Deliver Signal Phase and Timing (SPAT) for Energy Optimization of Vehicle Cohort Via Cloud-Computing and LTE Communications

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Abstract

Predictive Signal Phase and Timing (SPAT) message set is one fundamental building block for vehicle-to-infrastructure (V2I) applications such as Eco-Approach and Departure (EAD) at traffic signal controlled urban intersections. Among the two complementary communication methods namely short-range sidelink (PC5) and long-range cellular radio link (Uu), this paper documents the work with long-range link: the complete data chain includes connecting to the traffic signals via existing backhaul communication network, collecting the raw signal phase state data, predicting the signal state changes and delivering the SPAT data via a geofenced service to requests over HTTP protocols. An Application Programming Interface (API) library is developed to support various cellular data transmission reduction and latency improvement techniques. An emulation-based algorithm is applied to predict the traffic signal state changes to provide adequate prediction horizon (e.g., at minimum 2 minutes) for the cohort energy optimization. In fact, the same connectivity and SPAT delivery methodology has been applied to traffic signalized intersections nationwide in the United States upon public agency approvals for access to their firewalled traffic control network and signal control systems or directly to individual controllers. This methodology proves its effectiveness and potential for rapid growth of such SPAT deliveries at mass production scale without needing infrastructure hardware retrofit or excessive communication means. To support the energy optimization of light and heavy-duty vehicle cohorts of mixed automation and propulsion systems (EV, ICE and hybrid), the connection and SPAT deliveries at two sites were completed, including public roads in Washtenaw County, Michigan and closed track test sites at American Center for Mobility (ACM) in Ypsilanti, Michigan. However, only closed test track results at ACM will be presented in this paper. A neuroevolution based optimizer is developed and implemented to control the speed of a vehicle cohort with different propulsion systems and automation levels. Closed track tests were presented and showed significant energy savings of the cohort operation.

Introduction

Connected Vehicle applications including Eco-Approach and Departure (EAD) requires Signal Phase and Timing (SPAT) messages. EAD refers to a set of safety- or mobility-focused use cases, such as Red Light Violation Warning, Green Light Optimized Speed Advisory (GLOSA), eco-traffic signal timing and extension to vehicle cohort as coordinated platooning. Coupled with MAP [16] messages, SPAT message supplies EAD applications with data frames and elements including traffic signal controller operational information such as preemption, current signal phase states of green-amber-red and future timings of when the signal state will switch to next. In general, the signal phase states are mandatory, while future timings such as time to change are optional. It is well noted that mandatory frames and elements may be sufficient for safety related applications, while optional, future timings are necessary to support applications, for example, GLOSA for both human drivers and onboard computer systems to execute powertrain automations.

In literature and reported practices, two primary approaches exist to deliver SPAT messages to vehicles: field broadcast from roadside unit via Dedicated Short-Range Communication (DSRC) or C-V2X channels [17], or infra-red [11], and public cellular network via internet protocols from a backend cloud or edge-computing services. Field broadcast would require retrofit of existing traffic signal controls for installation and maintenance; this efforts would be costly: an earlier benefit-cost analysis projected $27.3 billion to upgrade both freeway and urban intersections in US alone [18]. Such huge investment and expected long span of time contributed to the vicious cycle of ‘chicken-egg’ problem stalling connected vehicle service adoption in the auto industry, particularly Vehicle-to-Infrastructure (V2I) applications. Roadside unit (RSU) deployment has been the government and industry push, such as the SPAT Challenge [19] and test tracks and pilot zones set up by different municipalities across the globe [1]. While seeing increased growth rates in some countries [1], such deployment pace is not satisfying the auto OEM’s desire for mass production. In the autonomous driving sector as represented by Waymo robotaxi and Tesla vehicles, the individual vehicle relies solely on the onboard sensors mainly of cameras to capture traffic signal head positions, analyze its current color and make corresponding continue-driving or stop decisions [10]. Some research explored smart phone apps to both capturing traffic signal state changes and estimating their timing parameters by switching time pattern analysis [13]. Understanding some traffic signals only run pre-timed time-of-day plans, a few studies have applied probe vehicle data mining techniques to derive the timing plans and resulting SPATs [7, 8].

