Signal Awareness Applications

September 2022 | Final Report

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16. Abstract
Intersection collisions account for 40% of all crashes on U.S. roadways. It is estimated that 165,000 accidents, which result in approximately 800 fatalities annually, are due to vehicles that pass through intersections during red signal phases. Although infrastructure-based red-light violation countermeasures have been deployed, intersections remain a top location for vehicle crashes. The Virginia Department of Transportation and its research arm, the Virginia Transportation Research Council, partnered with the Virginia Tech Transportation Institute to create the Virginia Connected Corridors (VCC), a connected vehicle test bed located in Fairfax and Blacksburg, Virginia, that enables the development and assessment of early-stage connected and automated vehicle applications. Recently, new systems have been deployed that transmit position correction messages to support lane-level accuracy, enabling development of signal awareness applications such as red-light violation warning. This project enhances the current capabilities of VCC platforms by developing new signal awareness safety and mobility features. Additionally, this project investigated the technical and human factors constraints associated with user interfaces for notifying and alerting drivers to pertinent intersection-related information to curb unsafe driving behaviors at signalized intersections.

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Abstract

Intersection collisions account for 40% of all crashes on U.S. roadways. It is estimated that 165,000 accidents, which result in approximately 800 fatalities annually, are due to vehicles that pass through intersections during red signal phases. Although infrastructure-based red-light violation countermeasures have been deployed, intersections remain a top location for vehicle crashes. The Virginia Department of Transportation and its research arm, the Virginia Transportation Research Council, partnered with the Virginia Tech Transportation Institute to create the Virginia Connected Corridors (VCC), a connected vehicle test bed located in Fairfax and Blacksburg, Virginia, that enables the development and assessment of early-stage connected and automated vehicle applications. Recently, new systems have been deployed that transmit position correction messages to support lane-level accuracy, enabling development of signal awareness applications such as red-light violation warning. This project enhances the current capabilities of VCC platforms by developing new signal awareness safety and mobility features. Additionally, this project investigated the technical and human factors constraints associated with user interfaces for notifying and alerting drivers to pertinent intersection-related information to curb unsafe driving behaviors at signalized intersections.

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Introduction

Intersection collisions account for about 40% of all crashes on our nation's roadways, and an estimated 50,000 accidents are due to illegal maneuvers such as passing through intersections during red signal phases [1]. Although red-light violation countermeasures exist (e.g., red-light violation ticketing cameras, "no turn on red" signs, and real-time changes to signal phase and timing [SpaT] based on kinematic vehicle approaches), intersections remain a top location for vehicle crashes. Further, such countermeasures are external to the vehicle and driver and may not always be effective, especially when a driver is distracted.

The Virginia Department of Transportation (VDOT), along with its research arm, the Virginia Transportation Research Council (VTRC), partnered with the Virginia Tech Transportation Institute (VTTI) to create the Virginia Connected Corridors (VCC). The VCC is a connected vehicle (CV) test bed located in Fairfax and Blacksburg, Virginia, that enables the development and assessment of early-stage connected and automated vehicle (CAV) applications. The VCC supports vehicle-to-everything (V2X) communications through more than 60 roadside units (RSUs) connected to a low-latency backhaul network via dedicated short-range communications (DSRC) and cellular technology. Thirty of these RSUs are connected to the local traffic signal controller, which provides raw traffic signal timing data that can be used to create and broadcast standard SPaT messages that enable end user traffic signal–related applications. The VCC Cloud provides a centralized system that supports the management of CV message traffic between entities interacting on the VCC, such as in-vehicle onboard units (OBUs), mobile devices, and connected intersection signal controllers. Recently, new systems have been developed and implemented on the VCC that transmit real-time kinematic (RTK) position correction messages that support lane-level accuracy, which enables development of signal awareness applications such as red-light violation warning (RLVW). The VCC can be leveraged to address safety issues intersections pose.

Background

VTTI has developed and deployed several VCC platforms able to test CV application exchanges with drivers. For example, the VCC mobile smart phone application communicates with the VCC Cloud server application via a public API and displays relevant, real-time information to the driver, including intersection SPaT data and traveler information messages (TIMs). This information can include work zone data, weather events, and active traffic management system status. VCC platforms such as these are not currently capable of providing information or alerting drivers to unsafe approaches to intersections or work zones. However, the new position correction capabilities do allow for the development of such signal awareness applications, which represent a disruptive technology that can promote safer, economic, and ecologically friendly driving. For example, signal awareness applications may encourage drivers to gradually slow down during intersection approaches upon seeing a green light countdown near zero or discourage unsafe driving behaviors such as accelerating through a yellow phase to avoid getting stuck at a red light.

To begin to understand intersection behaviors such as these, this project enhanced the current capabilities of the VCC platforms by developing new signal awareness safety and mobility features. Additionally, this project investigated technical and human factor constraints associated with user interfaces for notifying and alerting drivers to pertinent intersection-related information to curb unsafe driving behaviors at signalized intersections. Such efforts are meant to ensure that the VCC system, as developed, is robust enough to support an in-depth controlled evaluation with naïve participants in a future study.

Method

Task 1: Project Management

This task included overall technical program oversight to ensure the project achieved its objectives and produced deliverables within the timeframe and resources allocated for the effort. This task extended over the entire period of performance, and weekly meetings were established to review progress and collaboratively work to fulfill task objectives. During biweekly meetings, the research team conveyed high-level status updates to VDOT/VTRC partners. As part of Task 1, the researchers performed administrative tasks, including project management activities and preparation as well as attendance and participation in regular discussions with the research team.

Task 2: VCC System and Prototype Application Implementation Assessment

The VCC was developed based on expert stakeholder feedback from vehicle manufacturers, Departments of Transportation (DOTs), infrastructure owners and operators (IOOs), academic experts, and standards organizations such as the American Association of State Highway and Transportation Officials (AASHTO) and SAE International. In its current form, the VCC represents a mature world-class V2X test bed based on established standards. The VCC has attracted research sponsored by various public and private entities that have enabled standardized and developmental-based V2X applications.

Recent works by a growing number of worldwide V2X deployments warranted investigation to ensure that the VCC remains at the forefront of V2X environments. To understand the current state of the art and identify signal awareness–based applications, researchers performed an industry survey of published documentation from sources such as the Connected Vehicle Pooled Fund Study (CVPFS), SAE International, AASHTO, USDOT, IOOs, the Crash Avoidance Metrics Partnership (CAMP), OEMs, suppliers, other V2X test beds, and academia.

In one research application found while exploring current solutions, the algorithm considered the duration of the current and the next traffic light phases and the driver's speed and distance to the traffic light; based on that, the algorithm calculated target speeds [2]. First, the goal of this application was to guide drivers to achieve the required driving speed to pass the green light without a stop. Only speed reduction scenarios were included. To pass the intersection at the green light and without a stop, the scenarios required drivers to reduce speed sharply by braking to 30 km/h and subsequently reducing speed by coasting to around 20 km/h. Second, when drivers could only arrive at the intersection at a red light, the goal was to guide drivers to follow a predefined speed profile to initiate the stop. This included decreasing driving speed by braking to around 20 km/h and subsequently coasting to 0 km/h by releasing the accelerator and pressing the brake pedal shortly before arriving at the stop line, the system recommended braking to 0 km/h to make drivers press the brake pedal while waiting at the red light. The update frequency of the traffic light assistant display was 5 Hz [2]. The human machine interface (HMI) screen presented the recommendations of the traffic light assistant containing a combination of action and speed suggestions. Action recommendations were to either coast, brake, or drive, and speed recommendations were either 0, 20, or 30 km/h. The threshold for achieving a certain speed was within 5 km/h. For example, when the recommendation was to drive 20 km/h, the driver was in the correct mode if they drove between 15 and 25 km/h [2]. The recommendations contained text with colors corresponding to the longitudinal driving action (Figure 1). Research has shown that reductions in fuel consumption and emission rates can be reached when the traffic light assistant is activated up to 600 m in front of the intersection [3].

Figure 1. Image. HMI display suggestions.

Based on the requirements identified, the project team used the assessment of the current VCC system and reviewed any available open-source software implementations of signal awareness applications that could be successfully developed and deployed. Applications identified were: 1) Phase Service Remaining, 2) Eco Approach/Departure, 3) RLVW, 4) Pedestrian in Signalized Crosswalk Warning, 5) Mobile Accessible Pedestrian Signal System, 6) Signal Priority, 7) Emergency Vehicle Preemption, and 8) Probe Enabled Traffic Monitoring. The applications were at varying levels of proof-of-concept, prototype, and commercial production implementation across various public, private, and academic entities.

Review of each entity’s published documents, websites, mobile applications, and patents allowed the research team to identify methodologies and user interface examples in which organizations deployed in their applications. This allowed for the development of high-level requirements to meet the task objective and led the team to focus development on the Phase Service Remaining application using predictive SpaT.

VTTI created and shared final development plans that addressed any intellectual property (IP) issues surrounding their use. Requirements for such signal awareness applications were established and the resulting information was used to define the V2X infrastructure requirements to guide research, development, implementation, and analysis activities in the proceeding tasks.

Task 3: VCC Prototype Application Development

Based on the identification of the applications along with system requirements performed under Task 2, the technical team began the development process. This effort included defining a system architecture to inform the definition and execution of development activities. Development efforts were performed on the following relevant system components: OBUs, VCC Mobile smart phones, RSUs, intersection signal controllers, and/or VCC Cloud infrastructure, as depicted in Figure 2.

