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## Improving the Efficiency of Trucks via CV2X Connectivity on Highways

Gábor Orosz  
Hao M. Wang





**CENTER FOR CONNECTED  
AND AUTOMATED  
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# Improving the Efficiency of Trucks via CV2X Connectivity on Highways

by

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16. Abstract

Intelligent road infrastructure consisting of sensors and communications is needed to deploy connected and automated vehicles (CAVs) on real highways. Such infrastructure can support the operation of CAVs (e.g., maneuver coordination and onboard energy management), and bridge the connectivity gap resulting from the currently low penetration of connected vehicles and the limited range of vehicle-to-vehicle communication. Moreover, it also allows us to build high-efficiency transportation systems, leading to societal benefits such as emission reduction, energy efficiency improvement, and productivity increase. In this project, we deploy cellular vehicle-to-everything (CV2X) infrastructure along the highway I-275, which consists of roadside units (RSUs), a server managed by the University of Michigan, and communications between them. The RSUs collect traffic information from the downstream vehicles on highway via a custom V2X communication message called traffic history message (THM). The received THMs are transferred via the RSUs' LTE Internet to the university server for real-time processing. The processed information is then sent to the upstream RSUs and broadcast to vehicles nearby via another custom V2X message called traffic prediction message (TPM). This allows the upstream vehicles to predict the traffic ahead and plan their motions accordingly. This way, traffic prediction and control can be achieved. We conduct experiments on highway I-275 using the installed RSUs and the designed messages with real vehicles. We demonstrate the effectiveness of the infrastructure-supported traffic prediction tailored to the needs of automated vehicles.

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Cellular vehicle-to-everything communication, Infrastructure, Traffic prediction, Traffic control

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## Abstract

Intelligent road infrastructure consisting of sensors and communications is needed to deploy connected and automated vehicles (CAVs) on real highways. Such infrastructure can support the operation of CAVs (e.g., maneuver coordination and onboard energy management), and bridge the connectivity gap resulting from the currently low penetration of connected vehicles and the limited range of vehicle-to-vehicle communication. Moreover, it also allows us to build high-efficiency transportation systems, leading to societal benefits such as emission reduction, energy efficiency improvement, and productivity increase. In this project, we deploy cellular vehicle-to-everything (CV2X) infrastructure along the highway I-275, which consists of roadside units (RSUs), a server managed by the University of Michigan, and communications between them. The RSUs collect traffic information from the downstream vehicles on highway via a custom V2X communication message called traffic history message (THM). The received THMs are transferred via the RSUs' LTE Internet to the university server for real-time processing. The processed information is then sent to the upstream RSUs and broadcast to vehicles nearby via another custom V2X message called traffic prediction message (TPM). This allows the upstream vehicles to predict the traffic ahead and plan their motions accordingly. This way, traffic prediction and control can be achieved. We conduct experiments on highway I-275 using the installed RSUs and the designed messages with real vehicles. We demonstrate the effectiveness of the infrastructure-supported traffic prediction tailored to the needs of automated vehicles.

# 1. Introduction

During the last few decades there has been tremendous progress in road vehicle automation and the developed technologies led to significant improvements of vehicle safety and driver comfort. In the meantime, very little change occurred in the infrastructure supporting these vehicles. Not only the physical infrastructure was left essentially unchanged (that clearly requires large investments to maintain), but also very little cyber system infrastructure has been built that would support the connected and automated vehicles entering the transportation systems. This is in huge contrast to other large engineering systems like the power grid or air traffic systems. One reason for this lack of development is the lack of funding available from traditional funding sources like the gas tax. While many argue for the need of governmental support, there is a clear demand for a business model that allows sustainable transportation systems. One clear demand the vehicles have, in particular those with higher level of automation, is having real time data available about the status of the transportation system which allows them to plan their motion at different time and spatial scales.

To answer this challenge, we propose a scalable and sustainable model for deployment and operation of connected smart infrastructure (CSI) along highways that is capable of collecting traffic information in real time using cellular vehicle-to-everything (CV2X) communication. To demonstrate the functionalities of CSI, we utilize it to support the operation of heavy-duty vehicles that can gain day-one financial benefits from having additional infrastructure support. Since the primary goal of long-haul trucks is to ensure timely delivery of goods while consuming as little fuel as possible, and most trucking companies are already subscribing to different data services, they are likely to utilize new data sources that allow them to improve their fuel consumption and reduce their delivery time. Prior research shows that having information about the motion of vehicles ahead may benefit the fuel economy of trucks as it may allow them to have smoother motion that corresponds to lower energy consumption. Such traffic information may be obtained via vehicle-to-vehicle (V2V) connectivity for sufficiently large penetration of equipped vehicles and sufficiently long communication range. Adding vehicle-to-infrastructure (V2I) connectivity is beneficial to extend the range of communication and provide information about the motion of non-equipped vehicles.

The information collected via CV2X communication is then transmitted in real time to University of Michigan servers using 5G communication where the data is used for traffic forecasting. These forecasts are then sent back to the roadside units (via 5G) and sold to connected trucks (via CV2X). The purchased information will be used in the longitudinal control algorithms of the trucks and to select the lane they are driving at. The benefits in terms of fuel savings and travel time are expected to be significant when using level 2 automation that allows automatic control of the longitudinal speed while having manual steering. These trucks are also expected to have a positive impact on the traffic flow and the CSI will allow us to evaluate such impact by monitoring the traffic behind such a connected automated truck (CAT).

As highlighted in Fig. 1 we design and deploy a connected smart infrastructure (CSI) to provide real-time traffic predictions tailored to the needs of individual connected vehicles. The CSI makes traffic predictions using data collected at fixed locations by the roadside units as well as data collected from connected vehicles moving with the flow. We establish a unified modeling framework that allows us to incorporate both types of data in continuum traffic models. The longitudinal controllers of CATs can then be designed to allow them to respond to traffic perturbations efficiently. By estimating the energy benefits of an individual CAT based on the predicted traffic in front of the CAT, the CSI will be able to price the data dynamically. Moreover, the CSI can also be used to estimate the impact of CATs on the traffic flow and incentivize them to adjust their motion to smooth the flow. This improves the overall traffic efficiency and leads to societal benefits.

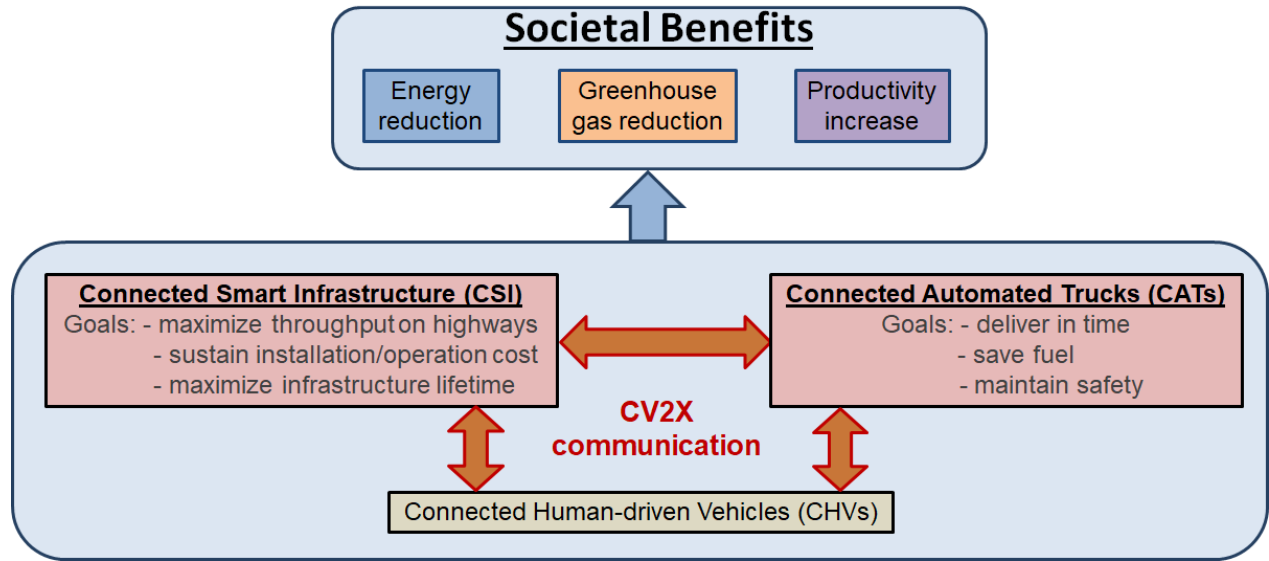


Figure 1. Information flow of the proposed system. Intelligent road infrastructure can support the deployment of connected automated vehicles, leading to transportation system-level benefits, including emission reduction, energy efficiency improvement, and productivity increase.

