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Evaluating the Environmental Impacts of Connected and Automated Vehicles: Potential Shortcomings of a Binned-Based Emissions Model

David Oswald, George Scora, Nigel Williams, Peng Hao, *Member, IEEE,* Matthew Barth, *Fellow, IEEE*

Abstract— **In addition to providing safety and mobility benefits, Connected and Automated Vehicles (CAVs) have the potential to reduce fuel consumption and emissions. As new CAV applications are developed, it is valuable to estimate these potential environmental benefits, typically using vehicle activity data and emissions models. To date, most researchers in the U.S. have used the MOVES vehicle emissions model, developed and maintained by the U.S. Environmental Protection Agency (EPA). However, because MOVES uses a binning approach, it is likely underestimating the true energy and emissions savings that occur when CAV applications smooth traffic flow. To illustrate this problem, we measure and model the fuel consumption and CO_2 emissions for a real-world CAV application: Eco-Approach and Departure (EAD) at signalized intersections. Real-world measurements are compared to a MOVES-based estimate, as well as to an estimate provided by the physical-based Comprehensive Modal Emissions Model (CMEM). Results show that MOVES consistently underestimates the energy and emissions benefits of the CAV application, primarily since the bin sizes in MOVES are too large to catch the nuances of traffic smoothing. On the other hand, CMEM provided a more accurate energy and emissions estimate, primarily since it uses analytical functions to model emissions and does not suffer from the same binning problem.**

I. INTRODUCTION

Connected and Automated Vehicle (CAV) technology has become a high area of interest in both academia and industry [1]. In addition to safety and mobility benefits, CAV technology can play an important role in reducing fuel consumption and emissions, particularly greenhouse gas (GHG) emissions. Transportation accounts for a large percentage of GHG emissions worldwide, and any intelligent vehicle technology that reduces these emissions should be deployed as part of the overall strategy to mitigate climate change.

Many emerging CAV applications are targeted to help reduce traffic congestion and associated high rates of fuel consumption and emissions. As these CAV applications are deployed, it is difficult to measure the energy and emissions of every vehicle in a given area of deployment. As a result, vehicle activity data are typically used together with energy and emission models to obtain estimates of fuel consumption and tailpipe emissions under different traffic scenarios [2].

Some energy and emission models only require average traveling speed to give estimates, and as a result, are insensitive to fuel consumption and emissions caused by a wide range of accelerations/decelerations. Other models use vehicle specific power (VSP) and speed to estimate energy and emissions, allowing for greater sensitivity to these speed deviations. These models typically require second-by-second vehicle activity inputs (e.g., a 1 Hz speed trajectory) [3]. Further, some other energy and emission models use analytical equations representing the physics of emissions process; these models usually require a good deal of calibration, but they typically provide higher accuracy [4].

The primary goal of this paper is to compare different energy and emissions modeling approaches for analyzing connected and automated vehicles. Actual energy and emissions are measured on a set of vehicles, which are then later compared to the U.S. Environmental Protection Agency's MOVES model and also to the Comprehensive Modal Emissions Model (CMEM). These measurements and model predictions are shown for the Eco-Approach and Departure (EAD) application, where two vehicles are compared: one that has the EAD technology and one that does not. In this paper, we first provide a brief background on the two energy and emission models, as well as the EAD application. The experimental methodology is then described, followed by the results and conclusions.

II. BACKGROUND

A. *Motor Vehicles Emission Simulator*

The EPA developed the Motor Vehicles Emission Simulator (MOVES) energy and emissions model originally in the year 2000 and has periodically updated it ever since. MOVES is used for a variety of applications, including a number of regulatory processes (see https://www.epa.gov/moves for details). MOVES can operate as either a macroscopic or microscopic model, depending on how it is used. MOVES is very data intensive, requiring estimates of vehicle activity, energy and emissions rates, and a number of other inputs. MOVES can assess the emissions of all vehicles on a road segment, based on aggregated data. The model represents the relationship between vehicle characteristics, operating conditions and the emission/fuel consumption rates from large datasets collected in both the

D. Oswald, G. Scora, N. Williams, P. Hao, and M. Barth are with the Center for Environmental Research and Technology, University of California, Riverside, CA, USA (e-mail: roswa001@ucr.edu, {gscora, nwilliams, haop, barth}@cert.ucr.edu

laboratory and on the road using on-board portable emissions measurement systems. [2].