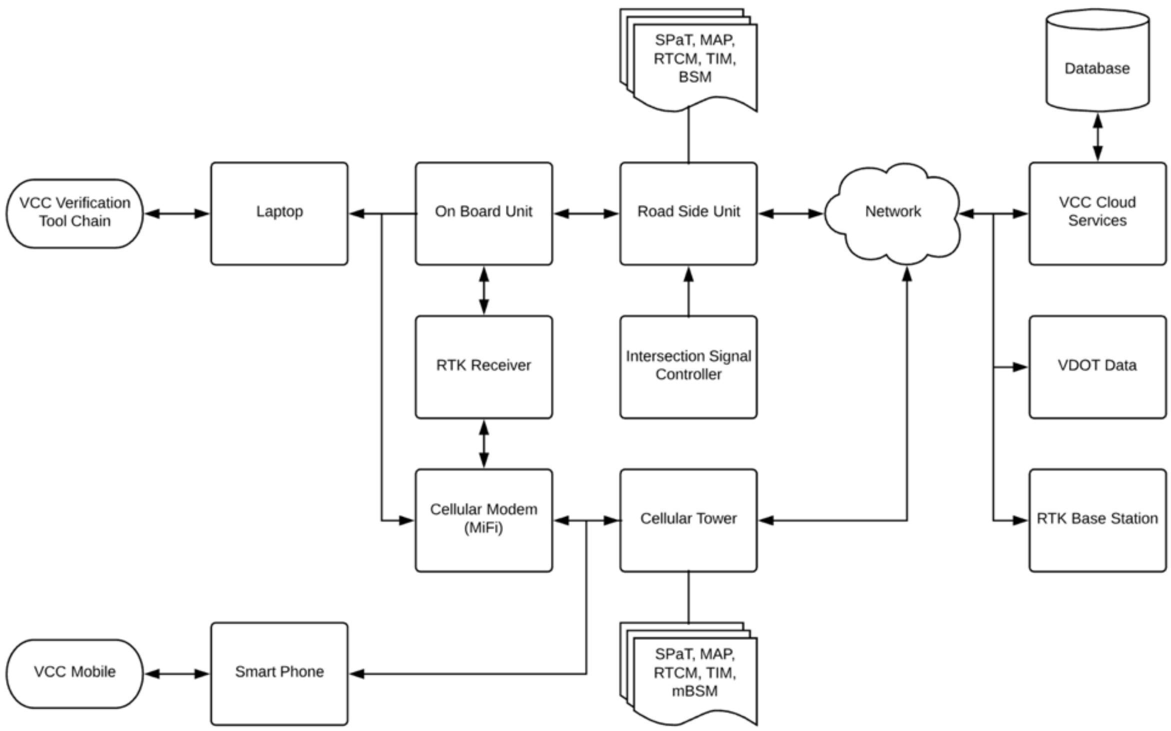

Figure 2. System diagram.

Prediction Model Development

Approach

Considering that the intersection controllers deployed in the VCC implemented adaptive rather than fixed timing plans, sudden change in signal timing could impact alerting for a vehicle approaching an intersection. Predicting the time remaining in every phase of a signal and providing the mobile application with predictions required developing a model to capture all different complex aspects that affect the remaining time in each phase. The complexity of this prediction task arises from the fact that the D4 controller is highly adaptable to changes in traffic conditions, which in turn makes it less predictable. Several studies have identified the complexity associated with making predictions for both time to switch to green and time to switch to red [4-6].

The complexity of predicting the traffic signal state can be attributed to two factors. The first is the controller logic, where the D4 controller logic is highly adaptable and allows different ways to adapt to the incoming traffic. Examples of this adaptability include having floating green times that can be allocated to different movements, allowing all settings to vary according to time of day, allowing locked calls for vehicles or pedestrians to be placed on a certain phase, and allowing reserving left turning vehicles that have not been serviced (meaning that one cycle can have two left turn phases, if needed). While some of these features are not used, they make the traffic signal highly unpredictable and increase the complexity of the prediction task. The second factor is the highly stochastic nature of traffic and pedestrian arrivals. Several studies have attempted to predict the effect of traffic arrivals on signal timing using low frequency probe vehicle data, GPS trajectory big data, and data from upstream intersections combined with platoon dispersion modeling [7-9]. Their results show the highly stochastic nature of traffic arrivals.

Our team proposed using long short-term memory (LSTM) recurrent neural networks as an approach for the prediction of signal switching time. This approach not only allows for including all data relevant to the prediction but also recognizes the temporal dependencies between the data elements at different time steps. This is made possible by the special building block of the LSTM network known as the LSTM cell, which allows building a temporal dependency among variables. This feature of capturing the temporal dependencies lends LSTM to areas such as language modeling, speech recognition, and stock market price prediction [10-12]. LSTM networks have also been used in transportation applications and applied to areas with strong reliance on temporal trends, such as roadway link travel time prediction, traffic flow prediction, and accident risk and severity prediction [13-17].

The research team recognized the importance of the temporal dependencies among signal states at different times and the temporal-dependent nature of most data used in predicting signal switching times, such as traffic volumes, speed, traffic arrivals, and pedestrian arrivals. These parameters not only depend on the time of day but also can show distinct trends in the very short term. For example, if the traffic volume on one of the roads has been increasing over the past few cycles, it might have a higher probability of increasing in the current cycle.

Methodology

Predicting the traffic signal switching times for the mobile application required five steps. Each step was coded separately as a separate module. A summary of all five modules is provided in Figure 3. All five steps have been undertaken for the intersection at Gallows Road and Willow Oaks Corporate Drive, shown in Figure 4. This intersection has four phases labeled as phase 1 (northbound left), 2 (southbound through), 4 (eastbound left), and 6 (northbound through), respectively, to be consistent with the data source. The intersection operates as a coordinated actuated signal from 6 a.m. to 10 p.m. and as a semi-actuated signal otherwise. This model was developed only for the coordinated actuated portion of the day. The remainder of this section includes discussion of each of the five modules in detail.

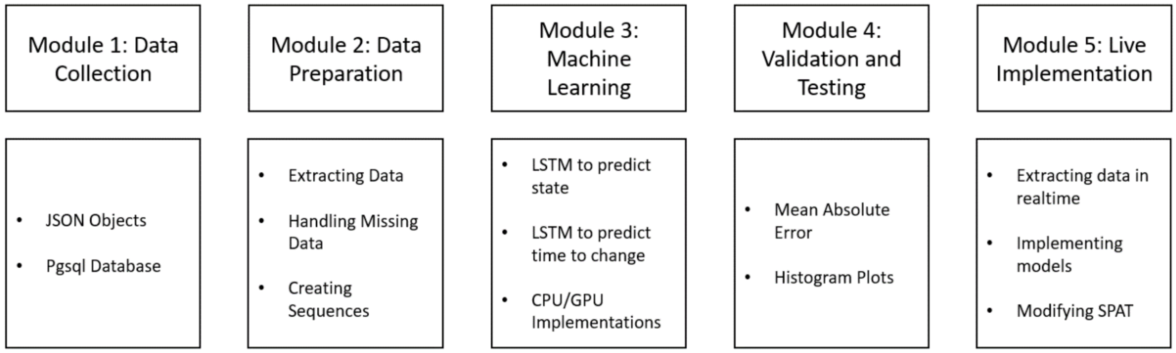

Figure 3. Chart. Five-step prediction model methodology.

Figure 4. Photo. Intersection at Gallows Road and Willow Oaks Corporate Drive.

Module 1: Data Collection

The first module concerns gathering and saving historical data. The data used was the signal data: controller status data provided by the Smarterroads portal, which updates every second and is provided as text in Javascript Object Notation (JSON) format. Module 1 involved gathering this data every second and storing it in a Postgresql (Pgsql) database through VTTI's Deepthought server. A simple representation of the data gathering process is provided in Figure 5.

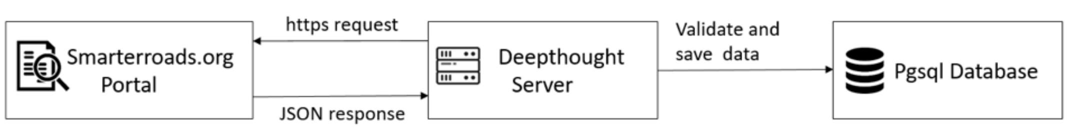

Figure 5. Diagram. Data collection server communications.

Module 2: Data Preparation

Once all historical data was gathered in the database, the second module involved preparing the data to be used in the machine learning module. The data was queried from the Pgsql database and converted to input files for the LSTM networks. This involved extracting all the relevant data from the JSON files, where the data included information about controller settings, signal timing, vehicles, and pedestrians, as shown in Figure 6. This data then had to be encoded into matrices where every matrix was comprised of a time series of data for a total of 120 seconds, referred to as a sequence, as shown if Figure 7. Creating these sequences required encoding categorical variables into dummy variables and dealing with missing data, which can arise due to communication latencies with the server. Every sequence was then associated with a prediction that was either the state of the traffic signal in the first network or the time until this state changes in the second network. Generating and handling these sequences was a memory-intensive task.