The second approach of cellular network delivery via internet protocols involves collecting traffic signal control data by either tapping into existing signal management systems or directly communicating with traffic signal controllers via standard or proprietary protocols, building the SPAT messages and relaying via 4G/LTE to target vehicles by Uu channels or mobile phone applications [9]. Originating from pioneering work like 'Travolution' project by Audi AG [3, 18], the authors of this report have developed a platform to deploy SPAT delivery mechanism via long range communication and demonstrated as a viable path towards mass market production [4, 16]. This approach is enabled by three main technology advances: standardized traffic signal control with widely available existing backhaul communication, continuous cellular network improvement of enlarged bandwidth and reduced latencies, and cloud/edge computing capabilities. The authors surveyed over two thousand road operators in US and Canada, finding over 55% of field traffic signals have backhaul communications allowing traffic engineers to remotely manage and monitor the operations. Already connecting to some of those networked traffic signals, one computing clusters in US is hosting the SPAT generation of over 60,000 signalized intersections (www.traffictechservices.com), and new such clusters are deployed in Europe and China connecting to traffic signals locally for commercial services. Evidencing the cellular communication capability for SPAT deliveries, a recent empirical study has shown that the end-to-end communications can reach 40ms as median value and maximum at 68 ms [14]. It is also worth noting that automotive engineers have been considering in-vehicle applications to be compatible in receiving data from either means. For example, Ford China has enabled their production vehicles to receive SPAT and MAP messages either from the Uu or PC5 port, while the in-vehicle applications would remain the same [9].

In this paper, the authors describe the data flow from traffic signal infrastructure data access to SPAT delivery into vehicle cohort for energy consumption optimization, and the intermediary steps and enhanced SPAT characteristics to reach the needed service levels. Various message delivery methods over internet protocol are described with the focus on the Application Programming Interface (API) one used in this study. The field study was conducted in both a closed test track and open roads in the Detroit, Michigan region; in this paper only the results from the closed test track at ACM are presented The neural network optimizer-based cohort speed planning output is implemented into a cohort of mixed automation levels and powertrain types; its energy saving benefits are documented. This paper is concluded with such SPAT delivery methods working for the demonstrated cohort powertrain automation functions and proving its potential of significant energy savings when introduced to mass market.

Methodology and Application in Detroit Michigan Region

The generation and delivery of SPAT for cohort energy optimization workflow is depicted in the following chart (Figure 1). As this workflow goes across multiple interfaces from traffic signal control, cloud or edge computing services and then to the vehicle cohort, time delays and performance is a challenge in this setup. It is important to synchronize the clocks of the system and create time stamps so the receiver can determine the delays due to the network, and subsequently compensate for any transmission latency. We must also note that while for many metro areas fiber optics are available in their central intelligent transportation system (ITS) communications including traffic signal control cabinets, other communications are also common such as radio-based systems or Wi-Fi broadbands or cellular modems.

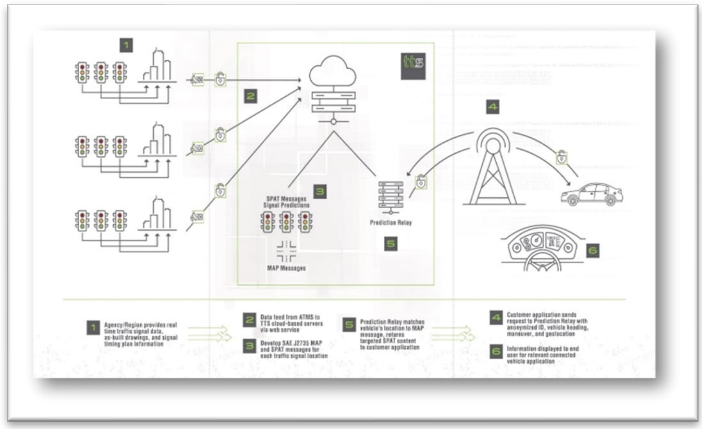

Figure 1. Generation and delivery of SPAT to support vehicle cohort energy optimization.

Connection to Traffic Signals for Raw Data Collection

Connecting to traffic signal control infrastructure is the first step in the SPAT generation workflow (Figure 1). The once-a-second data polling queries the following data at a minimum from either the signal controller directly or tied to the traffic signal control management system at the agency traffic management center (TMC):

- current signal timing plan,
- cycle second (if running on a coordination plan),
- phase call or detection call (pedestrian, bicycle, vehicle and/or transit), and
- emergency vehicle or railroad preemption status.

These data are used to feed into the SPAT data generator system. In this study, both direct polling and management system connections are used for two sites, respectively.