In this report, we document our preliminary results in deploying CV2X infrastructure along the highway I-275 in Southeast Michigan. This deployment bridges the connectivity gap resulting from the currently low penetration of connected vehicles and the limited range of vehicle-to-vehicle communication. The deployed CV2X infrastructure consists of roadside units (RSUs), a server managed by the University of Michigan, and communications between them. The RSUs collect traffic information from the downstream vehicles on highway via a custom V2X communication message called traffic history message (THM). The received THMs are transferred via the RSUs' LTE Internet to the university server for real-time processing. The processed information is then sent to the upstream RSUs and broadcast to vehicles nearby via another custom V2X message called traffic prediction message (TPM). This allows the upstream vehicles to predict the traffic ahead and plan their motions accordingly. This way, traffic prediction and control can be achieved. We conduct experiments on highway I-275 using the installed RSUs and the designed messages with real vehicles. We demonstrate the effectiveness of the infrastructure-supported traffic prediction tailored to the needs of automated vehicles.

The rest of this report is organized as follows. In section 2, we describe in detail how we bridge the connectivity gap using intelligent road infrastructure. In section 3, we showcase the deployment of the roadside units along a 4-mile-long corridor on highway I-275. In section 4, we present experimental results that validate the effectiveness of the deployed infrastructure in real-time traffic prediction and control. Finally, we summarize the outputs, outcomes, and impacts of this work in section 5.

## 2. Bridging connectivity gaps with infrastructure

In this section, we discuss how intelligent infrastructure can be used for bridging the connectivity gaps. Let us first lay down the basic principles for utilizing roadside units (RSUs) for traffic monitoring and prediction via vehicle-to-infrastructure (V2I) communication.

### 2.1 Traffic prediction using roadside units

In our proposed method, RSUs monitor the motion of vehicles that are equipped with V2X communication units, referred to as connected vehicles (CVs), while these are traveling in the RSUs' communication range. This provides high resolution velocity data along a few hundred meters long section of the highway that is not possible to obtain using cameras and loop detectors. We demonstrate below that even for low penetration of CVs this setup allows us to provide traffic forecasts for large spatial and temporal domains.

Consider the scenario in Fig. 2(a) where a string of vehicles is traveling on a highway, consisting of non-connected vehicles and connected vehicles, as indicated by gray and blue colors, respectively. Let us number the vehicles with an index  $n$  increasing upstream starting from a lead vehicle  $n=0$  highlighted by black. We seek to provide predictions about the future state of traffic at a certain location of interest (LoI) along the highway based on the motion of CVs ahead. For example, if we know that a CV is slowing down due to a traffic congestion downstream the LoI, then we may predict when and how much the traffic speed will decrease at the LoI due to the propagation of the congestion. Note that although we focus on prediction provided for a specific LoI, this location is arbitrary, and there could be a range of locations, or a section of road that receives the prediction.

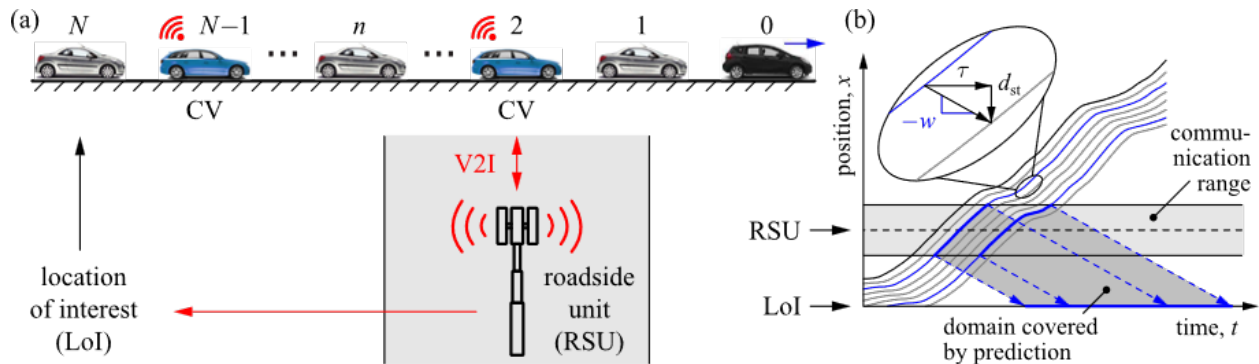


Figure 2. (a) Traffic flow consisting of non-connected (gray) and connected vehicles (blue), where a roadside unit provides traffic prediction for a location of interest. (b) Illustration of the vehicle trajectories, the RSU's communication range, and the region where traffic prediction is possible.

In order to achieve this goal, we propose to utilize roadside units as depicted in Fig. 2(a) whose communication range is highlighted by light gray shading. Such infrastructure is able to collect information about the motion of CVs and compute traffic forecasts from the available trajectories. To this end, consider the trajectories in Fig. 2(b) where the positions of the vehicles are depicted as a function of time. The trajectories of CVs are highlighted as blue with thick sections within the light gray shaded communication range of the RSU. These thick pieces of trajectories indicate the information that is available to the RSU about the motion of CVs. The motion of CVs affects the motion of other vehicles behind them over specific



time intervals such that the vehicles traveling farther behind are affected later in time. This is illustrated by the blue arrows and gray shading.

The information available to the RSUs (thick blue trajectories) enables traffic prediction in these specific domains of space and time (dark gray region). If one intends to predict traffic at a location of interest (here considered to be the horizontal axis  $x=0$ ), then predictions can be made during the time intervals where the dark gray shaded domain intersects the LoI; see thick blue section. Notice that there are time domains where multiple CV trajectories can be used for predictions despite the fact that a low CV penetration rate is illustrated in the figure. This is due to the fact that the RSU has a finite communication range.

## 2.2 CV2X communication network

So far, we see how the motion information from a downstream vehicle can be utilized by a single RSU to predict traffic for an upstream vehicle at a specific LoI. Let us now scale up such V2I communication to involve multiple RSUs and a server managed by the University of Michigan. This will enable traffic prediction and control over a larger distance scale.

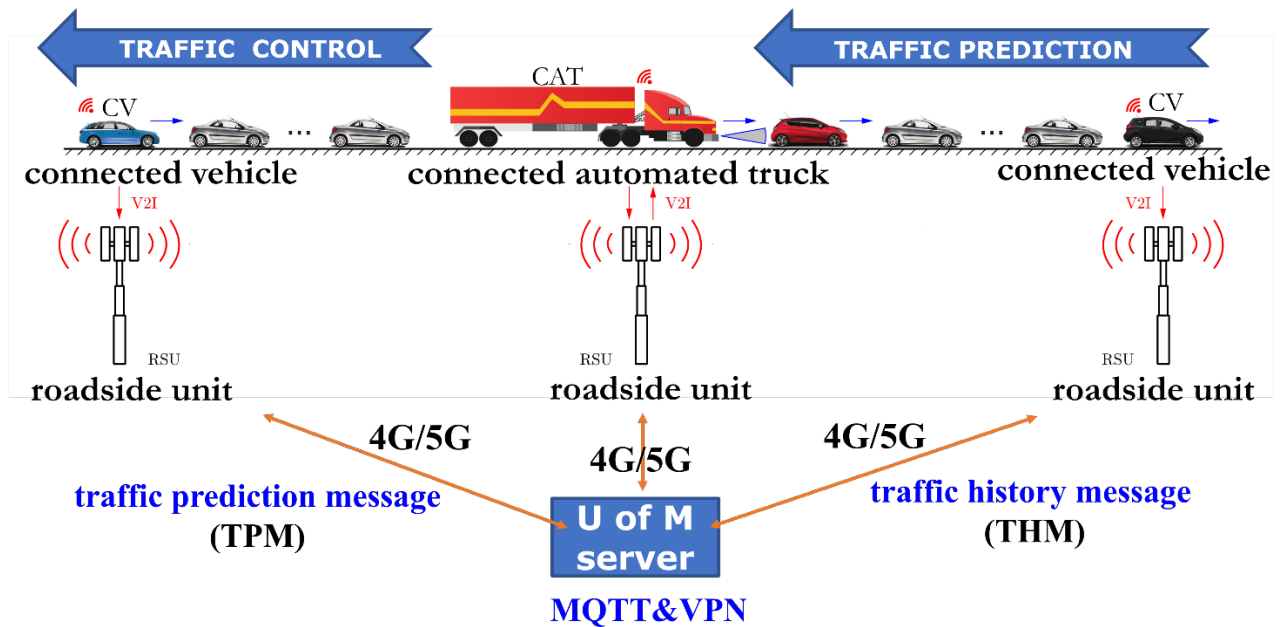


Figure 3. The communication network consisting of roadside units, university server, and the communications between them. The RSUs collect traffic information from the downstream connected vehicles on highway via a custom V2X communication message called traffic history message (THM).