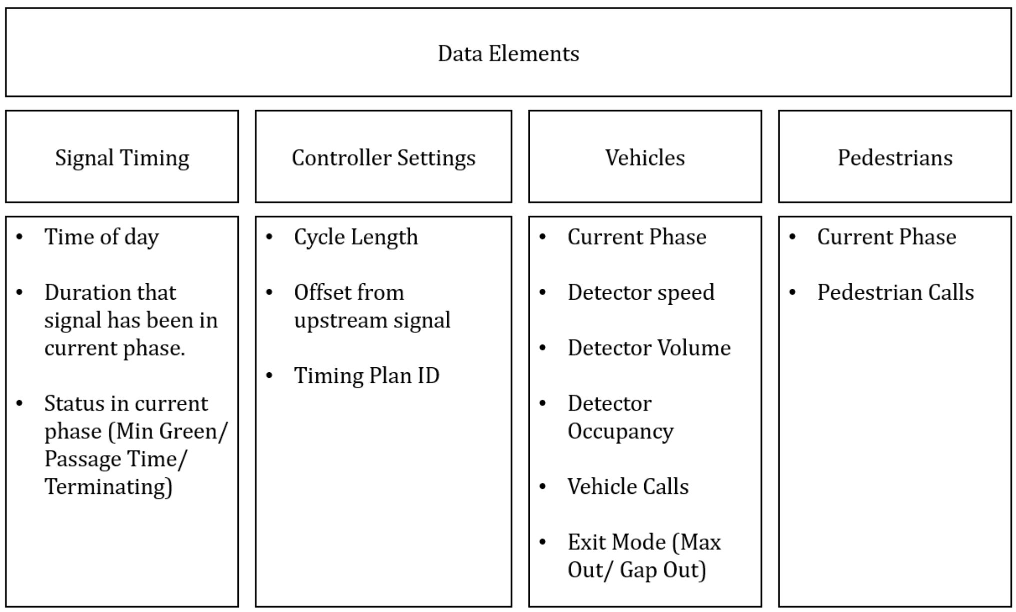

Figure 6. Chart. Data elements relevant for model predictions.

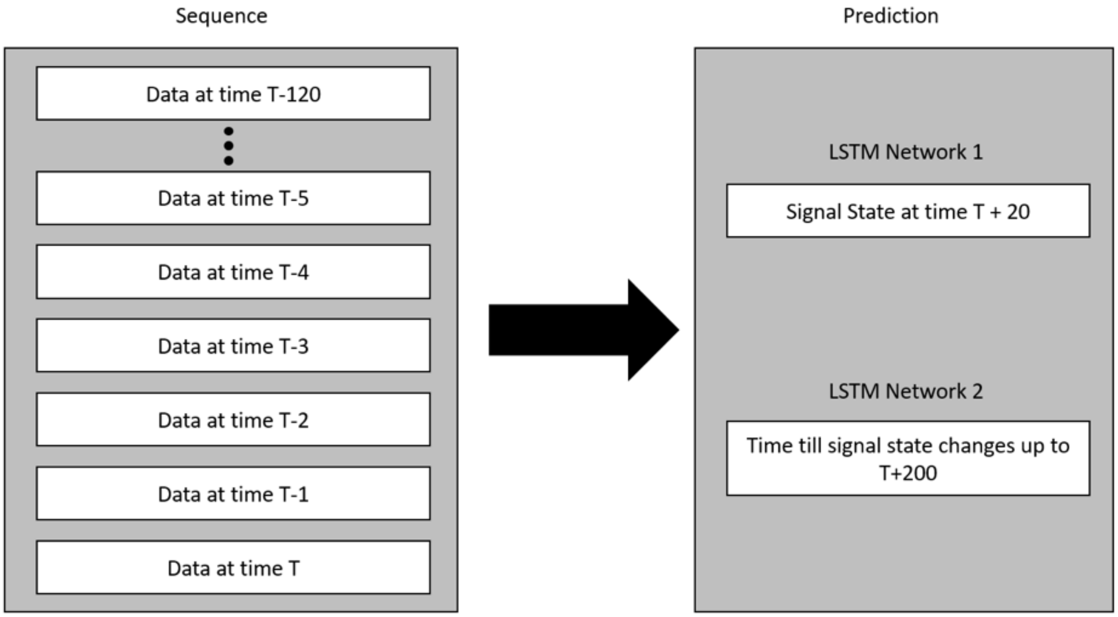

Figure 7. Diagram. Sequences and prediction variables.

Module 3: Machine Learning

The LSTM neural networks were built using Tensorflow Keras, which is a machine learning package in Python. The networks had two distinct architectures shown in Figure 8 and Figure 9. Both models used the ADAM optimizer, which is already coded in Keras and Rectified Linear Unit (ReLu) activation function for the hidden layers. The LSTM layers were chosen to have 20 nodes. Due to the very high dimensionality of the data, training the network took a very long time for larger numbers of nodes per layer without significant improvement in the predictions. A masking layer was added for both architectures to mask the missing data and prevent missing data from affecting the results. This was not done in the graphics processing unit (GPU) implementation due to the absence of a GPU implementation of the masking layer, but the effect of its absence was outweighed by the improvement in the implementation time due to the use of a GPU.

The first architecture was only applied to the preliminary model—which was a classification model intended to predict the state of the traffic signal exactly 20 seconds in the future—and was implemented using sparse categorical crossentropy loss function. The second architecture was applied to all subsequent models and is a regression problem to find the number of seconds until the signal switches state. The second architecture was applied using mean absolute error and mean absolute percentage error loss functions. While both architectures use data from the full previous 120 seconds, the second model prediction horizon is much higher, predicting times to switch for each phase up to 200 seconds in the future.

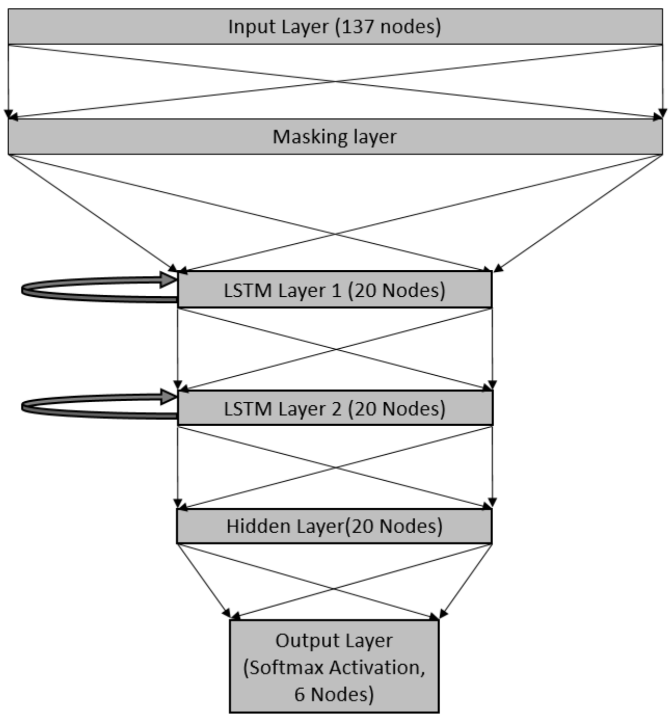

Figure 8. Diagram. Preliminary prediction model architecture.

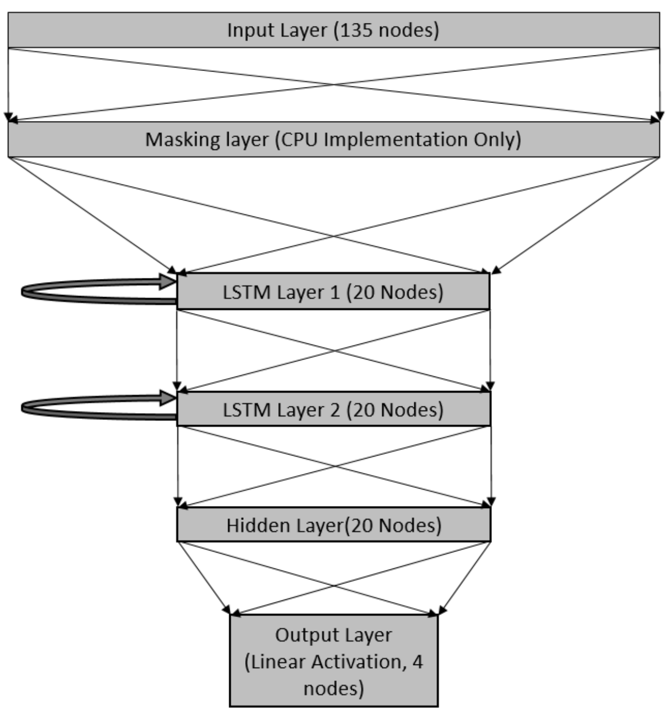

Figure 9. Diagram. Final model architecture.

Module 4: Validation and Testing

All models were validated using out-of-sample data for tuning the model parameters. Moreover, the models were tested against data outside the training set and validation set to ensure lack of bias in setting the model parameters to fit the validation data.

For the preliminary architecture, the model output reports 93.2% accuracy in classifying the state of the traffic signal after 20 seconds. However, if we observe the confusion matrix in Figure 10, it shows that the most accurate classifications are for when both through movements for northbound and southbound traffic are green (phases 2 and 6). Other states have much higher classification errors, and because this state is the most common with the highest number of observations, the model is a little biased toward optimizing this state. Another drawback of the model is that it only provides the state at a single point in time, which is not easily transferrable to the mobile application as it requires training multiple networks to obtain the state within a future time horizon. Accordingly, this research approach was abandoned in favor of the second model, which predicts how much time is remaining until each phase changes its state (from red to green or vice versa).