Direct Polling of Traffic Signals at American Center for Mobility (ACM) Test Track

ACM is the study facility for closed track real world testing of the cohort energy optimization algorithms. At its Smart Mobility Test Center, a 2.3 mile (3.7 km) multi-lane highway loop is equipped with two traffic signal controllers. An on-prem application developed by the study team polls the signal state (red, yellow, green) data every second for all phases from these two controllers. This polling is enabled by the standard communication protocols NTCIP1202 [2] supported by the two controllers. Relevant data objects are encoded and transmitted to the SPAT generator through ACM network firewalls.

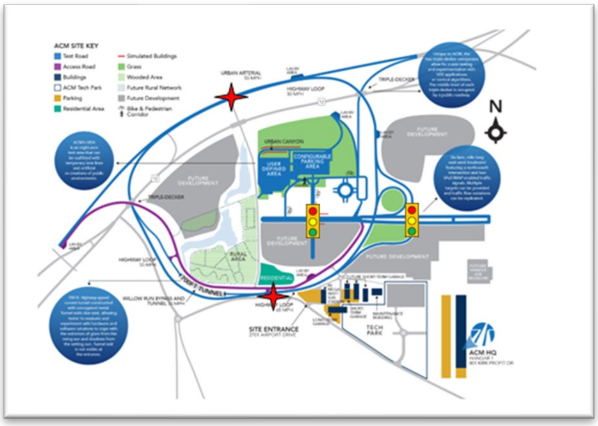

Figure 2. American Center for Mobility (ACM) test track layout (https://www.acmwillowrun.org/smart-mobility-test-center/); the traffic signal head icons indicating the two controllers that enable direct polling of signal state by NTCIP1202 protocol. The star icons represent virtual signals for lab tests.

The study team developed a virtual signal technique to support lab environment development efforts. By choosing a site where usually less traffic is present such as at a stop sign or a parking lot junction, the team set up a virtual signal on their backend to resemble the real-world operations such as various signal phasing combinations and protected-permissive sequences for in-vehicle application tests. In this study, two such virtual signals were set up on the test track, as depicted by star icons in Figure 2, with varying signal cycle lengths to mimic driving along high-speed corridors encountering traffic signals of different wait times.

Central Connection to Advanced Traffic Management System (ATMS) for All Networked Signals at Washtenaw County

To support a real-world environment with traffic flow and congestion, an existing deployment from the study team was used in nearby Washtenaw County, MI. The study team utilizes a software module added to the existing traffic control management system at the Traffic Management Center (TMC). This software module is built using an API developed by the study team that collects, encodes, and transmits traffic signal data to the SPAT generator. This system has also supported other individual powertrain studies in the region [6].

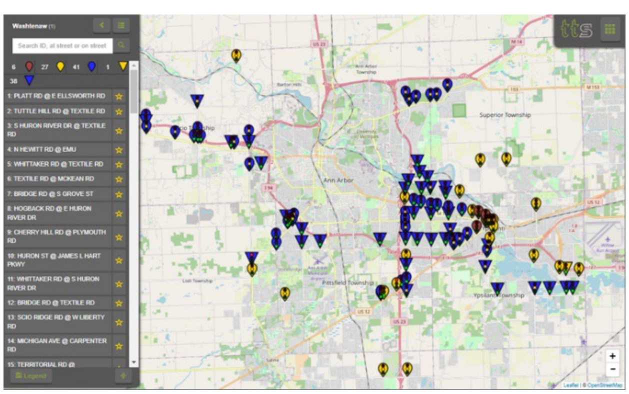

Figure 3. Washtenaw County, MI real-world deployment. Each icon is representing a signalized intersection on the SPAT generation and delivery system.

Prediction of Signal State Changes

SPAT data generation (2 in Figure 1) is located at the center of the overall SPAT delivery system. SPAT generator conforms to an industry standard, SAE J2735 [15], producing SPAT messages with emphasis on the optional data elements, i.e., the next signal switch times of *likelyTime* and associated *confidence* in the *TimeChangeDetails* data frame. These are the key data elements to support in-vehicle applications. Generating such data elements becomes an essential task, particularly for actuated or adaptive traffic signal control. Different methodologies were reported and validated [5, 21], which share architectural common features, such as analysis of historical and current traffic conditions including vehicle and pedestrian or cyclist actuations, priority routines and emergency vehicle or railroad preemption states. In this study, we adopt a patented [5] method to emulate the operations of traffic signal controllers (Figure 4).