MOVES categorizes all vehicles into source types and estimates the emission rates of the vehicles in one source type under specific operation mode (opmode). Consequently, when an individual vehicle is evaluated with MOVES, the average behavior of all vehicles of the same source type is given. Therefore, when evaluating the emission and fuel consumption of one specific vehicle, MOVES is not able to distinguish this vehicle from the average vehicle of the same source type [2]. It also uses a binning technique for its operation modes, using bins that generated for different levels of vehicle specific power (VSP) and average speed.

For MOVES, the user defines vehicle types, speed data, traffic activities, geographical areas, pollutants, vehicle operating attributes, and meteorology parameters as the inputs of the model; then the model provides estimates of total emission inventories or emission factors [2, 5].

B. Comprehensive Modal Emissions Model

The Comprehensive Modal Emission Model (CMEM) is a microscopic, physical emissions model that estimates the emissions of individual vehicles [6]. CMEM was developed to capture the physical relationships between vehicle characteristics, operating conditions, and the emission/fuel consumption rates [2]. One prominent advantage of this approach is that it is possible tailor many of the physical parameters to fit a very specific type of vehicle (i.e., down to make and model) [6].

Both MOVES and CMEM takes the attributes of an individual vehicle, and its second-by-second speed profile as input, and predicts second-by-second fuel consumption and tailpipe emissions of carbon monoxide (CO), carbon dioxide (CO_2), hydrocarbons (HC), and oxides of nitrogen (NOx). Like MOVES, CMEM can predict energy and emissions from individual vehicles and an entire fleet of vehicles [6].

C. Eco-Approach and Departure Application

Eco-Approach and Departure (EAD) is a CAV application that can be used for smoothing traffic flow along a signalized corridor. For this application, the signalized intersections are typically equipped with a Roadside Unit (RSU) which broadcasts Signal Phase and Timing (SPaT) messages and MAP messages via Dedicated Short-Range Communication (DSRC). These messages are then received by equipped vehicles that have an On-Board Unit (OBU), as shown in Fig. 1. The SPaT and MAP messages, together with the vehicle's position and speed (provided by GPS), are then used to calculate optimal speed trajectories as the vehicle approaches, travels through, and departs from the intersection. The driver can then follow these speed trajectories to pass through an intersection on a green light or to stop in an eco-friendly style.

Over the years, the authors have conducted a number of simulations and field studies of EAD at signalized intersections. Table 1 presents the results of the field tests with EAD technology. In Table 1, scenario 1 means the tests were performed with a single vehicle, and scenario 2 means that the tests were performed in mixed traffic. As the key component of Applications for the Environment: Real-Time Information Synthesis (AERIS) Research Program, Xia et al. [7] tested an EAD application on an intersection with pre-timed signal and no traffic. The measured fuel consumption and CO_2 emissions indicated that the EAD application had an average savings of 14%.

Altan et al. [8] tested a partially automated version of the EAD application, called the GlidePath Prototype, at Turner-Fairbank Highway Research Center in McLean, Virginia. The tests were done on a closed-traffic intersection. The GlidePath Prototype showed an average fuel consumption savings of 17%.

Hao et al. [9] performed tests using an EAD application developed for actuated signals. The tests were done in real-world traffic on the El Camino Real corridor in Palo Alto, California. The corridor is equipped with eight DSRC enabled intersections. The tests showed a 6% energy savings in segments within DSRC range.

D. Relevant Work

In 2002, Cappiello et al. [10] presented a statistical emissions model called EMIT (EMIssions from Traffic), where CMEM and EMIT were compared to measured data. For fuel consumption rate, CMEM had a -2.2% error, while EMIT had a 5.3% error. However, the data used by Cappiello et al. came from the same database that was used to develop CMEM, so the results are somewhat biased.