The received THMs are transferred via the RSUs' LTE Internet to the university server for real-time processing. The processed information will then be sent to the upstream RSUs and broadcast to vehicles nearby via another custom V2X message called traffic prediction message (TPM). This allows the upstream vehicles to predict the traffic ahead and plan their motions accordingly. This way, traffic prediction and control can be achieved.

Fig. 3 shows an illustration of the designed communication system. Here, a downstream CV traveling on the highway collects its own historical motion information (over the past few minutes), which contains the vehicle's speed, position, and lane information with corresponding GPS time stamps. The collected

historical trajectory is then encoded into a custom V2X communication message which we refer to as traffic history message (THM). Once entering the communication range of an RSU, this downstream CV broadcasts the THMs periodically to the RSU. The received THMs are transferred via the RSU's LTE Internet to the university server for real-time processing. Such processing on the server side results in predicted speed trajectories corresponding to the positions of each upstream RSUs. The predicted trajectories are then encoded into another custom V2X message called traffic prediction message (TPM), which enables position-based traffic prediction. Still via Internet, the server sends these TPMs to the corresponding upstream RSUs which then, upon receiving the TPMs, broadcast them via V2X to upstream CVs nearby. Such information helps the upstream vehicles to predict the traffic ahead and plan their motions accordingly. This way, upstream vehicles (e.g., CATs) may improve their individual performance in terms of energy and time efficiency, and in the meantime also help smoothen the traffic flow behind them, leading to larger scale benefits on traffic efficiency.

Note that the transmission of THMs and TPMs between V2X devices (i.e., between the on-board units equipped on CVs and the RSUs) is realized using a V2X protocol called WSMP, which is a network layer messaging protocol allowing the transmission of messages with customized payload and packet sending rate. On the other hand, the transmission between RSUs and the server is realized via an IoT protocol called MQTT, which may be realized through 4G/5G Internet.

We use Fig. 4 to further explain the traffic prediction mechanism, that is, how a TPM is generated out of a THM. As indicated by the green curve, the THM of a downstream vehicle contains a time history of its motion trajectory, both in terms of speed and path (i.e., the traveled distance). Using such historical traffic information, traffic prediction for an upstream location can then be done by utilizing appropriate traffic models. For example, under Lighthill–Whitham–Richards (LWR) model (Lighthill and Whitham, 1955; Richards, 1956), which is one of the simplest continuum traffic models, the follower vehicles' trajectories can essentially be obtained by copying the lead vehicle's trajectory and then shifting it in time and space. Such space-time shift may be done for a specific upstream location using a quantity called wave speed, which indicates how fast the congestion waves propagate upstream along the highway. With a constant wave speed, an example of shifting historical trajectory encoded in THM is shown by the purple curve in Fig. 4, considering the RSU's position. This leads to a predicted trajectory based on the specific location of the upstream RSU. Note that the server calculates such predicted trajectory for all upstream RSUs (with their corresponding locations) in a centralized manner. The server then publishes the predicted trajectories to each RSU via Internet in the form of TPMs, which are broadcast to nearby CVs. Notice that the vehicles that receive such TPM must perform a second space-time shift to obtain the predicted trajectory based on its current position; see blue curve in Fig. 4.

We remark that while traffic predictions can be done by other, more sophisticated models as well (such as the ones in (Daganzo, 1994; Berg et al., 2000; Aw and Rascle, 2000; Zhang, 2002; Garavello and Piccoli, 2006; Jin, 2016)), the regions where traffic predictions are available in space and time are well-captured by the constant wave speed assumption. Moreover, as will be demonstrated later in experiments via real traffic data, such simple approach provides reasonably accurate traffic predictions.

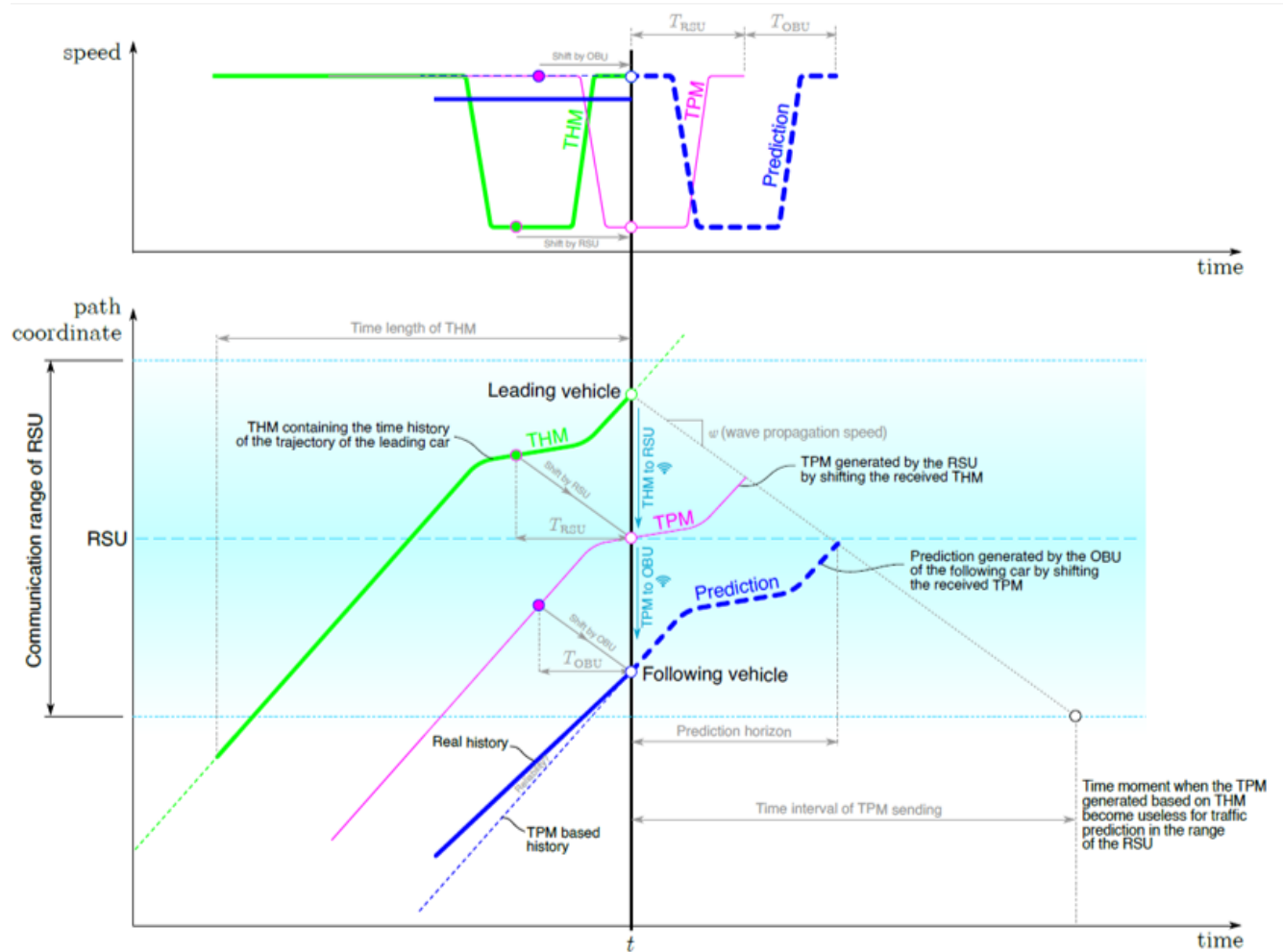


Figure 4. Traffic prediction mechanism based on traffic history information. The traffic history message (THM) of a downstream vehicle contains a time history of its trajectory (green curve) which, after a space-time shift using appropriate traffic models, leads to a predicted trajectory based on the position of the upstream RSU (purple line). This predicted trajectory is then encoded into the traffic prediction message (TPM) and broadcast to a nearby connected vehicle. The vehicle that receives such TPM will perform a second space-time shift to obtain the predicted trajectory based on its current position (blue curve.)