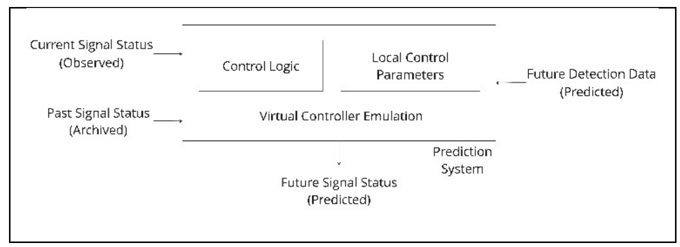

Figure 4. Emulation-based signal state change prediction conceptual flow [5].

The emulation-based prediction system has its core replicating both control logic as well as the localized parameters included in a timing plan. Feeding it with the same input, the program will react similarly to the field controllers and generate the outputs. These outputs will include signal group state changes, which are translated into SPAT messages. With predicted detection input, the prediction system can fast-forward the emulation and thus generate future state changes. These future state changes become the estimation of the *LikelyTime* as part of SPAT. This system has been adopted and deployed in different countries for powering various V2X applications [4].

One important aspect of the SPAT messages must be illustrated to show its impact upon the service stability, that is the predicted signal switch times (*likelyTime*) will need to be sufficiently long for the EAD applications. This attribute can be characterized as a prediction horizon, as illustrated in Figure 5. If the provided *likelyTime* is outside the reach of the travel from the current vehicle position to the stop line under speed limit, then the application will have no way to plan its speed trajectories. On the contrary, if the prediction horizon is provided sufficiently long, some typical applications can be conveniently introduced and integrated together to achieve both mobility and energy saving goals as well as safety benefits. By this emulation approach, the prediction horizon is introduced by fast-forwarding the process to more traffic signal cycles, fed by the forecasted traffic patterns. A minimum horizon of two signal cycles or two primary signal switches (red-green, green-amber-red) is stipulated in the designed system, whichever may come later. For example, if a signal cycle length is 60 seconds, then multiple switches will be introduced as stacked in the SPAT as future *likelyTime* arrays.

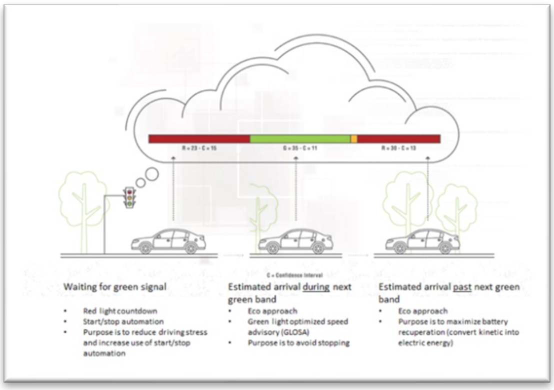

Figure 5. An array of predicted *likelyTime*, spans the Prediction Horizon. Its sufficiently long forecasts enable various EAD applications to reach their speed trajectory planning goals.

Delivery of SPAT via Internet Protocols

After the predictions are generated, they are packaged together with signal state and other controller operation status information and formatted into SPAT messages [15]. By providing various webservices in the cloud, any vehicle or mobile device that is connected to the internet through a cellular network has the potential to receive these SPAT messages. These webservices provide the following core functions:

- map-match the vehicle or mobile device to the target intersection and approach
- receive customized service requests and respond with only data of interest, and
- maintain security and service integrity, while reducing the risk of malicious attacks or misuse of the system

A REST webservice (https://en.wikipedia.org/wiki/Representational_state_transfer), dubbed *Prediction Relay*, has been designed and developed to fulfill such requirements. Its *geo-referenced predictions* web method provides enhanced map-matching to anonymized GPS data (latitude, longitude, heading), and then combines the current SPAT with the corresponding MAP data. A *targeted prediction* method is also included in this webservice, which bypasses the map-matching to fetch the latest SPAT from a particular target (as specified by an intersection ID and approach). Various methods have been incorporated into this Application Programming Interface (API) library to support payload reduction so as to achieve minimal cellular data rates and lowered transmission latency.

One important such technique is using a method called *targeted predictions*. When the response from a *geo-referenced prediction* request includes the target (as specified by an intersection ID and approach) of its last match, the targeted prediction will then allow the users only to specify the same information to get the select SPAT components for only the intersection and approach of interest.