For the second architecture, one key question was how valuable other data elements are apart from signal timing (Figure 6) for making the prediction. Therefore, two models were developed: one that included only signal timing data to resemble predictions based on only SPaT data, and the other developed using all the data. As shown in Figure 11, the comprehensive model performed significantly better than the SPaT-only model, resulting in a reduction in the error by a factor of 4 relative to the SPaT-only model after 100 epochs of training when trained on 5 days of data.

Another key question for the second architecture was which loss function to use to optimize for lower error in predictions. Mean absolute percentage error and mean absolute error functions were both tested (Appendix A). For 5 days of data, the results showed that while both loss functions yielded errors in prediction of less than 2 seconds about 81% of the time, the error distribution for the mean absolute error function was more left skewed, leading to a larger percentage of lower error, as shown in Figure A1 and Figure A2, respectively. Accordingly, the mean absolute error function was used to train for the entire dataset of 39 days and yielded an error of less than 2 seconds 83% of the time, as shown in Figure A3. This is a small marginal gain compared to the 8-fold increase in the training dataset size. It should be noted, however, that the last bar of each of the three histograms in Appendix A refers to errors in excess of 8 seconds (10 seconds for Figure A3). This includes deviating figures, which are far from the actual due to skipping phases. There are much fewer deviating figures in the 39-day model compared to the 5-day model.

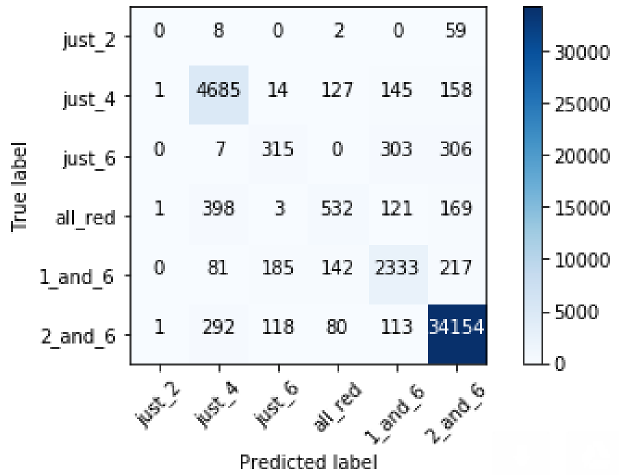

Figure 10. Chart. Preliminary model confusion matrix.

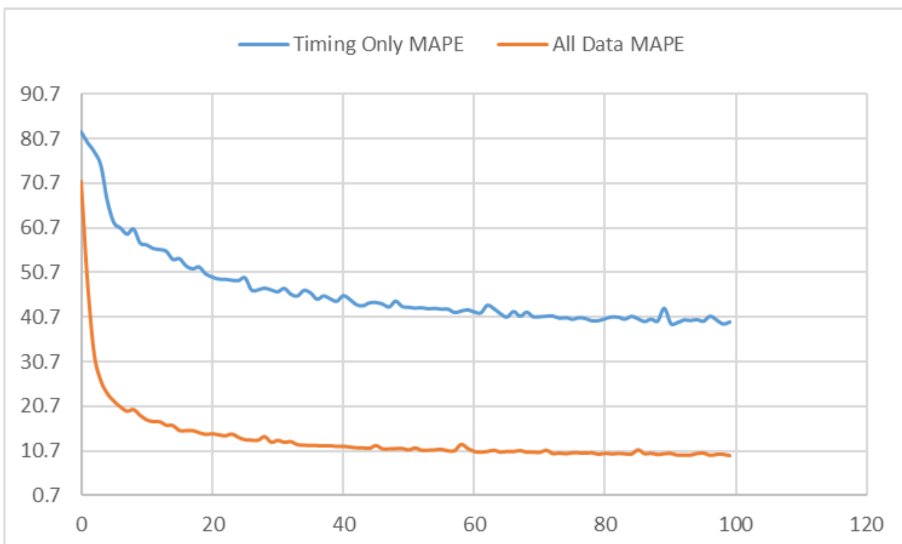

Figure 11. Graph. Timing only model vs. model containing all data elements (mean absolute percentage error vs. number of training epochs).

Module 5: Live Implementation

The live implementation module uses the best performing model in validation and testing. The implementation consists of two processes interacting via a queue (Figure 12). The first process obtains SPaT information from the VCC that contains the minimum and maximum traffic signal switching times. This information is then stored in the queue for the other process to access.

The other process collects second-by-second controller status data live from the Smarterroads portal and handles missing data. Once it has collected data for the past 2 minutes, it can feed that to the best model from module 4 to obtain a prediction. Once a prediction is obtained, the process checks the queue for the most recent SPaT data and compares the prediction against the minimum and maximum traffic signal switching times; if the prediction is within range, the process checks it against the past prediction for the most likely switching time, and if it is not in range, then the process sends the server a push request with the new updated most likely time to be used to modify the SPaT stream. This stream can then be broadcast to the mobile application through the server. The logic for this process is depicted in the flow chart in Figure 12.

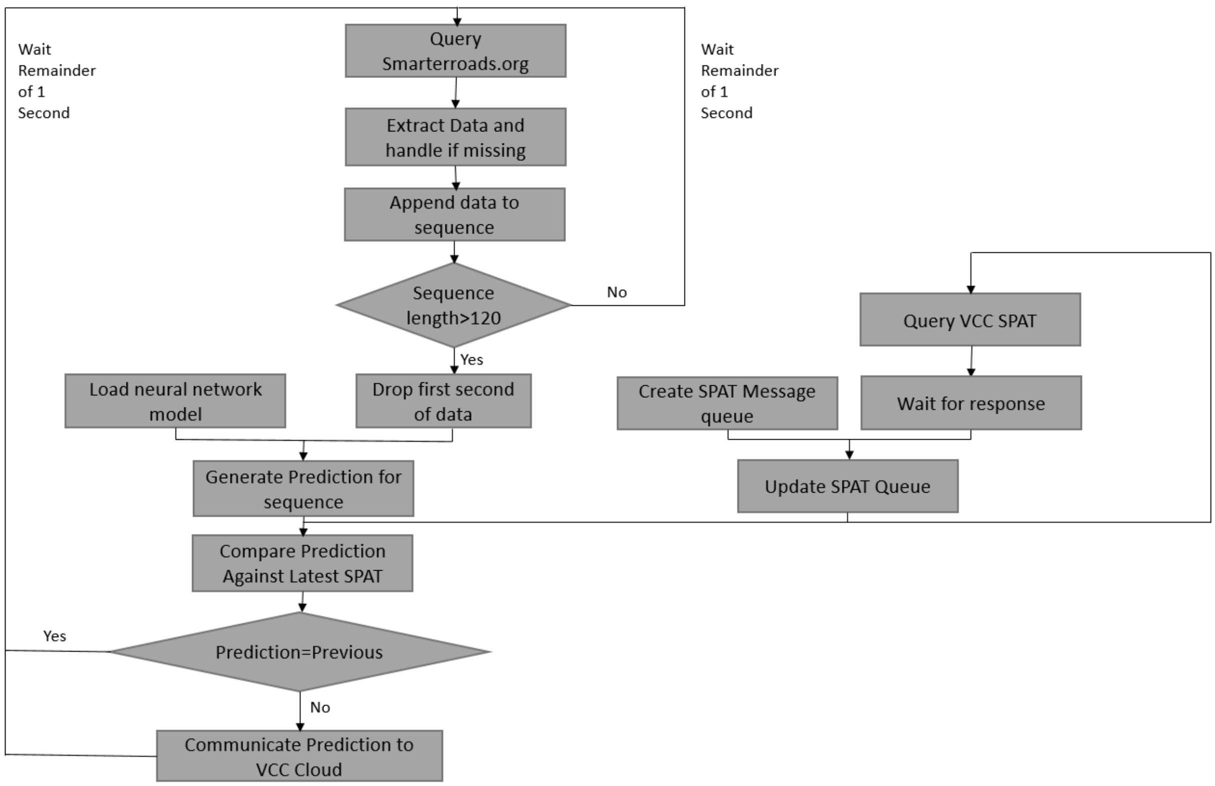

Figure 12. Diagram. Live implementation flow chart.

Due to the underlying programming language used to develop the predictive model, integration into the existing real-time VCC application server was not performant enough to produce results in real time due to system constraints. These non-real-time results could thus introduce signal offset times that would negatively affect the alerting mechanism and user acceptance. Although the current implementation was not able to produce results in real time, future developments and optimizations could enable this component.

Mobile Application Development

Implementation of the prototype signal awareness applications required development of algorithms to calculate the relative distances, lane position, and approach vectors between the vehicle and the signalized intersection. Development of these algorithms required vehicle data such as GPS position, speed, and heading in conjunction with intersection SPaT and MAP data processed by an OBU and/or smartphone application. This algorithm enables calculating vehicle time to intersection and could be used to determine if a signal violation warning is imminent.

The team developed the HMI to convey such signal awareness information to a driver. As indicated in Figure 13, a mobile application graphical user interface (GUI) included traffic light status, timing information, and vehicle location (e.g., intersection map view). The conceptualized alerting component included visual and/or auditory elements to best convey advisory and warning conditions involving dynamic (e.g., RLVW, Eco-Approach) and static (e.g., Green Time, Eco-Departure) applications. The interface was designed to convey critical information effectively while limiting distraction.