TABLE I CE-CERT FIELD STUDIES

Technology	Location	Scenario	Communication	Energy Savings	Ref
EAD with Fixed Signals	Richmond, CA	1	4G/ LTE	14%	[7]
	Riverside, CA	1	DSRC	11%-28%	[10]
	McLean, VA	1	DSRC	2.5%-18%	[10]
EAD with Actuated Signals	Riverside, CA	1	DSRC	5%-25%	[11]
	Palo Alto, CA	2	DSRC	7%	[9]
GlidePath	McLean, VA	1	DSRC	10%-20%	[8]

In 2003, Rakha et al. [11] compared CMEM, MOBILE5a, and MOBILE6, which are the EPA's predecessors to MOVES, and VT-Micro. In this comparison, VT-Micro and MOBILE6 were shown to be more accurate than CMEM, but the database used in the study was the same database used to develop VT-Micro and MOBILE6.

Chamberlin et al. [12] developed a microsimulation of a 3-leg intersection and used MOVES and CMEM to evaluate the different intersection control strategies. In the study, only NOx and CO were considered; MOVES and CMEM showed similar results for NOx but had disparities for CO outputs.

Zhang et al. [2] used MOVES and CMEM to evaluate the fuel consumption and emissions for a variable speed limit. In the study, the I-710 freeway in California was built in VISSIM and used historical data from the California Department of Transportation. The study showed that CMEM and MOVES were qualitatively similar, but there were discrepancies in the actual values output from the two models.

Many CAV applications use MOVES to evaluate simulations or estimate emission outputs. Abou-Senna et al. [13] used MOVES to estimate emissions for a limited access highway simulation built in VISSIM. Liu et al. [14] used smoothing techniques on EPA eco-autonomous driving cycles. The emission results were estimated using MOVES. Xu et al. [15] simulated transit eco-driving methods using an algorithm that limits vehicle specific power while preserving the average speed, and the MOVES was used for the analysis.

At UC Riverside, Jin et al. [16] proposed a longitudinal control algorithm for eco-driving systems. The algorithm considers the vehicle's brake specific fuel consumption, as well as other constraints, in the calculation of the optimal speed profile. The energy and emissions were estimated using MOVES.

III. METHODOLOGY

A. Experiment Setup

In our experiments, we utilized a test vehicle (2008 Nissan Altima with a 4-cylinder, 2.5-liter engine) that is equipped with EAD enabling hardware. The vehicle has a radar system in front to detect preceding vehicles; it is also equipped with a Savari MobiWAVE MW1000 as a DSRC on-board unit (OBU), a laptop computer with Linux operating system, and a built-in driver-vehicle display. The operating system used on this OBU is Linux.

Fig. 1 shows the on-board devices and the interaction between them. In Fig. 1, the radar sends information to the laptop through Kvaser CAN (Controller Area Network) Interface, the OBU receives the SPaT message from the RSU and then sends those to the laptop, and an ELM327 OBD-II to USB cable sends the vehicle operational data to the laptop, including fuel consumption.

B. Innovation Corridor

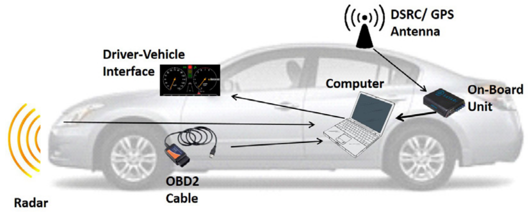

Figure 1. Experiment vehicle with on-board devices.

The experiments were carried out on University Avenue in Riverside, California (referred to as Riverside's Innovation Corridor). This six-mile corridor has three consecutive intersections (Iowa Street, Cranford Avenue, and Chicago Avenue) that are equipped with DSRC road-side units (RSU) that can transmit SPaT and MAP information.

This corridor is located between the University of California, Riverside and downtown Riverside. The corridor has proximity to expanding transit and alternative transportation network, research institutions associated with UCR, and the ever-expanding entertainment destinations in the downtown region, as shown in Fig. 2. Along the corridor, all traffic signal controllers have been updated to be compatible with SAE connectivity standards. DSRC roadside-units are mounted along with each traffic signal. SPaT messages are directly transmitted to the DSRC units and forwarded to the vehicles equipped with onboard units. Meanwhile, RTCM and MAP messages are broadcasted via DSRC devices to support geofencing and accurate positioning. This Innovation Corridor serves as a critical testbed in southern California for Connected and Automated Vehicles (CAVs) applications, such as connected eco-approach and departure, eco-transit operation, smart Intersection management, and other applications to improve safety, mobility and environmental sustainability.