The following two example requests showcase the geo-fenced and targeted prediction requests. For demonstration purposes, actual domain name, IP addresses and port numbers are omitted.

https://DOMAIN:port/APhA/Services/GeoReferencedPredictions?sessionCode=*&latitude=42.248365&longitude=-83.647604&heading=0...

https://DOMAIN:port/APhA/Services/TargetedPredictions?sessionCode=*&targetRegion=Washtenaw%20County&targetSCNr=9036&targetApproach=903603...

As the first request will map-match to the same intersection in Washtenaw County as targeted by the second, the *Prediction Relay* service responses will filter data to include the same relevant phases, that is, the northbound through phase 8 and left turn phase 3. Figure 6a shows the example signal location and partial MAP and SPAT (Phase 3 and 8) visualization on the SPAT generation system. Main body of the API response is shown for the request time indicated in the response (Figure 6b).

(a) (b)

Figure 6. SPAT generation and delivery via Prediction Relay API web service, example signal location Washtenaw Avenue and N Hewitt Rd in Washtenaw County. (a) SPAT generation system on the cloud backend; (b) main body of the Prediction Relay API response from both geofencing and targeted prediction requests are the same.

Application & Demonstration in Energy Optimization for Vehicle Cohort

Application Setup

The Gen II Chevrolet Volt and Gen I Chevrolet Bolt were used in the cohort testing of this investigation and were outfitted with a drive-by-wire system. The Connected and Automated vehicle cohort is formed around SAE Level 2 vehicles enabling Adaptive Cruise Control (ACC), Lane Keep Assist (LKA) and Lane Centering Assist (LCA). The signalized intersections SPAT messages are only communicated to the cohort's lead vehicle. The processing unit of each vehicle is comprised of a dSpace MicroAutoBox II (MAB II) which is a real-time system for performing in vehicle rapid control prototyping. For the purposes of this investigation the MAB II serves as an I/O microcontroller to interface with the cloud compute platform housing the neuroevolution controller and real-time vehicle cohort simulation. The MAB II receives vehicle CAN, GPS and drive-by-wire data and sends to the cloud and receives prediction horizon speed profiles with approximate 200 ms communication loop time for automated longitudinal driving. The lead vehicle in the cohort receives the optimized speed control while the follower vehicles are continuously receiving speed profile changes to achieve a constant gap target determined from GPS positioning. Each test vehicle utilized OEM proprietary CAN data for energy consumption calculations as well as vehicle and propulsion system dynamic tracking. Single antenna GPS units were utilized on the Volts, while a dual GPS and IMU were used on the Bolt. The MAB II speed controller and the drive-by-wire system interface via the vehicle CAN channels and various instruments are shown in Figure 7.

The Neuroevolved controller developed in MATLAB Simulink was compiled to C code and uploaded to the MAB II. The stochastic-based development of the Neuroevolved controller was performed over thousands of use cases which enables it to be integrated and readily usable without additional tuning. The Neuroevolution process allows the controller to adapt to any variations of its inputs from the vehicle system, including delays due to latency, allowing for a seamless transfer learning from simulation to its hardware application. The neurocontroller is trained over a large set of scenarios where speed, vehicle distances, traffic timing and cohort length are varied dynamically. The process enables the neurocontroller to infer the impact of any dynamic variations over its global objective function and therefore enable real time adaptive behavior, where changing boundary conditions will trigger a new behavior. This process improves the robustness of the controller from variation that may emanate from the communication or sensor systems latency, just as it handles the planned and unplanned environmental variations that forms the real-world test operation domain.

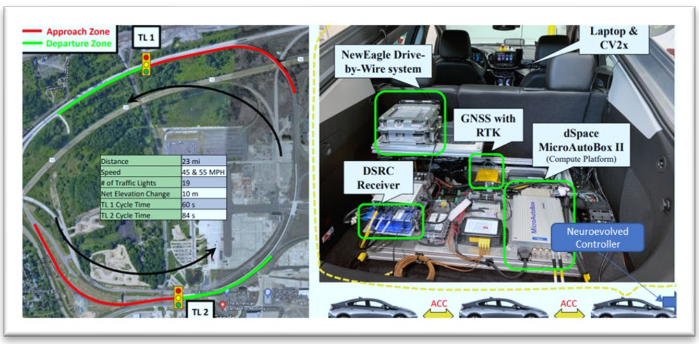

Figure 7. Neuroevolution controller integration into the cohort vehicles and ACM closed track test.