### 3. Deployment of C-V2X infrastructure

Having established the theoretical basis for infrastructure-enabled traffic prediction and designed the necessary communication network, in this section, we give details on the deployments of the C-V2X infrastructure on the highway I-275 in southeast Michigan.

The research team secured four CV2X on board units (OBUs) and four CV2X roadside units (RSUs) from Commsignia Inc; see Fig. 5. The OBU pack contains a Linux computer, a GPS antenna and a tablet that can show the location of nearby connected vehicles on a digital map. The devices are powered using a cigar lighter connector. These OBUs were utilized on the CVs to transmit/collect the above-mentioned wireless communication messages. The roadside unit also contains a Linux computer, a GPS antenna as well as 4G/5G LTE antennas, the latter allowing the device to connect to the internet (via an AT&T subscription). The team made significant efforts to configure the OBUs and RSUs such that they have the capability of transmitting/receiving custom wireless messages via both V2X ports and the Internet.

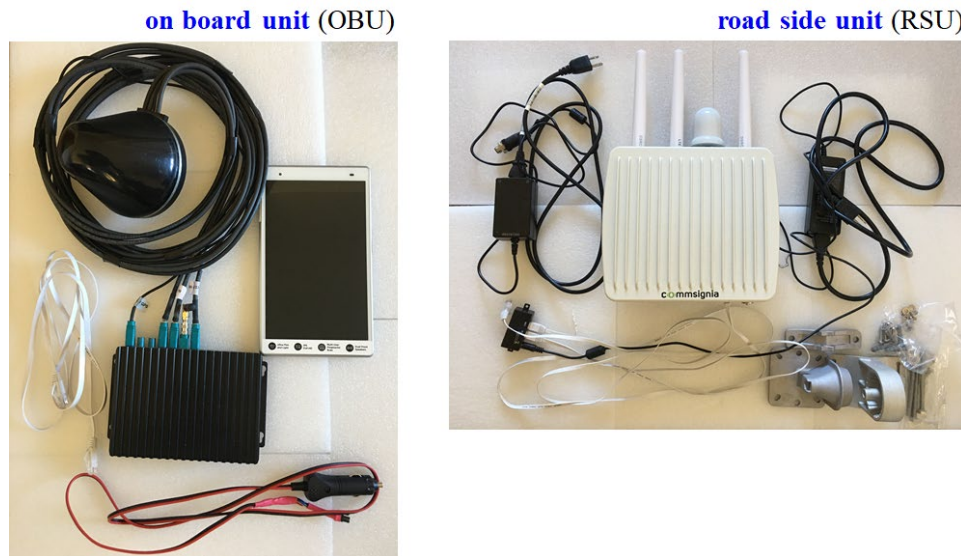


Figure 5: Left: on board unit (OBU) used in experiments; Right: roadside unit (RSU) deployed on I-275.

In collaboration with MDOT engineers the contractor DES electric, we installed four CV2X roadside units (RSUs) along the chosen section of highway I-275; see Fig. 6 right side. At the 5-mile Road location (shown in Fig. 6 left side) the RSU was powered using the 110V power supply available from the MDOT cabinet while internet connection was established with the help of an AT&T sim card installed in the RSU. At the 6-mile Road, 7-mile Road, and 8-mile Road locations (shown in Fig. 7), power was obtained via a power-ethernet, and internet connection was established using an AT&T sim card. Utilizing a local VPN network that was established at the University of Michigan, the team is able to communicate with the RSUs through the internet. This allows us to collect data and to deploy codes on the RSUs, which are necessary for the planned experiments. The RSUs after installation are shown in Fig. 7. This leads to a 4-mile-long corridor with infrastructure-enabled CV2X connectivity.



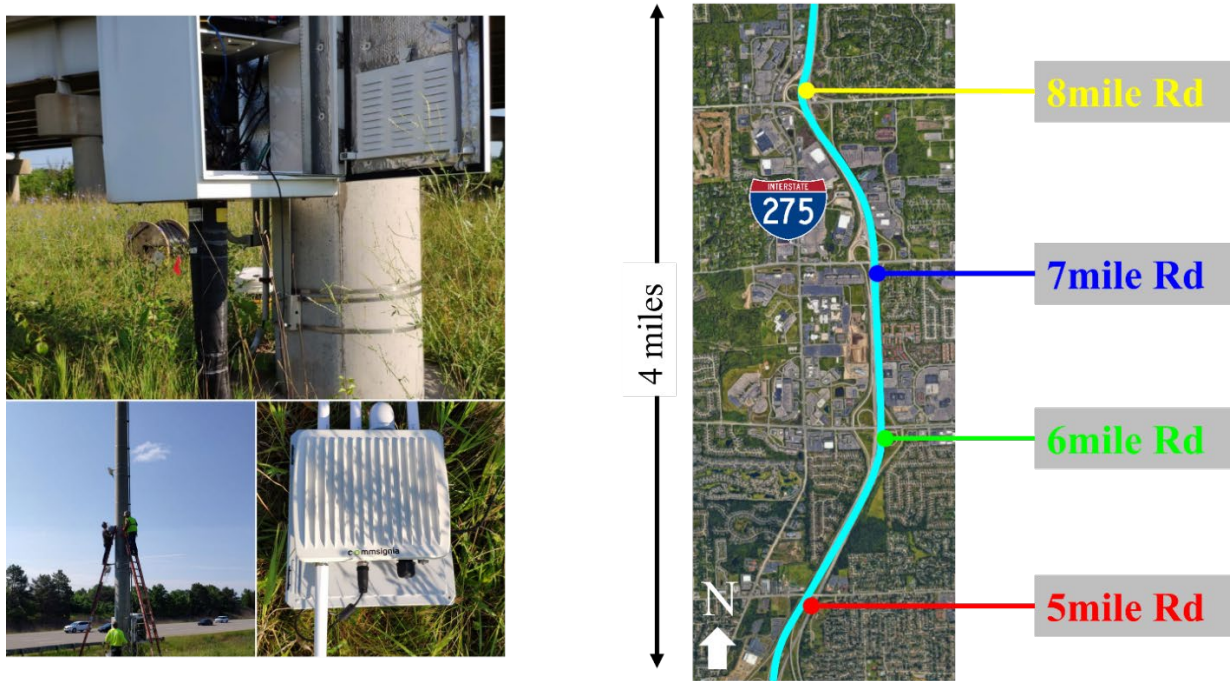


Figure 6. Bridging connectivity gap using C-V2X infrastructure. (a) roadside unit and the installation scene on highway I-275. (b) Positions of the RSUs deployed along the highway I-275 (at the intersections of Five, Six, Seven, and Eight Mile Roads, respectively, in southeast Michigan). This leads to a 4-mile-long corridor with V2X connectivity.