There are many state-of-the-art elements to the Innovation Corridor that address not only transportation but also energy and air quality. New generation air quality sensors are planned to be deployed at buses stops intersections and downwind/upwind of the freeways to evaluate the air quality and health impact of the traffic. A variety of other futuristic elements will also be integrated into the corridor, such as user-focused shared zero-emissions mobility services, renewable energy generation, and vehicle-to-grid interaction.

C. Eco-Approach and Departure for Actuated Signals

The aim of the EAD algorithm used for testing is to reduce the idling time at intersections, and avoid unnecessary accelerations, while also allowing for safe driving. The EAD algorithm calculates an optimal acceleration to minimize fuel consumption as described in [9].

The signal controllers along the innovation corridor transmit SPaT information, providing a timestamp for the minimum time remaining and maximum time remaining. The traffic signals along the innovation corridor are actuated signals, making it difficult at times to predict the remaining time. For these reasons a variant of the Eco-driving strategy for actuated signals in [9] was employed. Note that in [9], due to the limited field of variables, only minimum time-to-change was provided for the green phase by the RSU, while maximum time-to-change was provided for the red phase. In our experiments, both maximum and minimum time-to-change are utilized.

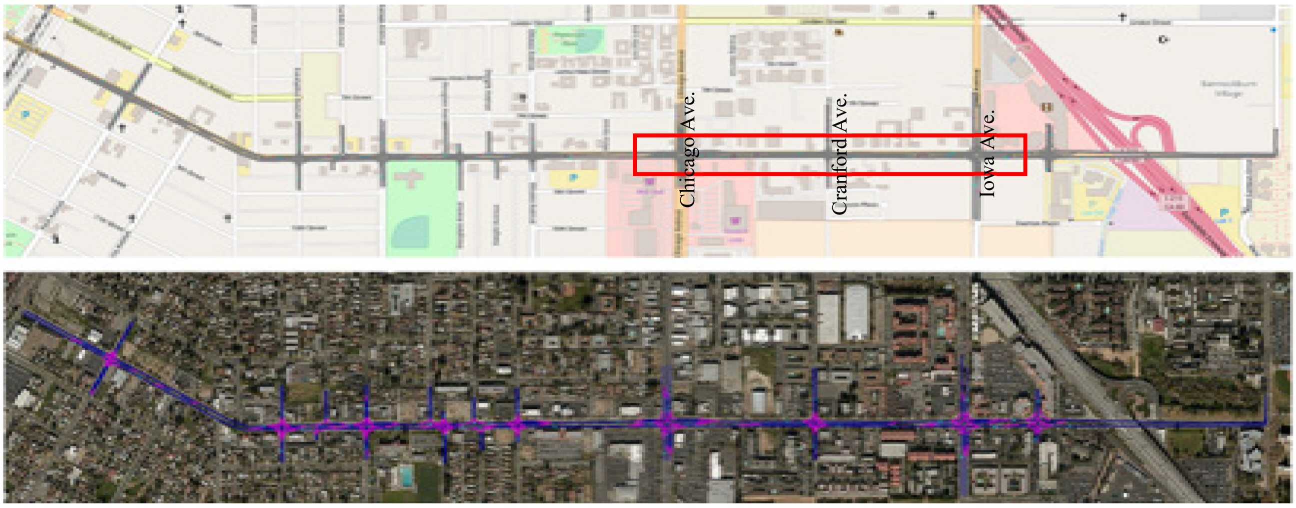

Figure 2. City of Riverside, CA Innovation Corridor.

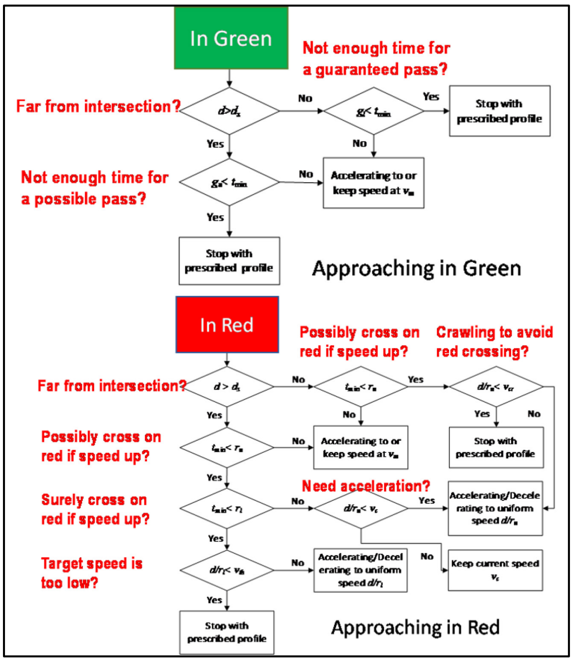

Figure 3. Flowchart for eco-approach to intersection.