The SAE Level 2 Automated Cruise Control (ACC) capability enables the follower vehicle to stay at a safe distance from each other while the lead vehicle follows the optimum cohort speed target based on the SPAT inputs, received from the cellular network. In doing so, the Neuroevolved controller achieves a "Green Wave" through the traffic network which is designed to minimize the overall cohort energy usage. In doing so, the Neuroevolution process considers the cohort's dynamic length variation as the lead vehicle target speed change and the follower ACC systems adjust to a safe distance (Figure 8).

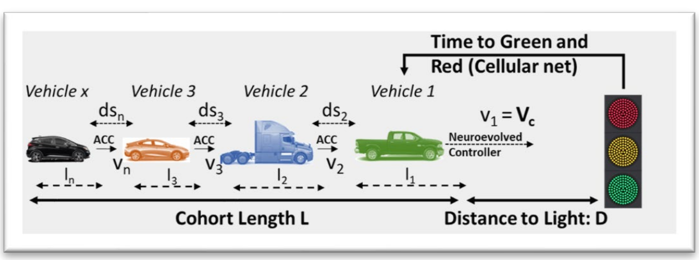

Figure 8. Light and heavy-duty vehicle cohort characteristics.

The simulation-based training of the controller through the stochastic process considers the following inputs, which abstract the CAV cohort into one entity – and maintain its integrity across the traffic network:

- Dynamic Cohort Length
- Time to green
- Time to red
- Minimum possible acceleration of the cohort (bounded by the lowest performance vehicle)
- A fix "comfortable deceleration" factor
- Current road speed limit

It is to be noted that the target velocity of the lead vehicle does not overwrite the ACC safety limitation. The Neuroevolved controller adapts accordingly when the cohort is not able to achieve the targeted speed for some reason such as safety. To achieve this optimal and adaptive behavior, the training involved the use of an agent-based simulation model as described in [12] which allowed for a wide array of scenario and variations to learn upon (Figure 9 as example).

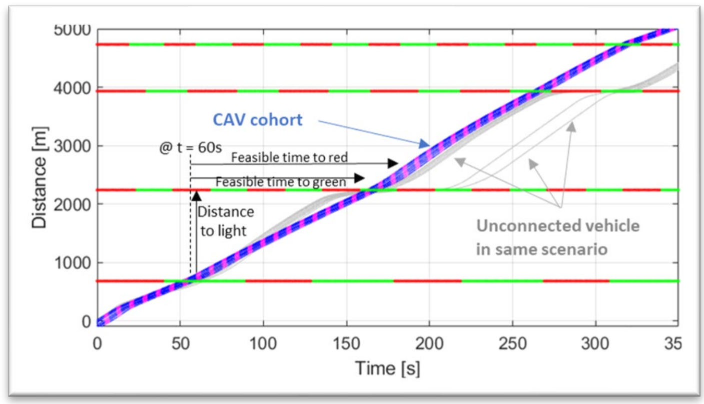

Figure 9. Example successful scenario with an eight-vehicles cohort (L is around 200m).

Test Results

Results from closed loop track testing are summarized Table 1 and the corresponding vehicle dynamics of baseline and optimized testing are shown in Figures 10 and 11. The tests were performed at the American Center for Mobility (ACM). Two virtual traffic lights were set up along the highway loop. Different cohorts were tested, changing vehicle order and type. The energy baseline for each scenario was human drivers behaving as normal driving, while the optimized scenarios were conducted with the automated longitudinal driving control enabled and governed by the speed profile generated by neuroevolution controller. In all the test scenarios presented, the Bolt was always running is charge depletion (CD) mode as the Bolt is a BEV, while the Volts were run in charge sustaining (CS) mode so that the impact on battery and fuel energy could be gleaned from an abbreviated matrix of test scenarios. With the Volts running in CS mode, battery SOC at the start and end of testing were not always equal. To compensate total propulsion system energy consumption at the end of the test, the delta SOC in the battery was converted to kWh, then made equivalent to fuel energy using the EPA specified 33.7 kWh/gallon of gasoline equivalency and then converted to gasoline energy consumption with an LHV of 41.28 MJ/kg.