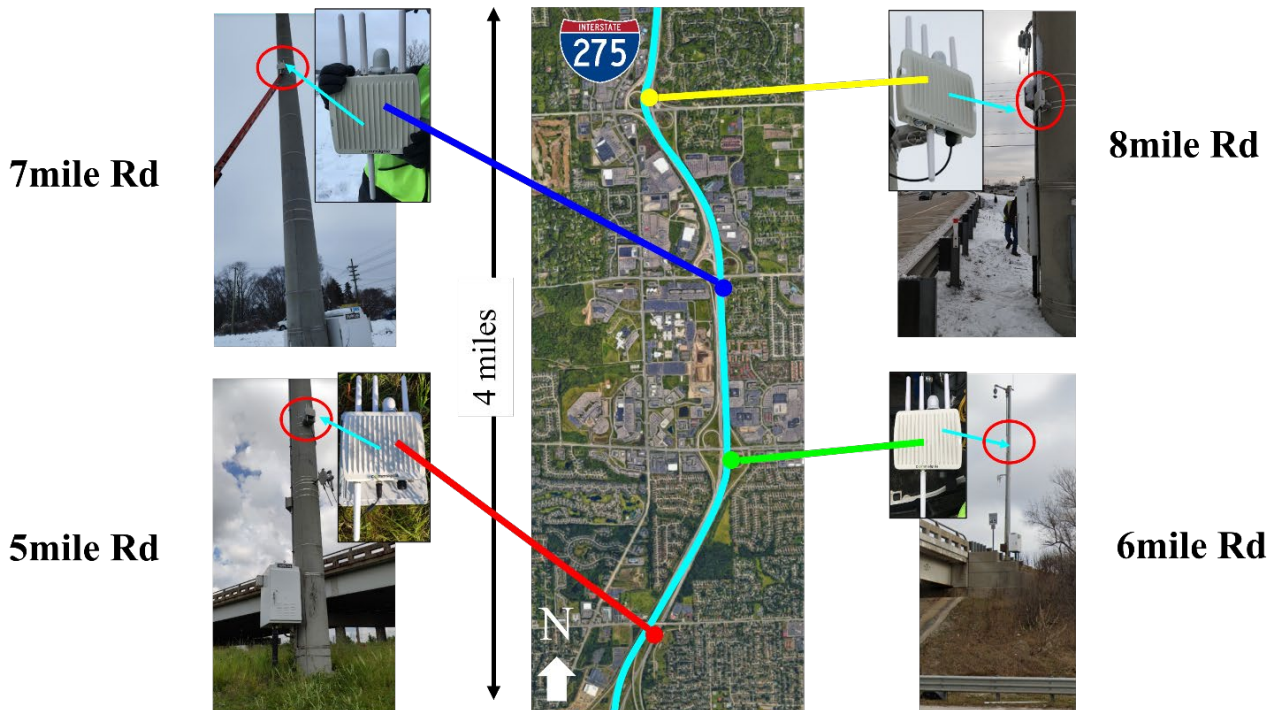


Figure 7. RSUs after installation on highway I-275 in southeast Michigan.

## 4. Experiments on highway I-275

After the deployment of the CV2X infrastructure, the team carried out extensive experiments with real vehicles equipped with CV2X on-board units (OBUs). We first tested the RSU-to-OBU communication by sending and receiving traditional basic safety messages (BSMs) as well as the new traffic history messages (THMs) and traffic prediction messages (TPMs) developed for this project. Then, we tested the whole CV2X communication network we built, i.e., downstream OBU → downstream RSU → Server → upstream RSU → upstream OBU. In this section, we present results of real vehicle-based experiments to demonstrate the benefits of the constructed CV2X communication system in traffic prediction and control.

### 4.1 Testing RSU-to-OBU communication

Fig. 8 illustrates the experimental setup which was used to test basic safety messages (BSMs). A vehicle, equipped with an OBU, was driven along the highway I-275 while sending BSMs. Both the North bound and the South bound parts of the highway were explored. When the vehicle was in the range of the RSU, the received BSMs were recorded by the RSU. This way we were able to evaluate the communication range of the RSU. We observed that the range was larger toward the Southern directions, which is likely due to the interference caused by the 5 mile Road bridge on the north side of the RSU. Multiple experiments were carried out and the obtained results were consistent with the one displayed in the figure.

#### Experimental setup 1

- Car  $\xrightarrow{\text{BSM}}$  RSU
- Green curve: GPS-based trajectory
- Green dots: position of vehicle when Basic Safety Messages (BSMs) were received by the RSU

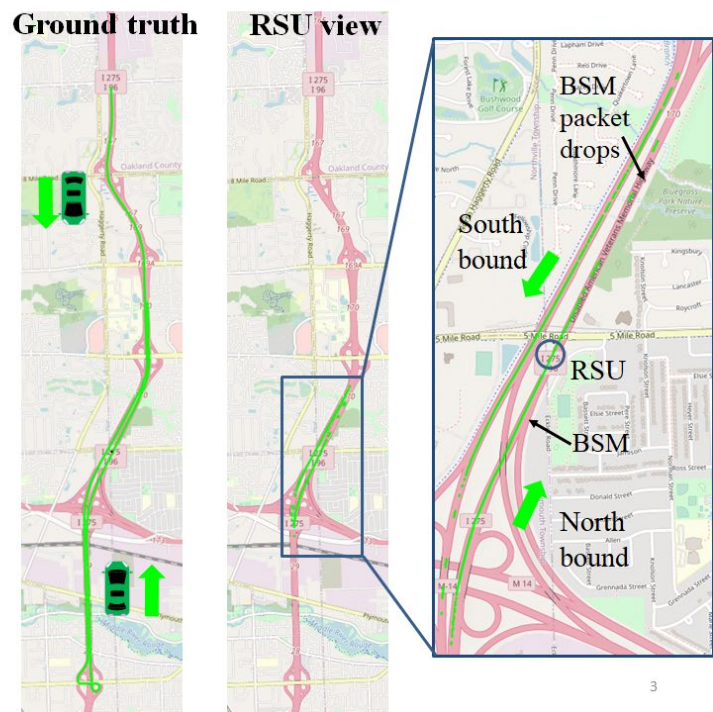


Figure 8: Experimental results on sending and receiving basic safety messages (BSMs).

In Fig. 9 the experimental results related to testing the newly established traffic history messages (THMs) are shown. The key idea is that vehicles equipped with OBUs can record their velocity history and share it with RSUs while they are in the communication range. Such information may become useful for other vehicles traveling upstream as they will eventually experience the same traffic conditions. The results indicate that the communication range for THMs is smaller, compared to BSMs, which is likely due to the increased packet size. Asymmetry, in term of the range toward the north vs toward the south, can also be observed for THMs similar to BSMs. Again, the results shown in the figure are similar to those obtained among multiple runs.

## Experimental setup 2

- Car  $\xrightarrow{\text{THM}}$  RSU
- Green curve: GPS-based trajectory
- Green markers: position of vehicle when Traffic History Messages (THMs) were received by the RSU

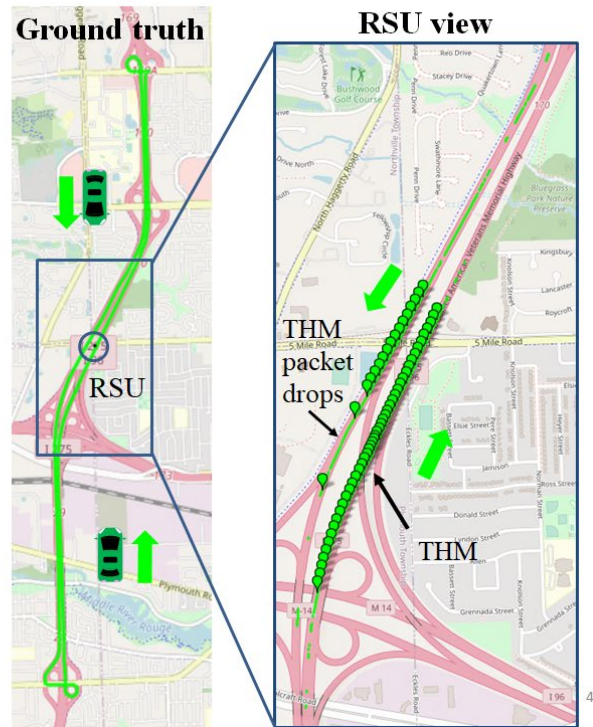


Figure 9: Experimental results on sending and receiving traffic history messages (THMs).

Fig. 10 shows the experimental results testing traffic history messages (THMs) and traffic prediction messages (TPMs) at the same time. After collecting THMs from bypassing (green) connected vehicle, the received information was processed by the RSU and it was broadcasted in the form of TPMs. The TPMs were received by another connected vehicle (blue), which travelled the same highway section a little later. In the receiving vehicle further processing was carried out in order to tailor the predictions to its location as TPMs are “anchored” at the location of the RSU. This procedure is illustrated at the bottom of the figure for one of the THM-TPM message pairs. Comparing the recorded trajectory of the blue vehicle with predictions demonstrates that high-accuracy predictions were generated. These experiments allowed us to demonstrate that even for lean penetration of connected vehicles, the infrastructure will enable traffic monitoring as well as real-time traffic prediction.