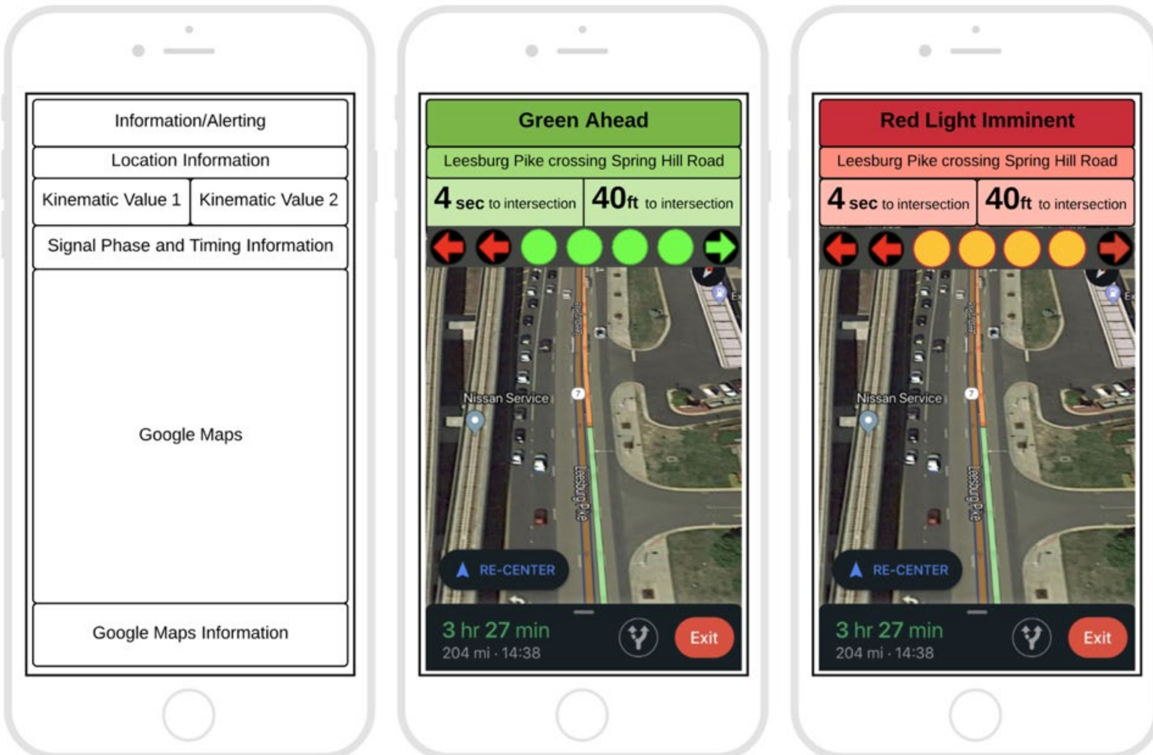

Figure 13. Image. Conceptualized mobile application GUI.

The current project is designed to provide a proof-of-concept mobile application that can be used to assess the efficacy of providing traffic signal data to a driver through a mobile application interface. Several key limitations must be acknowledged as they affected the design of the user interface and the project team's ability to provide a realistic user experience. As the driver approaches each intersection, the only way the application might know which direction the driver intends to go is if the driver had input a navigation route. The native smartphone GPS accuracy was not reliable enough to determine the lane of approach and, even if it were, it would not provide enough advance warning of the intended maneuver (straight, right turn, left turn) to support providing a single traffic light status and countdown to the driver. The project did not have the funding to create a fully featured navigation application, so the team developed a rudimentary route selection capability that would tell the app the driver's navigation intent so it could filter the displayed information to the driver, provided they stayed on the route they had input into the phone.

Appendix B includes a set of screenshots highlighting the key functional features of the prototype application. The application allows a user to enter trip start and stop locations on a map, provides a suggested route between those two points (Figure B1), and then uses SPaT and MAP messages received from connected intersections to provide signal timing information from intersections the user is approaching (Figure B2). When the user is within 400 feet of an intersection, the application will display the light countdown for the vehicle's current lane. When the vehicle passes through the light, the application reverts to a map view that shows the vehicle's location (Figure B3).

In addition, the team finalized the testing, verification, validation, and analysis protocol focused on the prototype application assessment for Task 4. The protocol defined performance measures of interest, test procedures, data collection, and analysis activities to understand any real-world technical and human constraints that would affect overall safety effectiveness.

Task 4: VCC Prototype Application Assessment

Upon completion of the prototype signal awareness application by the development team, the system verification and validation plan developed in the previous task was executed. This involved researchers verifying overall application stability while also verifying that the algorithm correctly reports information such as roadway position, approach vectors, intersection SPaT configuration, and latency. The team used resources from previous and ongoing VCC-based projects to verify the latency and accuracy of the application's algorithmic output.

For all tests, data was collected using recorded video and VCC technical system performance subsystems to support testing, verification, validation, and analysis. This data collection included standardized timestamped messages such as SPaT and MAP messages flowing end-to-end throughout the system. By performing video reduction of recordings and leveraging analysis scripts to measure accuracy and latency of visual intersection SPaT, the team used a quantitative measure of technical performance to enhance and refine the overall system. Applications were refined by continually discussing observations with application developers in an iterative process.

Task 5: Demonstration and Final Reporting

An on-road demonstration of the signal awareness applications was planned to showcase the application to stakeholders. However, this demonstration was postponed indefinitely due to COVID-19 restrictions. The research team created a video to demonstrate the proof of concept and shared it with stakeholders, including VDOT and VTRC.

Lastly, the research team compiled and summarized documentation developed throughout this project into a journal article and targeted publications to showcase the technical considerations and the potential safety and mobility impacts of signal awareness applications on driver behaviors.

Results

To verify the prototype signal awareness application, a system verification and validation plan was executed. The configuration for assessment involved using the Samsung Galaxy Tab S4—the same device used for mobile app Android software development—and communicating through the Verizon 4G LTE cellular network. Testers traversed routes in a vehicle through SpaT-enabled intersections in Tysons and Merrifield in Fairfax County, Virginia, to validate the application, as depicted in Figure 14 and Figure 15.

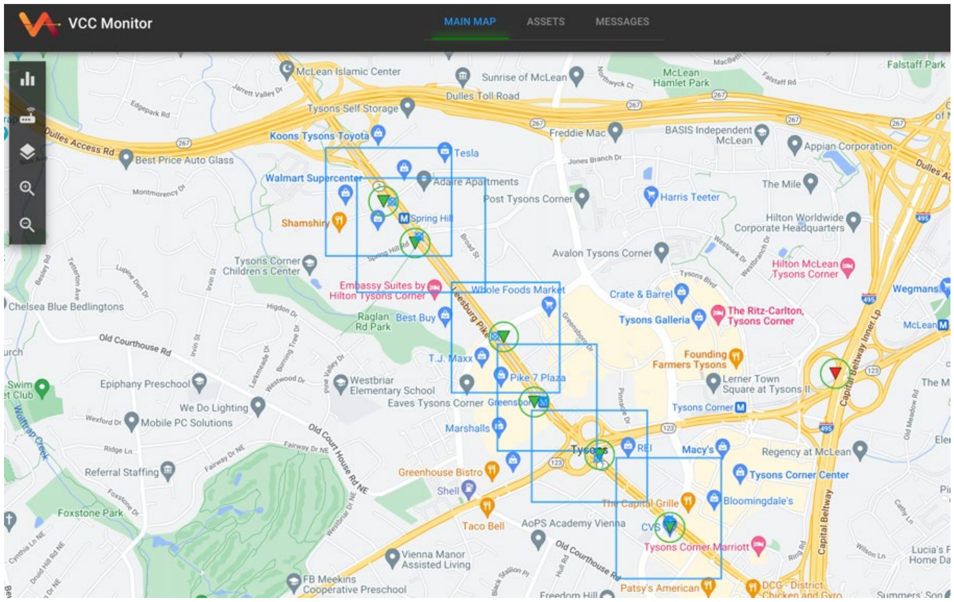

Figure 14. Map. Tysons Route.

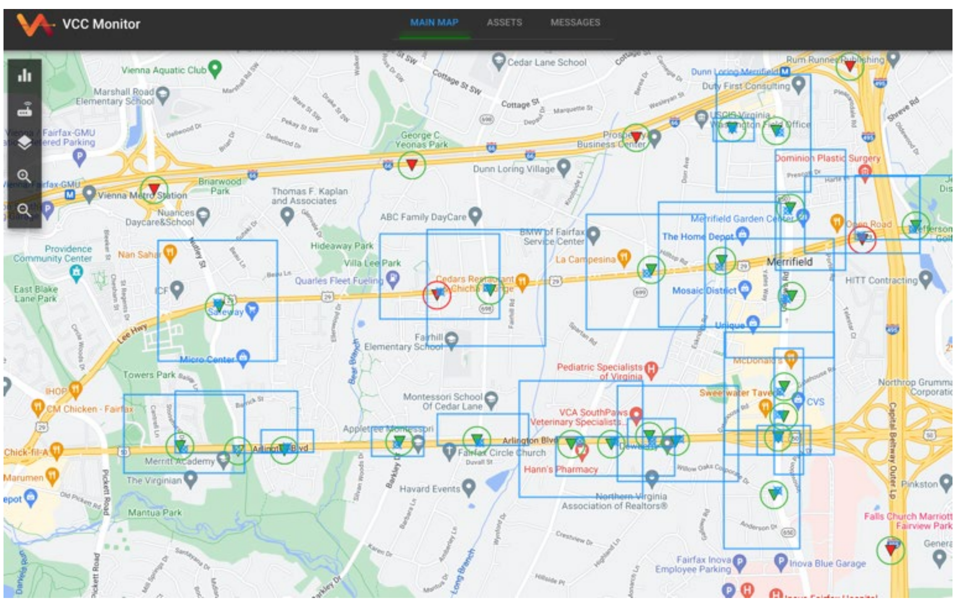

Figure 15. Map. Merrifield Route.