Table 1 summary results for three test scenarios shows energy savings ranging for 7 to 22% and minimal savings of transit time. With the PHEV Volt operating in CS mode and leading the cohort, a 22% reduction in energy consumption was achieved. With the BEV Bolt leading, energy savings were in the low 7% range. It can be noted that higher cohort energy savings is realized with the PHEV in CS mode leading vs. following is related to the sufficiency of cloud based ACC gap control of follower vehicles. Due to latency in the vehicle to cloud communication loop and latency in the vehicle drive-by-wire systems to commanded speed profile, the cloud based ACC gap control was less than idea in these initial test results, reducing the energy consumption benefit for the two follower vehicles in the cohort. Unnecessary accelerations and decelerations were noted for the follower vehicles leading to suboptimal energy consumption, whereas the lead vehicle's neuroevolution controlled speed profile is very smooth, producing near optimal energy consumption relative to traffic infrastructure. Obviously with fuel energy at nearly a 3X premium than battery, anytime there are unnecessary vehicle dynamics for the follower vehicles involving an ICE torque fluctuation will compound and lead to increased energy consumption. However, even with a non-ideal performing cloud ACC controller, reduced energy consumption was still realized. The non-ideal behavior of the cloud ACC control will be mitigated with the refinements of the current drive-by-wire system autonomous stack and an enhanced tuning to the vehicle following algorithm running in parallel with the neuroevolution controller. Another set of tests are being conducted to overlay the archived MAP and SPAT data from five signals on Plymouth Rd at Washtenaw County, which coincides in the length to the ACM test track.

Table 1. Individual and cohort level energy and time saving during close loop track testing at ACM using random traffic light phasing and timing.

	Speed Limit (mph)	Total Distance (km)	3 Vehicles Cohort	Energy Saved %	Cohort Energy Saved %	Travel Time Saved %
Test 1	45	6.70	Volt PHEV	29%	22.0%	0.4%
		6.70	Bolt	20%		
		6.72	Volt PHEV	16%		
Test 2	45	6.65	Bolt	16%	7.4	1.2%
		6.67	Volt PHEV	12%		
		6.70	Volt PHEV	0%		
Test 3	45	6.65	Bolt	16%	7.3	0.5%
		6.67	Volt PHEV	7%		
		6.69	Volt PHEV	4%		

The comparison of the human driven baseline scenario and optimized automated testing of a three vehicle cohort traversing a three traffic light 6.7 km track are shown in Figures 10 (Test 1) and 11 (Test 2). In Figure 10, the baseline scenario, the cohort is stopped by all three traffic lights (top) while in the optimized scenario, the connectivity and neuroevolution optimization slows the cohort before each traffic light, but maintains highest possible speed. As discussed previously, the non-optimal cloud ACC results in excessive dynamics, particularly for the second follower vehicle, in this case the Volt in CS mode, causing a noticeable increase in cumulative energy consumption relative to the leader-follower in the baseline scenario. However, the net cohort energy savings was 22%.

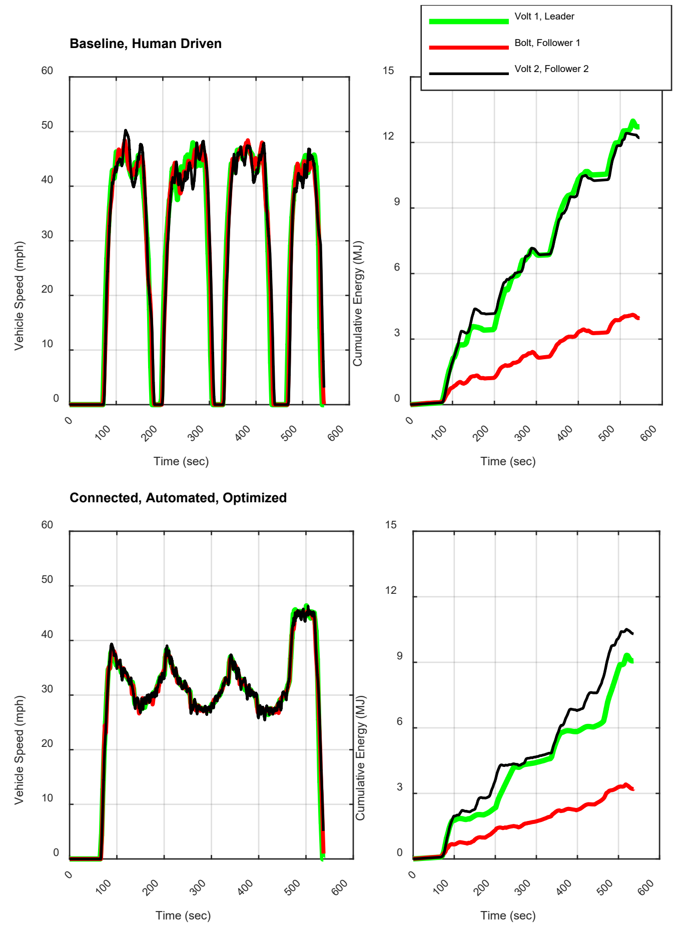

Figure 10. Test 1, 45 mph, Volt in CS mode leading cohort, with Bolt and Volt in CS mode following, with baseline, human-driven control (top) vs. connected, automated, optimized control (bottom).