### Experimental setup 3

- Green car  $\xrightarrow{\text{THM}}$  RSU  $\xrightarrow{\text{TPM}}$  Blue car
- Curves: GPS-based trajectories
- Green markers: position of green car when Traffic History Messages (THMs) were received by the RSU
- Blue markers: position of blue car when Traffic Prediction Messages (TPMs) were received by the blue car

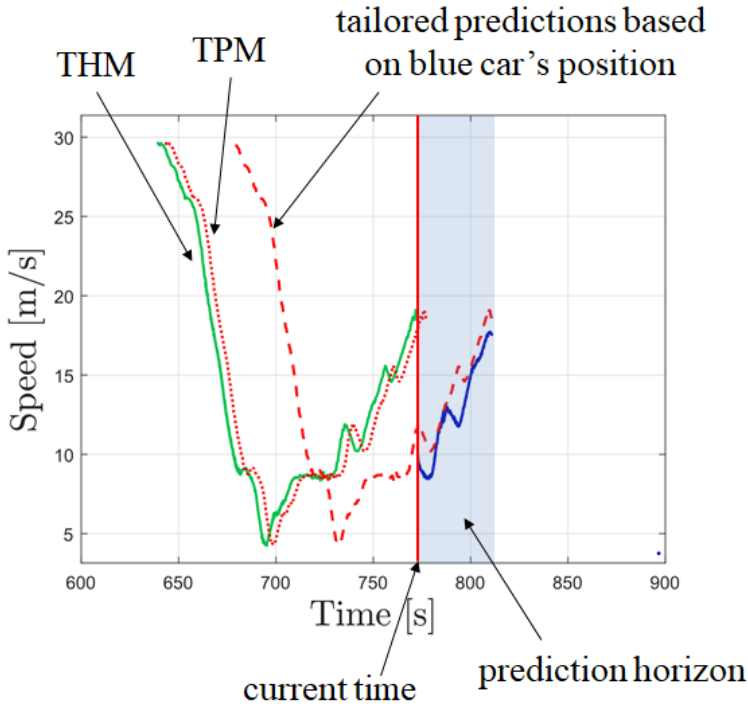
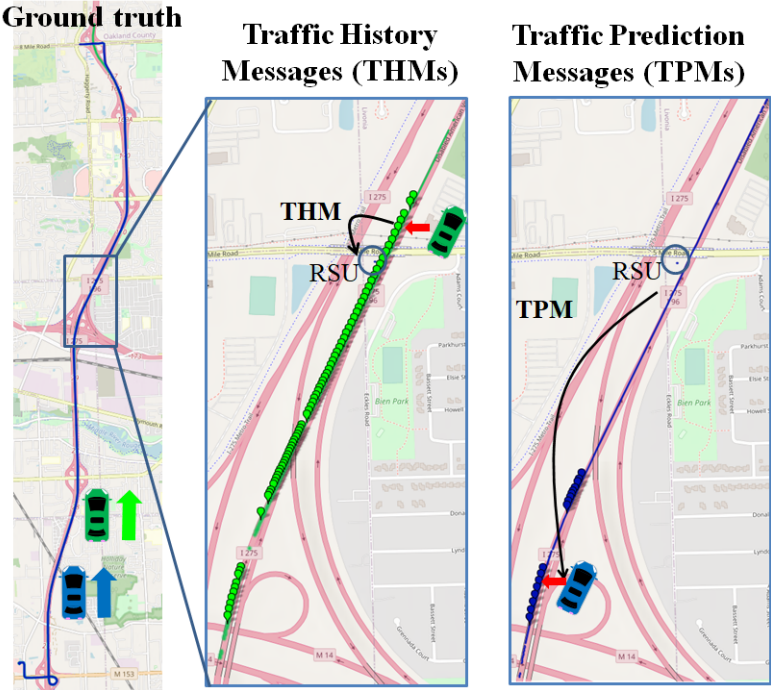


Figure 10: Experimental results on sending and receiving traffic history messages (THMs) and traffic prediction messages (TPMs). One of the THM-TPM message pairs is shown at the bottom panel.



## 4.2 Testing CV2X communication network for traffic prediction

So far, we have presented experimental results demonstrating the infrastructure-enabled traffic prediction where only a single RSU is involved. In what follows, we will show experimental results using the whole CV2X communication network, involving four RSUs and a server managed by the University of Michigan, along the 4-mile-long corridor on highway I-275.

Fig. 11 illustrates an example of our experiments on highway I-275, where a downstream connected vehicle 1 transmitted its THMs to the nearby RSU at 7-mile Road, and the RSU transferred such THMs to the Server in real time. The calculation for predicted trajectories was conducted on the server side for all upstream RSU positions (i.e., 6-mile Road and 5-mile Road), and the corresponding TPMs were generated and sent to the upstream RSUs. An upstream connected vehicle 2, within the communication range of the 5-mile Road RSU, captured such TPMs (broadcast from the corresponding RSU) and calculated its predicted future velocity trajectory. This way, the traffic information from a downstream vehicle more than 2 miles ahead was able to help the traffic prediction for an upstream vehicle. We emphasize that, without the help of CV2X infrastructure network that we constructed, this prediction is not achievable by using pure V2V with limited communication range and lean penetration of connected vehicles, nor is it realizable by using on-board sensors with limited perception range.



Figure 11: Experimental setup for testing CV2X infrastructure. Two connected vehicles equipped with OBUs, four RSUs, and a U of M server were used in the experiments.

Fig. 12 shows the experimental results when the two vehicles were traveling northbound I-275. Here, from the perspective of each RSUs, the distances between the vehicles and the RSUs at the indicated locations are plotted along time, from which the communication range can be observed. Note that here, the solid curves are obtained based on the GPS information from the default BSMs, while the circles and stars highlight the positions where the downstream vehicle sent THMs to the corresponding RSU and where the upstream vehicle received TPMs from the corresponding RSUs, respectively. The vertical dashed line at around 400 [s] highlights the scenario that a THM sent by the downstream vehicle 1 to the 7-mile Road RSU was processed by the server and used in real time for predicting trajectory for the upstream vehicle 2 when it was inside the communication range of 5-mile Road RSU.