Each route involved passing through pinned intersections that provided SPaT data displayed in the prototype signal awareness application. For each traversed intersection, testers observed the following assessment criteria and, when safe, recorded video with a cellphone to validate the performance of the application.

- Intersection Configuration
    - Traveling and Intersecting Road Names

    - Intersection MAP Lane Configuration
    - Intersection MAP Signal Configuration
  - Application Algorithm Reporting
    - Vehicle Lane Position
    - Vehicle Approach Vectors
    - SpaT Accuracy
    - Display Latency
  - Application Stability

To assess accuracy of intersection configuration and application algorithm reporting, several test runs were performed to record assessment observations, and feedback was provided to the developers as software bugs were experienced. Reporting involved use of application screenshots, screen recordings, recorded videos of the roadway with application in view, developer application troubleshooting logs, and written bug reproducing reports.

Intersection configuration assessment identified minor issues in terms of mislabeled roadway names; otherwise, manually configured intersection information was correct. Integration of the HERE map into the application allowed for visual tracking of the vehicle on the roadway route as well as approximate approach distances to SpaT-enabled intersections. From visual observations, the application and corresponding mobile GPS module accurately tracked the vehicle approach vector to the connected intersection and displayed the corresponding SPaT configuration of the intersection correctly.

To assess the application algorithm reporting SPaT accuracy and display latency assessment items, the team performed limited reduction of recorded video displaying both the physical intersection light and the application. This method provided an end-to-end ground truth assessment as this captured the physical roadway signal, transfer of signal data across network device points, processing of data, and HMI display on the mobile cellular connected device. Assessment involved stepping through each video frame, which is ~33.3 ms per frame, and determining the time delta between the signal awareness application and change of physical intersection light from red to green, as depicted in Figure 16. Results of observed intersection latency are provided in Table 1.

Table 1. Observed Visual Latency

Intersection ID	Cross Intersection	Observed Latency
127	Gallows Road and Gatehouse Plaza	800 ms
122	US-50 and Williams Drive	600 ms
118	US-50 and Jaguar Trail	800 ms
153	US-50 and Prosperity Avenue	800 ms

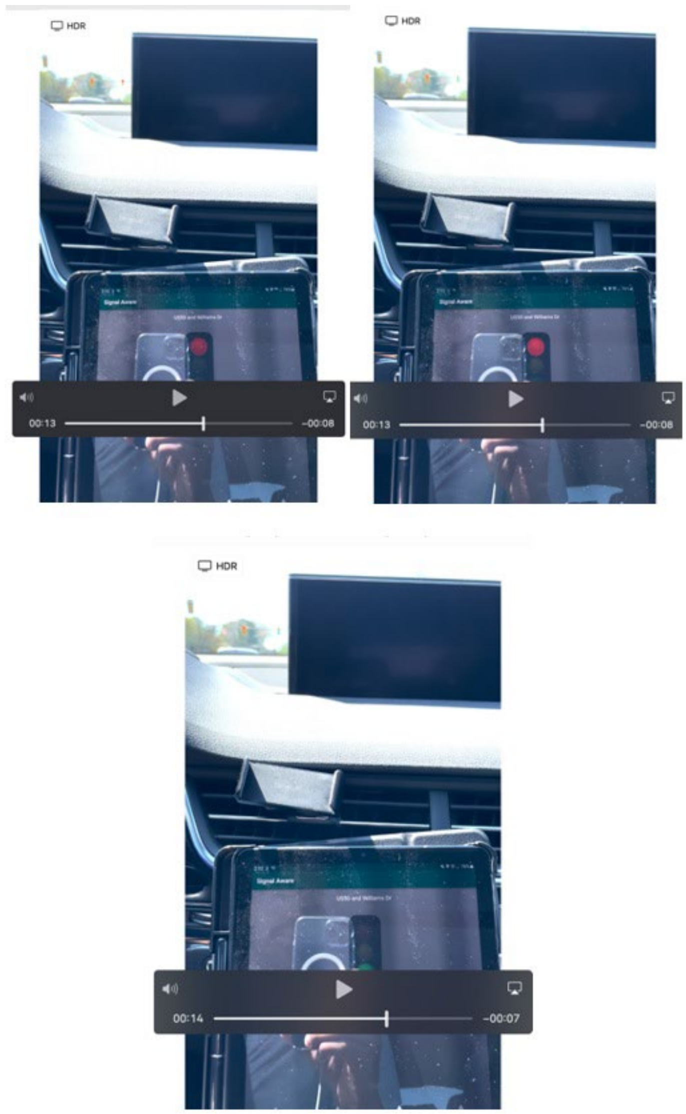

Figure 16. Photos. SPaT accuracy and latency video reduction assessment.

To better understand what contributed to the observed visual latency, a technical communication system performance study was performed in a parallel project effort, as depicted in Figure 17. This assessment involved inserting synchronized device clock timestamps starting at the SPaT data from controller to RSU, through the communication network, and then ending once received at the 4G LTE cellular modem on a data collection laptop. The delta between the two timestamps was used to calculate the roundtrip latency for all observed messages. Figure 18 provides a box plot summarizing the latency observed within the deployment area per intersection with an overall average of 140 ms.

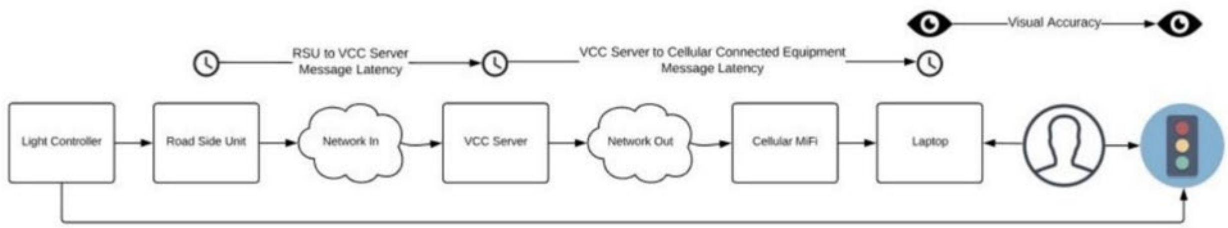

Figure 17. Diagram. End-to-end SPaT latency points.

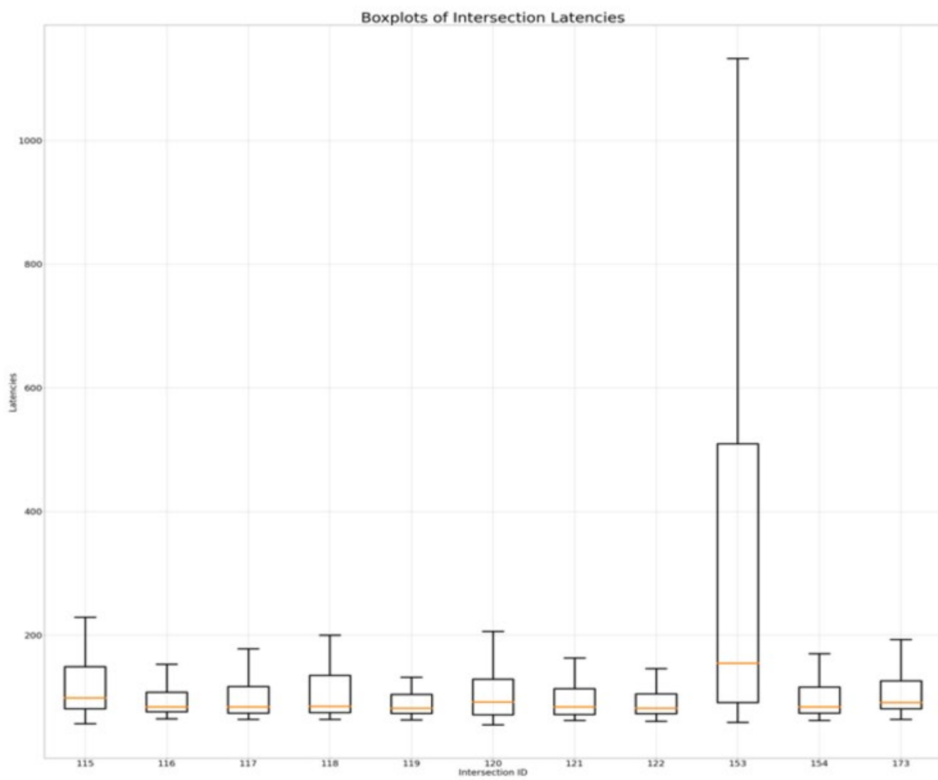

Figure 18. Graph. Network latency.

There were several early software stability bugs, including the application crashing during transition between the HERE vehicle map tracking and the SPaT user interface visualization. After this was reported, the developers identified and resolved the software bug in a subsequent application release.