The flowchart for this EAD algorithm is shown in Fig. 3. Like other EAD algorithms, the objective is to provide a recommended trajectory that will have the vehicle pass the intersection as the signal turns green. The major difference of this EAD algorithm is that for the red-light case, the maximum time is used in order to check safety and determine if the vehicle needs to accelerate. For the other cases, the minimum time is used as the pivotal measure for planning.

D. Experiment

The experimental tests were performed along a section of the Innovation Corridor spanning three traffic intersections, indicated by the red box in Fig. 2. Each test run started 100m east of Iowa Ave. to 100m west of Chicago Ave., then a U-turn was made and then return to 100m east of Iowa Ave. The entire length of each run was 1.38 miles.

$$FC = \frac{MAF}{14.64 * CER} \tag{1}$$

For the EAD application, two light-duty vehicles were tested at the same time. One vehicle was employing the EAD application for actuated signals while the other driving normally with traffic. Tests were done between 10:00 am to 12:00 pm and 1:30 pm to 3:30 pm on weekdays.

MOVES uses vehicle specific power (VSP) and vehicle speed data to select emission values from an operation mode (opmode) bin. The MOVES-based binning model utilized in this experiment uses the same approach as MOVES, but the data the values are chosen from were calibrated specifically for the test vehicle.

For CMEM, the model was calibrated specifically for the test vehicle. This means that the readily available parameters, such as mass, engine displacement, the idle speed of the engine, were obtained, and the calibration parameters were derived, as described in [17].

IV. NUMERICAL RESULTS

The fuel consumption estimates given from the emission models CMEM and MOVES were compared to the measured fuel consumption. The measured fuel consumption (FC), in grams, is obtained from (1) using the mass airflow (MAF) and commanded equivalence ratio (CER), which are read from the vehicle via the OBD-II cable (Fig. 1). The actual air/fuel ratio is obtained by multiplying the stoichiometric air/fuel ratio, 14.64, by the CER. Dividing the MAF by the actual air/fuel ratio gives the fuel consumption.

As an example, Fig. 4 shows the comparison of CO_2 outputs from the binning model and CMEM, to the measured value along with the velocity profile for a portion of the test data. In Fig. 4, the overestimation of emission output from the binning model can be observed.

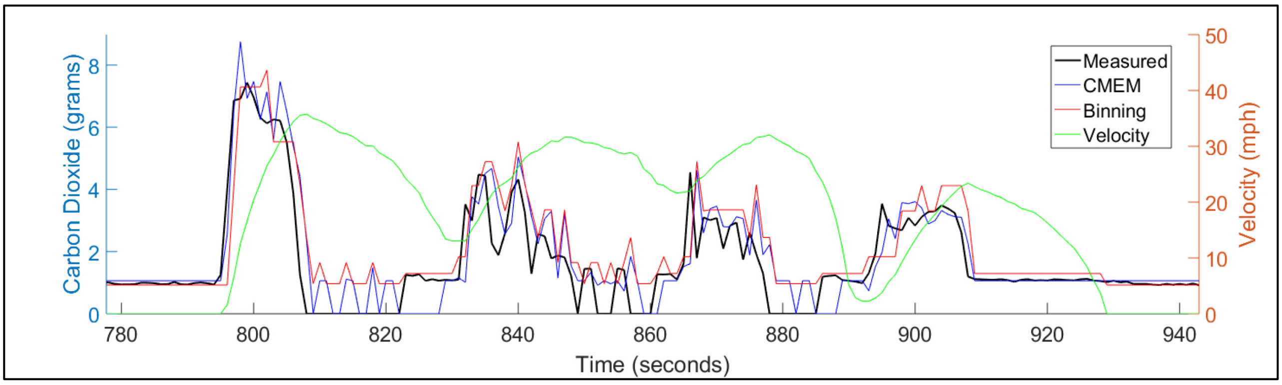

Figure 4. Emissions model comparison with velocity for an example experimental run.