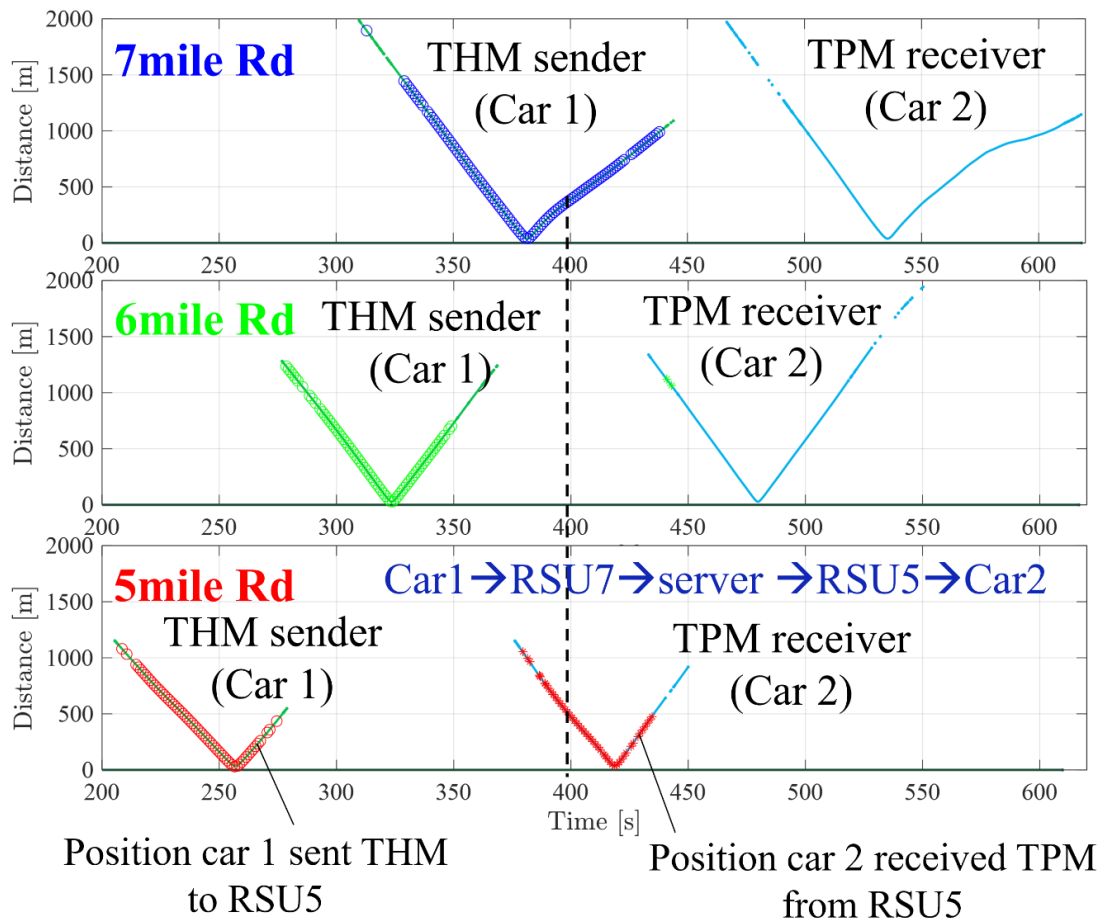


Figure 12: Experimental results showing the distance between the two vehicles and the RSUs at the indicated locations. Positions where the downstream vehicle sent THMs and the upstream vehicle received TPMs are highlighted.

Fig. 13 illustrates the traffic prediction for the specific scenario mentioned above. The blue curve shows the speed profile encoded in the THM of the downstream vehicle 1, which was sent to 7-mile Road RSU. On the server side, this speed trajectory was shifted ahead in time domain to obtain the TPM for 5-mile Road RSU, highlighted in red. The upstream vehicle that captured such TPM performed a second time shift to obtain the predicted speed trajectory (purple) based on its current position. This leads to a 2-minute-long prediction horizon into the future. The predicted speed trajectory indicates that a traffic jam is expected ahead with a sharp speed drop, and thus, the downstream vehicle shall be well-prepared and adjust its behavior accordingly in advance. The light blue curve highlights the actual speed profile of the upstream vehicle, where a significant speed decrease happened when encountering traffic congestion. We remark that such prediction is reasonably accurate considering the long prediction horizon, which is not achievable with only V2V communication and/or on-board sensors. On the other hand, the accuracy of prediction may be improved by utilizing more sophisticated traffic models in the calculation. This is left as future work. We emphasize that such prediction can be significantly useful for an automated vehicle/truck's motion planning and controller design, which contributes to less energy consumption and smoother traffic flow behind.

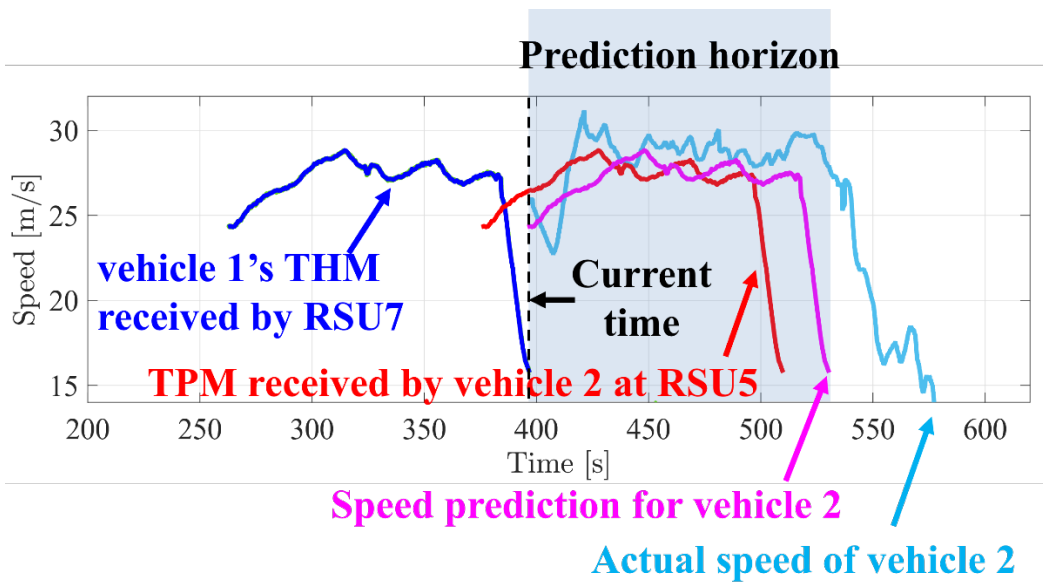


Figure 13: An example of real time traffic prediction during experiments. The speed profile (blue) contained in the THM of the downstream vehicle (near 7-mile Road RSU) was shifted ahead in time domain to obtain the TPM (for 5-mile Road RSU), highlighted in red. The upstream vehicle that captured such TPM performed a second time shift to obtain the predicted speed trajectory (purple) based on its current position. The light blue curve highlights the actual speed profile of the upstream vehicle.

## 5. Conclusions

In this project, we deployed cellular vehicle-to-everything (CV2X) infrastructure along the highway I-275. Such intelligent road infrastructure can support the operation of CAVs (e.g., maneuver coordination and onboard energy management), and bridge the connectivity gap resulting from the currently low penetration of connected vehicles and the limited range of vehicle-to-vehicle communication. Moreover, it also allows us to build high-efficiency transportation systems, leading to societal benefits such as emission reduction, energy efficiency improvement, and productivity increase. In particular, we designed a scalable communication network of CV2X infrastructure, which consists of roadside units (RSUs), a server managed by the University of Michigan, and communications between them. The RSUs collect traffic information from the downstream vehicles on highway via a custom V2X communication message called traffic history message (THM). The received THMs are transferred via the RSUs' LTE Internet to the university server for real-time processing. The processed information will then be sent to the upstream RSUs and broadcast to vehicles nearby via another custom V2X message called traffic prediction message (TPM). This allows the upstream vehicles to predict the traffic ahead and plan their motions accordingly. This way, traffic prediction and control can be achieved. The transmission of THMs and TPMs between V2X devices is realized using the V2X protocol WSMP, while the transmission between RSUs and server is realized via the IoT protocol MQTT. We conducted experiments on highway I-275 using the installed RSUs and the designed messages with real vehicles. We demonstrated the effectiveness of the infrastructure-supported traffic prediction tailored to the needs of automated vehicles.

## 6. Outputs, outcomes, and impacts

This project has resulted in a wide variety of outputs. The scientific results on traffic modeling and forecasting have been published in high impact factor journals such as Transportation Research Part C and IEEE Transactions on Intelligent Transportation Systems, while the results on vehicle control have been published in IEEE Transactions on Intelligent Vehicles. A list of papers, book chapters and presentations generated out of this project is summarized below. In particular, in articles [5, 6, 10, 13] we establish the fundamental principles of V2X-based traffic prediction, while in papers [2, 3, 9, 12, 15] we present methods that enable connected automated vehicles to utilize traffic information in their energy-efficient controllers. In the book chapter [7] we propose novel methods about how connectivity and automation can be used to mitigate traffic congestion and thus make a positive impact on the energy efficiency of the overall transportation system.

Based on these results, patents are expected to be generated in particular related to V2X-based traffic predictions and V2X-based controllers for automated vehicles. In order to disseminate the results to a broader audience the team also participated in the creation of the youtube video <https://www.youtube.com/watch?app=desktop&v=o1xgz8AO-54>. Moreover, while current V2X message sets, like the basic safety message, can be used when collecting data about the motion of V2X-equipped vehicles, new message sets have been developed in order to be able to send traffic forecasts to the connected trucks. We are planning to participate in SAE's standardization process in order to make the developed message sets available to industry. Finally, some of the results have been incorporated in the course ME599/CEE501/ISD599/ROB599 - Dynamics and Control of Connected Vehicles where multiple PIs serve as instructors.