Discussion

The application algorithm is based on using live GPS position data and referencing manually created intersection MAP configuration files. These MAP configurations are then used to integrate the corresponding SPaT of the lane to be displayed on the application. Per the assessment, the prototype signal awareness application performed well. There were challenges in terms of limiting technical capabilities of mobile device platform. Built-in GPS module performance on mobile devices is still not performant enough to enable lane-specific accuracy. However, it does perform well enough to determine the vehicle approach vector and relative distances to match to a roadway, which enables the display of SPaT data at intersections while traversing through a straight lane. The lack of lane-level accuracy limits the ability of the application to detect the exact lane the vehicle is currently in, which is a problem if the vehicle is in a turn lane that may have a different SPaT than a straight lane or vice versa. RTK GPS correction information could be used and is available within the development area, but built-in GPS modules in current mobile devices do not currently leverage this information.

Ground truth video latency assessment has shown that there are approximately 750 ms of visual delay between the physical signal and the digital signal user interface on the application. Considering that the average round-trip network induced latency accounts for 140 ms, this leaves 610 ms of latency induced by a process on the mobile device. The latency on the mobile device could be due to several factors, such as hardware processing constraints, custom developed data handling modules, and graphical user interface rendering. To better understand this latency and to correct the end display, enhanced mobile application latency logging could be implemented to account for any compounding delay to offset any induced latency at the user interface display.

Conclusions and Recommendations

Although there were several technically limiting factors of the device platform, much has been gained in developed capabilities and understanding the current limitations to inform next steps. The previous generation of the VCC SPaT mobile application (developed in 2017) experienced SPaT display latency greater than 1 second, which may pose a safety risk when the mobile phone application displays a digital green light while the physical intersection signal is yellow and on the verge of turning red. This latency factor is precipitated by the round-trip transfer of data from input device communication network, cloud server data processing, output devices communication network, user equipment data processing, and HMI rendering. Introducing device synchronized timestamps to calculate the current latency could be used to buffer any user interface delays. Although latency has improved to less than 1 second in observed cases, there is still room for improvement to reduce such latency before safety critical alerts are deployed.

This recent test of the prototype signal awareness application appears to have benefited from recent upgrades to public and private communication networks, VCC system improvements, and mobile device capabilities to improve on the latency performance in the previous mobile application. Another improvement in this application testing iteration was the inherent hardware and software capabilities of the mobile device used. The prototype signal awareness system integrated HERE visual mapping into the application, enabling visual validation of current position to intersection SPaT on the route. The device GPS module was performant enough to support visual tracking on the HERE map to observe road level vehicle tracking and approach vector toward the closest connected intersection providing SPaT. Future iterations could potentially leverage RTK GPS correction to enable lane-level accuracy and enhanced alerting.

Mobile phone turn-by-turn direction mapping apps such as Google and Apple Maps recently began indicating location markers for signalized intersections. It is conceivable that those companies will eventually incorporate SPaT data into their applications in a similar fashion to the prototype signal awareness application we developed. These mapping apps provide an ideal platform to reach a mass of users who can benefit from these intelligent transportation system investments. Thus, there is a need to support industry consensus on system architecture, performance requirements, and data interfaces across industry partners of SPaT intersection data to enable adoption of intersection efficiency enabling applications.

Additional Products

The Education and Workforce Development (EWD) and Technology Transfer (T2) products created as part of this project are described below and are listed on the Safe-D website here. The final project dataset is located on the Safe-D Dataverse.

Education and Workforce Development Products

The project presented an opportunity for students to work on one of the most advanced V2X test bed deployments available made in partnership with VDOT and VTRC. Such experiences enrich the student's coursework by having them consider real-world implications in the development and implementation of a commercial application/product. The tasks in this project exposed the student to a variety of experiences typically found in mobile application start-ups, product development engineering, and transportation-based consulting jobs. This level of enrichment readies the student to enter the workforce exposed to both soft and hard technical skills to advance the industry.

In addition to the experience gained, the datasets generated were used as a source to support course assignments and projects. In particular, the researchers involved with this project generated lecture materials and course exercises that were incorporated into Dr. Zac Doerzaph's course on advanced vehicle safety systems. Further, the data collected represented the current state of the art and provided a unique opportunity for the student to understand the challenges and limitations associated with real-world data. Such applied activities resulted in a thesis; however, with the breadth of data captured and disseminated, a dissertation could also have been developed.

Technology Transfer Products

The work built upon one of the world's most advanced V2X test beds. Considering the VCC development and implementation to date, end-user signal applications requiring lane-level accuracy are now realizable using the VCC's resources. Such a capability positions the VCC to enhance existing research programs while also attracting new sponsors to take advantage of a mature V2X test bed featuring dynamic and challenging roadway environments. More importantly, VDOT and VTRC are positioned to continue to leverage the myriad research, development, and implementation activities in this project to expand operational deployments across the commonwealth.

One or more prototype signal awareness applications were developed as a result of this project. Depending on the development approach, the project team will either disclose the signal application(s) in a single IP package for licensing or share the open-source software back to the community. If new software is developed that could be licensed, it will be managed through Virginia Tech Intellectual Properties (VTIP). Likely candidate IP products include signal awareness algorithms, the user interface and GUI design, and the VCC Cloud server software that embodies the algorithms. Any design, software, or hardware IP developed through this project will be declared and protected and may be marketed through the licensing agreement. Likely consumers of this IP package will include other DOT or public agencies deploying CV applications and commercial CV application developers.

The research team created a video to demonstrate the proof of concept of the signal awareness applications and shared it with stakeholders, including VDOT and VTRC.

The research team compiled and summarized documentation developed throughout this project into a journal article and targeted publications to showcase the technical considerations and the potential safety and mobility impacts of signal awareness applications on driver behaviors.

Data Products

MAP data of intersections along with raw SPaT data noted within the Tysons and Merrifield Routes will be uploaded to the UTC Safe-D Dataverse.

References

1. Choi, E. Crash Factors in Intersection-Related Crashes: An On-Scene Perspective. NHTSA, Washington, DC, 2010. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811366

2. Rittger, L. Driver Behaviour and Driver Assistance at Traffic Light Intersections. Dissertation, Julius Maximilian University, Würzburg, Germany, 2015. https://d-nb.info/1111636737/34

3. Tielert, T., M. Killat, H. Hartenstein, R. Luz, S. Hausberger, and T. Benz. The Impact of Traffic-light-to-vehicle Communication on Fuel Consumption and Emissions. In *Internet of Things (IOT) 2010 Conference*, Tokyo, Japan, 2010.

4. Weisheit, T., and R. Hoyer. Prediction of Switching Times of Traffic Actuated Signal Controls Using Support Vector Machines.In *Advanced Microsystems for Automotive Applications 2014*, Springer, 2014. pp. 121-129.

5. Scheepjens, R., A. Mortazavi, and V. Krishnamurthy. Traffic Signal Timing Estimation Using a Support Vector Regression Model. In Google Patents, 2017.

6. Koukoumidis, E., M. Martonosi, and L.-S. Peh. Leveraging Smartphone Cameras for Collaborative Road Advisories. *IEEE Transactions on Mobile Computing*, Vol. 11, No. 5, 2011, pp. 707-723.

7. Axer, S., and B. Friedrich. A Methodology for Signal Timing Estimation Based on Low Frequency Floating Car Data: Analysis of Needed Sample Sizes and Influencing Factors. *Transportation Research Procedia,* Vol. 15, 2016, pp. 220-232.

8. Baluja, S., M. Covell, and R. Sukthankar. Approximating the Effects of Installed Traffic Lights: A Behaviorist Approach Based on Travel Tracks. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, IEEE, 2015. pp. 2205-2212.

9. Paul, B., S. Mitra, and B. Maitra. Calibration of Robertson's Platoon Dispersion Model in Non-lane Based Mixed Traffic Operation. *Transportation in Developing Economies,* Vol. 2, No. 2, 2016, p. 11.

10. Sundermeyer, M., R. Schlüter, and H. Ney. LSTM Neural Networks for Language Modeling. In *INTERSPEECH 2012, 13th Annual Conference of the International Speech Communication Association*, 2012, pp. 194-197.

11. Nelson, D. M., A. C. Pereira, and R. A. de Oliveira. Stock Market's Price Movement Prediction with LSTM Neural Networks. In *2017 International Joint Conference on Neural Networks (IJCNN)*, IEEE, 2017. pp. 1419-1426.

12. Han, S., J. Kang, H. Mao, Y. Hu, X. Li, Y. Li, D. Xie, H. Luo, S. Yao, and Y. Wang. Ese: Efficient Speech Recognition Engine with Sparse LSTM on FPGA. In *Proceedings of the 2017 ACM/SIGDA International Symposium on Field-Programmable Gate Arrays*, 2017. pp. 75-84.

13. Duan, Y., Y. Lv, and F.-Y. Wang. Travel Time Prediction with LSTM Neural Network. In *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, IEEE, 2016. pp. 1053-1058.

14. Yuan, J., M. Abdel-Aty, Y. Gong, and Q. Cai. Real-time Crash Risk Prediction Using Long Short-term Memory Recurrent Neural Network. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2673*, TRB, National Research Council, Washington, D.C., 2019, pp. 314-326.

15. Sameen, M. I., and B. Pradhan. Severity prediction of traffic accidents with recurrent neural networks. *Applied Sciences,* Vol. 7, No. 6, 2017, p. 476.

16. Fu, R., Z. Zhang, and L. Li. Using LSTM and GRU Neural Network Methods for Traffic Flow Prediction. In *2016 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, IEEE, 2016. pp. 324-328.