Table II summarizes the results of the MOVES-based binning model and CMEM compared to the measured data, and shows the relative error for each model. It can be seen that the MOVES-based binning model overestimates the fuel consumption and CO_2 emissions. This is most likely due to the fact that the MOVES-based binning approach does not take into account the vehicle's fuel shutoff effects during decelerations. In this case, CMEM also over predicts emissions, but to a lesser extent than the MOVES-based binning approach.

One of the reasons why the binning model misrepresents emission savings is presented in Fig. 5. Fig. 5 shows how the MOVES opmode bins are defined by several VSP ranges and three vehicle speed ranges. One opmode bin can be used for a wide range of VSP or vehicle speeds, and each data point will generate the emissions rate associated with the bin in which the data point falls. If a CAV application, such as EAD, is implemented and the VSP goes down slightly, but the data point is in the same bin, the benefit of the CAV application will not be captured, and this is illustrated in Table III.

Table III shows the results of the EAD application with the CMEM and the binning model estimates compared to the measured values. As previously mentioned, the measured values were recorded at the same time with two vehicles, one implementing EAD technology and one driving normally. Each time the corridor was entered, both vehicles entered at the same time and stayed in different lanes to not influence the other driver. The CO_2 and fuel consumption used in Table III are the average grams per mile where the total grams from the measured values and the outputs from both models are individually summed, and then divided by the total miles travelled. The improvement column from Table III is the

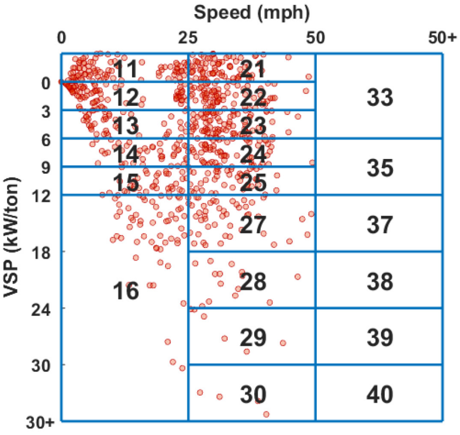

Figure 5. MOVES binning method showing MOVES opmode bins with measured test data presented in red.

TABLE II EMISSIONS MODEL COMPARISON

Method	Fuel Consumption Avg. g/mile	CO_2 Avg. g/mile
Measured	144.66	457.84
CMEM	152.29	481.99
	+5.27%	+5.27%
MOVES-based Binning Model	163.58	517.72
	+13.08%	+13.08%

TABLE III ECO-APPROACH AND DEPARTURE EVALUATION

		No EAD	EAD	Improvement
Actual	CO_2 (g/mi)	430.7	402.3	6.6%
	Fuel (g/mi)	137.63	128.5	6.63%
CMEM	CO_2 (g/mi)	439.9	419.83	4.5%
	Fuel (g/mi)	138.97	132.5	4.65%
MOVES-based binning	CO_2 (g/mi)	475.4	462.69	2.67%
	Fuel (g/mi)	151.87	147.8	2.7%

percentage decrease from no EAD to EAD. The MOVES-based binning model underestimated the benefits of EAD by about half, whereas the CMEM estimate was closer to the actual measured improvement.

V. CONCLUSION

In this paper, the fuel consumption and emissions of a light-duty vehicle recorded during real-world tests are compared to the fuel consumption estimates given from the Comprehensive Modal Emissions Model (CMEM) and a binning model based on the binning method of the Motor Vehicles Emission Simulator (MOVES) emission model.

CMEM overestimated fuel consumption by 5.3%, and the binning model overestimated it by 13.1%. Therefore, this experiment suggests that CMEM is a more accurate emissions model. MOVES is a data-driven model and is less sensitive to transient processes because it describes the average behavior of a general vehicle type (e.g., passenger car, pickup truck) [2].

To demonstrate binning models' underestimation of the fuel saving from CAV applications, an Eco-Approach and Departure application was performed on the Innovation Corridor with real-world traffic. When comparing two vehicles with and without the technology, the CMEM-based method gave a more accurate estimate of the energy and emissions differences than the MOVES-based model. The results of these tests demonstrate the importance of using a physical model for connected vehicle applications.

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