### **A list of publications (including Journal papers, book chapters, and conference papers) generated from this project:**

1. S. Guo, G. Orosz, and T. G. Molnár.  
Connected cruise and traffic control for pairs of connected automated vehicles.  
*IEEE Transactions on Intelligent Transportation Systems*, published online, 2023.  
<https://doi.org/10.1109/TITS.2023.3285852>
2. M. Shen, R. A. Dollar, T. G. Molnár, C. R. He, A. Vahidi, and G. Orosz.  
Energy-efficient reactive and predictive connected cruise control.  
*IEEE Transactions on Intelligent Vehicles*, published online, 2023.  
<https://doi.org/10.1109/TIV.2023.3281763>
3. M. Shen, C. R. He, T. G. Molnár, A. H. Bell, and G. Orosz.  
Energy-efficient connected cruise control with lean penetration of connected vehicles.  
*IEEE Transactions on Intelligent Transportation Systems*, 24(4):4320-4332, 2023.  
<https://doi.org/10.1109/TITS.2022.3232105>

4. S. S. Avedisov, G. Bansal, and G. Orosz.  
Impacts of connected automated vehicles on freeway traffic patterns at different penetration levels.  
*IEEE Transactions on Intelligent Transportation Systems*, 23(5):4305-4318, 2022.  
<https://doi.org/10.1109/TITS.2020.3043323>
5. L. Jiang, T. G. Molnár, and G. Orosz.  
On the deployment of V2X roadside units for traffic prediction.  
*Transportation Research Part C*, 129:103238, 2021.  
<https://doi.org/10.1016/j.trc.2021.103238>
6. T. G. Molnár, D. Upadhyay, M. Hopka, M. Van Nieuwstadt, and G. Orosz.  
Delayed Lagrangian continuum models for on-board traffic prediction.  
*Transportation Research Part C*, 123:102991, 2021.  
<https://doi.org/10.1016/j.trc.2021.102991>
7. T. G. Molnár, M. Hopka, D. Upadhyay, M. Van Nieuwstadt, and G. Orosz.  
Virtual rings on highways: traffic control by connected automated vehicles.  
*AI Enabled Technologies for Autonomous and Connected Vehicles*, Lecture Notes in Intelligent Transportation and Infrastructure,  
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8. D. Assanis, A. C. Mersky, J. Han, T. Langer, J. Lidicker, R. Mihelic, G. Orosz, and M. Sofos.  
Automated Vehicle Fuel Efficiency Town Hall  
*Road Vehicle Automation 9*, Lecture Notes in Mobility,  
G. Meyer and S. Beiker, eds., Springer, 53-70, 2023.  
[https://doi.org/10.1007/978-3-031-11112-9\\_6](https://doi.org/10.1007/978-3-031-11112-9_6)
9. M. Shen and G. Orosz.  
Data-driven predictive connected cruise control.  
*Proceedings of the IEEE Intelligent Vehicles Symposium*, IEEE, 2023.  
<https://doi.org/10.1109/IV55152.2023.10186677>
10. T. G. Molnár, X. A. Ji, S. Oh, D. Takács, M. Hopka, D. Upadhyay, M. Van Nieuwstadt, and G. Orosz.  
On-board traffic prediction for connected vehicles with Kalman filter,  
*Proceedings of the American Control Conference*, 1036-1041, IEEE, 2022.  
<https://doi.org/10.23919/ACC53348.2022.9867497>

11. X. A. Ji, T. G. Molnár, A. A. Gorodetsky, and G. Orosz.  
Bayesian inference for time delay systems with application to connected automated vehicles.  
*Proceedings of the 24th IEEE International Conference on Intelligent Transportation Systems*,  
3259-3264, IEEE, 2021.  
<https://doi.org/10.1109/ITSC48978.2021.9564457>
  
12. M. Shen, C. R. He, A. H. Bell, and G. Orosz.  
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13. S. Wong, L. Jiang, R. Walters, T. G. Molnár, G. Orosz, and R. Yu.  
Traffic forecasting using vehicle-to-vehicle communication.  
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14. M. Shen, T. G. Molnár, C. R. He, A. H. Bell, M. Hunkler, D. Oppermann, R. Zukouski, J. Yan, and  
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Saving energy with delayed information in connected vehicle system.  
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15. R. A. Dollar, T. G. Molnár, A. Vahidi, and G. Orosz.  
MPC-based connected cruise control with multiple human predecessors.  
*Proceedings of the American Control Conference*, 404-410, IEEE, 2021.  
<https://doi.org/10.23919/ACC50511.2021.9483272>
  
16. T. G. Molnár, D. Upadhyay, M. Hopka, M. Van Nieuwstadt, and G. Orosz.  
Open and closed loop traffic control by connected automated vehicles.  
*Proceedings of the 58th IEEE Conference on Decision and Control*, 239-244, IEEE, 2020.  
<https://doi.org/10.1109/CDC42340.2020.9304471>



**Below is a list of presentations generated in this project.**

*Deploying CV2X infrastructure on highway I-275*

Automobili-D, North American International Auto Show, Detroit, Michigan, 13-24 Sep 2023

*Connected and automated vehicles: improving safety and efficiency across the scales - Keynote Talk*

18th International Conference on Intelligent Autonomous Systems (IAS18), Suwon, South Korea, 7 Jul 2023

*Connected and automated vehicles: improving safety and efficiency across the scales*

University of Michigan - Shanghai Jiao Tong University Joint Institute, 30 Jun 2023

*Connected and automated vehicles: improving safety and efficiency across the scales - H. S. Tsien International Distinguished Scientists Lecture*

The State Key Laboratory for Management and Control of Complex Systems  
Chinese Academy of Sciences, Beijing, 28 Jun 2023

*How connectivity can help the safety and efficiency of automated vehicles*

Department of Robotics and Mechatronics Engineering Seminar, Daegu Gyeongbuk Institute of Science & Technology (DGIST), 9 Aug 2022

*How connectivity can help the safety and efficiency of automated vehicles*

Department of Applied Mechanics Seminars, Budapest University of Technology, 6 May 2022

*How connectivity can help the safety and efficiency of automated vehicles*

Department of Automotive Engineering Seminars, Clemson University, 26 Apr 2022

*From adaptive cruise control to connected cruise control*

Traffic Flow Committee - ACC Webinar Series, 28 Jan 2022

*Infrastructure assisted automated driving on highways*

Automated Road Transportation Symposium, 12-15 Jul 2021

*Connectivity assisted automated driving among human-driven vehicles*

IEEE Intelligent Vehicles Workshop on Cooperative Driving in Mixed Traffic, 11-12 Jul 2021

*Deploying cellular vehicle-to-everything infrastructure on highway I-275*  
Center for Connected and Automated Transportation Research Review  
University of Michigan, 17 November 2020

*Controlling traffic with connected automated vehicles*  
Next Generation Transportation Systems Seminars  
University of Michigan, 19 March 2020

The outputs mentioned above are expected to turn into outcomes in longer time scale. The material published in the papers enhanced our understanding on traffic data collection, traffic modeling and control. In particular, the concept of V2X-based traffic prediction has been established. This is different from the existing approach used by traditional data providers that is based on collecting data from large samples of road users and presenting the aggregated data on maps. The traditional approach produces predictions on large spatial and temporal scales often with minutes of delays involved. Instead, our new approach focuses on real time predictions that are tailored to the needs of individual vehicles. Such on-demand predictions can be very beneficial for connected automated vehicles (including CATs) when planning and controlling their motion in traffic. The patents and standards generated will allow the scientific ideas to penetrate engineering practice and this transition is expected to be accelerated by industrial collaborators on the project. Finally, the education activities are expected to produce a new generation of engineers who are equipped with the skill sets required by the industry pursuing connected and automated transportation.

The societal impacts of the outputs are huge. Class-8 vehicles are responsible for approximately 60% of the fuel consumption of all trucks in the United States. This means that saving fuel for these road giants have a large impact on the energy consumption of the nation. Burning less fuel also positively impacts the greenhouse gas emission significantly which has a positive effect on the environment. Moreover, appropriately controlled CATs expected to mitigate traffic congestion by smoothing the flow which can positively impact the travel time of all vehicles leading to increased productivity. Each year approximately \$160 billion is spent on congestion in the US. Once CSI is widely spread, we expect this cost to be reduced by 10-20%. Finally, the knowledge transferred in the education activities are expected to have a long-term impact on the society regarding the view of sustainable transportation systems.

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