17. Tian, Y., K. Zhang, J. Li, X. Lin, and B. Yang. LSTM-based Traffic Flow Prediction with Missing Data. *Neurocomputing,* Vol. 318, 2018, pp. 297-305.

18. Eteifa, S.*, H. A. Rakha, and H. Eldardiry. Predicting Coordinated Actuated Traffic Signal Change Times using Long Short-Term Memory Neural Networks. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2675*, TRB, National Research Council, Washington, D.C., 2021, pp. 127–138. https://doi.org/10.1177/03611981211000748.

Appendix A. Mean Absolute Percentage Error and Mean Absolute Error Distribution

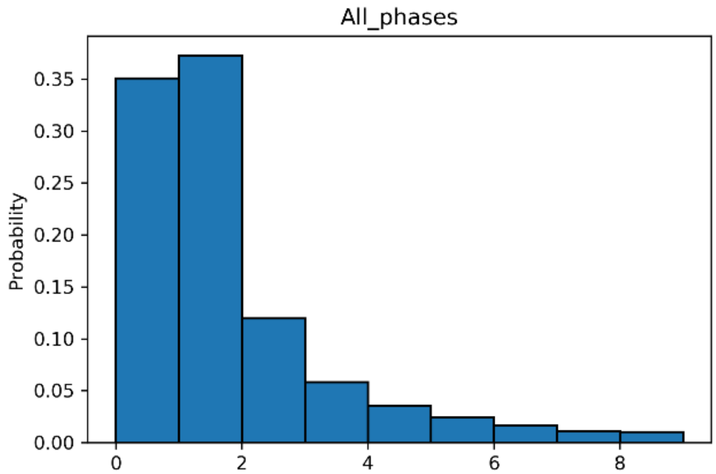

Figure 19. Histogram. Error distribution in seconds for mean absolute percentage error function for 5-day data.

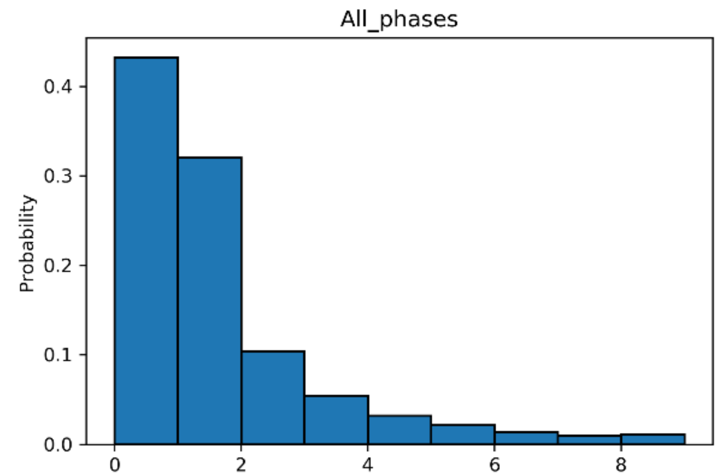

Figure 20. Histogram. Error distribution in seconds for mean absolute error function for 5-day data.

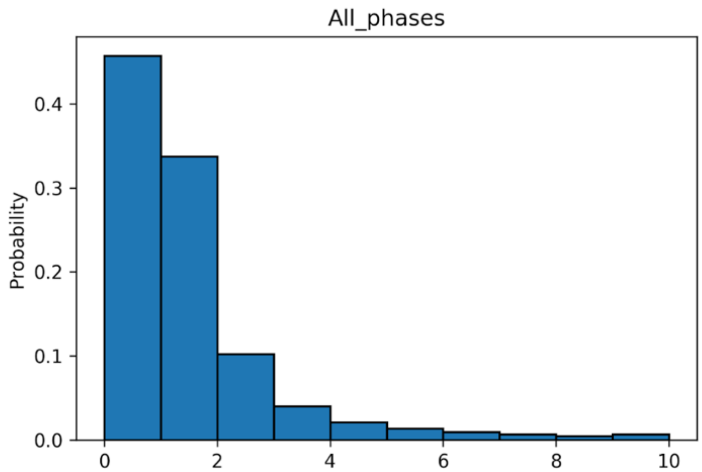

Figure 21. Histogram. Error distribution in seconds for mean absolute error function for 39-day data.

Appendix B. Prototype Mobile Application GUI

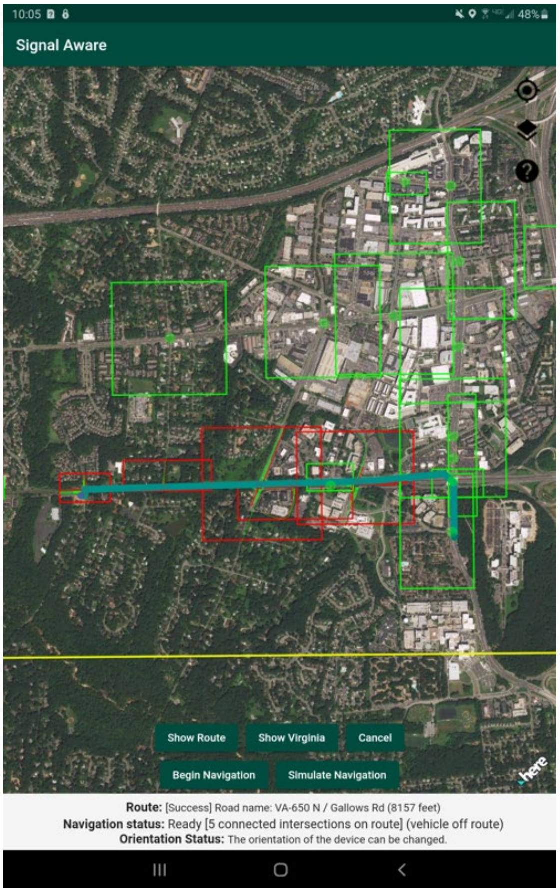

Figure 22. Screenshot. Prototype mobile application GUI – start, stop, and route.

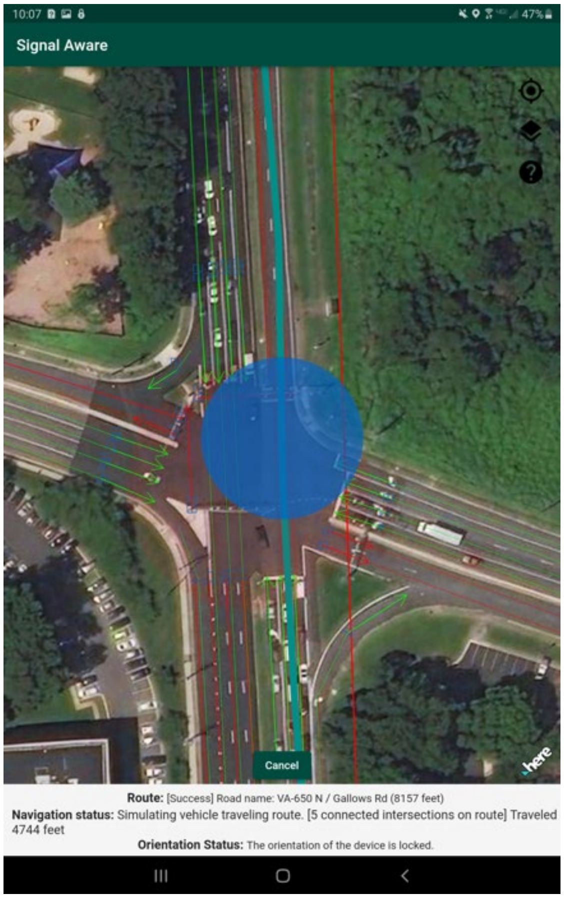

Figure 23. Screenshot. Prototype mobile application GUI – SPaT and MAP.

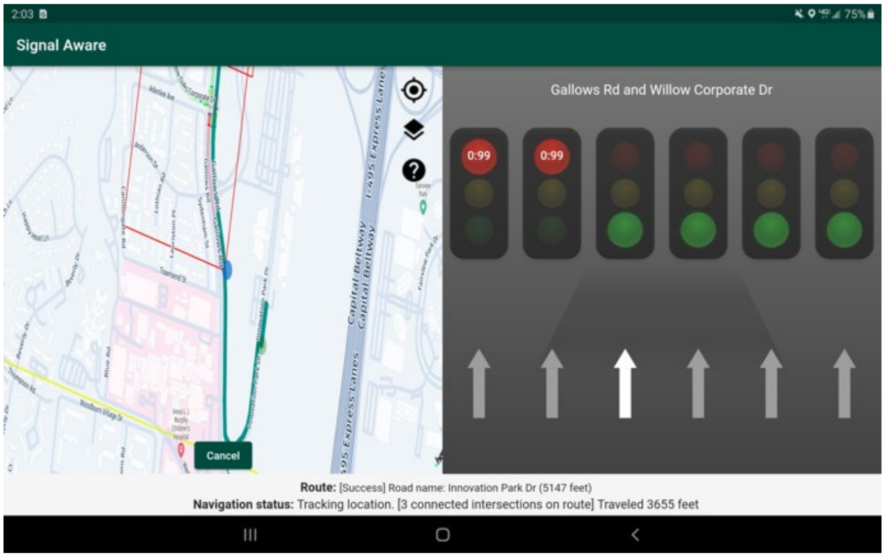

Figure 24. Screenshot. Prototype mobile application GUI – map and signal view.