety measures.

5

SAE J2945/3 - V2I Communication

- Specifies guidelines for Vehicle-to-Infrastructure (V2I) communication.
- Enhances traffic management through interaction with traffic signals and road signs.
- Supports adaptive traffic control and infrastructure-based safety messages.

6

SAE J2945/4 - V2B Communication

- Focuses on communication between vehicles and bicycles to improve cyclist safety.
- Enables vehicles to detect bicycles, especially in blind spots or intersections.
- Improves the visibility of cyclists and reduces accident risks.

7

SAE J2945/9 - Security Standards for V2X Communication

- Establishes security protocols for V2X communication to ensure data integrity and protection.
- Implements encryption, authentication, and secure communication protocols to protect V2X data.
- Essential for maintaining trust and security in connected and autonomous vehicle systems.

8