For test 2, see Figure 11, the baseline scenario was two traffic light stops and one slow down and zero stops for the connected and optimized scenario. A moderate energy reduction is noted for the first follower Volt in CS mode, but a near zero cumulative energy savings for the second follower Volt in CS mode. An overall energy savings for the cohort was still realized of 7.4%.

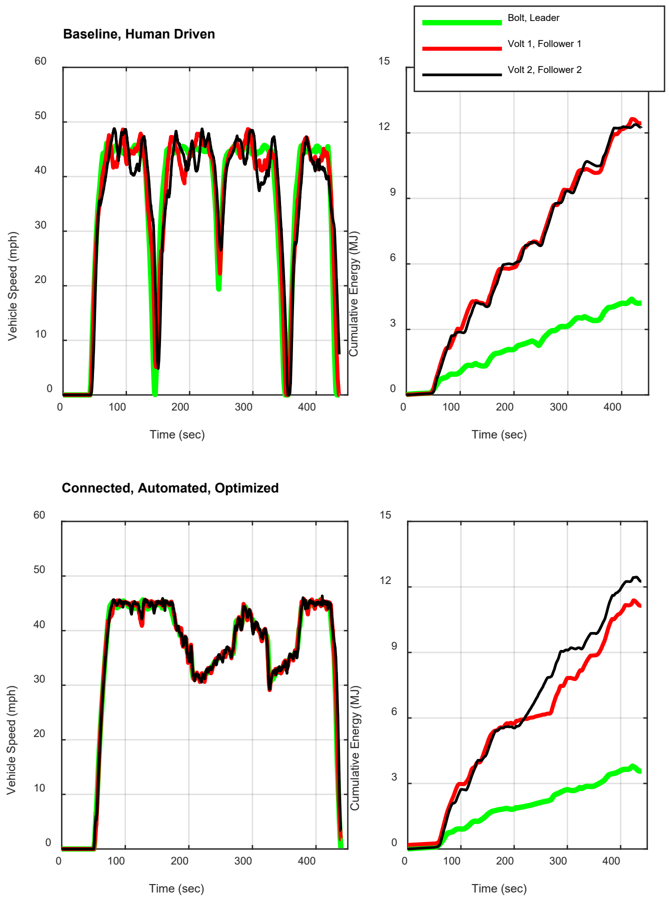

Figure 11. Test 2, 45 mph, Bolt leading cohort, two Volts following in CS mode, with baseline, human-driven control (top) vs. connected, automated, optimized control (bottom).

Conclusions

This paper first documents the group efforts of representing infrastructure owners, traffic signal control and management technology vendors and the study team themselves as information service providers to generate and deliver SPAT over cloud-computing platform and 4G/LTE cellular network for connected vehicle applications. The second part describes the development of a neurovolution based vehicle speed controller implemented to a vehicle cohort of various automation levels and powertrain types and tests at a close track, with the delivered SPAT messages as one sensory input to the neural network. The test results not only showcased the significant energy saving potentials of the entire experimental system, but also provide evidence that such SPAT information service provisions can be rapidly expanded to mass market deployment with existing ITS infrastructure and current cellular network technology. Note that the telecommunications industry is evolving the 5G and edge computing stacks that could further improve the reliability and reduce the latency of SPAT generation and transmission; with the delivery method described in this paper, such SPAT generation and delivery would enable both safety and mobility use cases. The study in this direction is beyond the scope of this paper and future research is needed.

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Definitions/Abbreviations

ACM	American Center for Mobility
BEV	Battery Electric Vehicle
CD	Charge Depletion mode
CS	Charge Sustaining mode
DSRC	Dedicated Short-Range Communication
V2I	vehicle-to-Infrastructure
C-V2X	cellular vehicle-to-everything
EAD	Eco-Approach and Departure
EV	electric vehicle
GLOSA	Green Light Optimized Speed Advisory
ICE	internal combustion engine
ITS	Intelligent Transportation System
LTE	Long Term Evolution
MPH	miles per hour
PHEV	plug-in hybrid electric vehicles
PI	Application Programming Interface
SoS	system of systems
SPAT	Predictive Signal Phase and Timing
TSP	Transit Signal Priority