Testing an Eco-Cooperative Adaptive Cruise Control System in a Large-scale Metropolitan Network

Hao Chen[a] and Hesham A. Rakha[b]

Charles E. Via, Jr. Department of Civil and Environmental Engineering, Virginia Tech Transportation Institute, Virginia Polytechnic Institute and State University, 3500 Transportation Research Plaza, Blacksburg, VA 24061, U.S.A.

Keywords: Eco-driving, Large-scale Traffic Network, Vehicle Engine Type, Signalized Intersections, Energy Optimized Solution, Connected and Automated Vehicles.

Abstract: This study implements and tests an Eco-Cooperative Adaptive Cruise Control at Intersections (Eco-CACC-I) system in a large-scale metropolitan network to quantify the system-level performance considering different vehicle powertrains, connected automated vehicle (CAV) market penetration rates, and congestion levels. Specifically, three vehicle powertrains are considered in this study, including internal combustion engine vehicles (ICEVs), battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs). This study integrates the Eco-CACC-I controller with different fuel/energy consumption models, so that the controller can compute energy-optimized solutions to assist ICEVs, BEVs and HEVs traverse signalized intersections. A simulated traffic network in the Greater Los Angeles Area including the downtown LA and the immediate vicinity is used to implement and test the Eco-CACC-I controller. The test results demonstrate that the controller produces positive impacts on saving fuel/energy consumption, reducing travel time and delays on urban networks for different combinations of CAV market penetration and congestion levels.

1 INTRODUCTION

Studies have showed that vehicle acceleration, deceleration maneuvers and idling events near signalized intersections increase vehicle energy consumption and emission levels on arterial road, since vehicle are forced to stop ahead of traffic signals when encountering red indications, producing shock waves within the traffic stream (Barth & Boriboonsomsin, 2008). The communications between vehicles (V2V) and between vehicles and infrastructure (V2I) provide additional data for researchers to develop control strategies such as eco-driving systems to optimize vehicle trajectories in the vicinity of signalized intersections to enhance mobility and reduce vehicle fuel consumption and emissions (Saboohi & Farzaneh, 2008).

Most of the studies in this area have focused on developing eco-driving strategies for ICEVs, since the current car market is dominated by fuel-powered vehicles. For example, a cooperative adaptive cruise control system using SPaT information was proposed to minimize the absolute acceleration levels of vehicles and reduce vehicle fuel consumption levels (Malakorn & Park, 2010). A dynamic programming-based fuel-optimization strategy was developed using recursive path-finding principles, and evaluated the developed strategy using an agent-based modeling approach (Kamalanathsharma & Rakha, 2014). Moreover, an eco-driving system entitled Eco-CACC for fuel-powered vehicles was developed, and field tests were conducted to demonstrate that the developed system can efficiently reduce stop-and-go traffic and produce significant fuel and delay savings of 31% and 9%, respectively (Almannaa, Chen, Rakha, Loulizi, & El-Shawarby, 2019).

With the rapid growth of electric vehicles in the past decade, recently some researchers have started to develop speed control strategies for electric vehicles, including BEVs and HEVs. For instance, an eco-driving technique for BEVs was developed in (Miyatake, Kuriyama, & Takeda, 2011), and the vehicle trajectory control problem was formulated as an optimization problem to minimize the summation

[a] https://orcid.org/0000-0001-8272-734X
[b] https://orcid.org/ 0000-0002-5845-2929

Chen, H. and Rakha, H.
Testing an Eco-Cooperative Adaptive Cruise Control System in a Large-scale Metropolitan Network.
DOI: 10.5220/0011039200003191
In *Proceedings of the 8th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2022)*, pages 265-272
ISBN: 978-989-758-573-9; ISSN: 2184-495X

of vehicle power. However, a simple energy model was used by assuming that the recharge efficiency is a constant value. Another BEV eco-driving algorithm was proposed in (Zhang & Yao, 2015), in which an energy consumption model based on the VT-Micro model was developed for different operation modes of BEVs, then an eco-driving model for a single signalized intersection was proposed using the developed energy model. However, the proposed energy consumption model was a statistical model based on limited collected data, thus the accuracy may not be good enough for the purpose of developing an optimal control strategy for dynamic vehicle maneuvers. The same energy consumption model was used in (Qi, Barth, Wu, Boriboonsomsin, & Wang, 2018) to develop a connected eco-driving system for BEVs. However, the case study used a 2012 Ford Escape with a hybrid engine to represent the performance of an actual BEV. A more robust algorithm which uses a realistic energy consumption model for BEV was developed in (Chen & Rakha, 2020) and the simulated test results demonstrated the benefits of the developed controller to save energy consumption and delays. An extension work further expanded the controller to HEVs, and the test results from an arterial corridor with three signalized intersections demonstrated that the proposed system can effectively reduce stop-and-go traffic in the vicinity of signalized intersections (Chen & Rakha, 2021).

Most of existing studies investigated the eco-driving strategies for a single vehicle engine type. Moreover, the developed algorithms were generally tested using simplified or small traffic networks, and none of these studies investigated the performance on large-scale traffic networks calibrated to real traffic conditions. Considering the abovementioned problems, this study implements and tests an Eco-CACC-I system using a large-scale metropolitan network to investigate the system-level performances for different vehicle powertrains (ICEV, BEV and HEV), CAV market penetration rates and congestion levels. Based on the previous work, the optimal speed profiles for different vehicle powertrains are generally very different under certain conditions, such as different speed limits and roadway grades. This study integrates the Eco-CACC-I controller with different fuel/energy consumption models, so that the controller can compute energy-optimized solutions to assist ICEVs, BEVs and HEVs traverse signalized intersections. A simulated traffic network in the Greater Los Angeles Area including the downtown LA and the immediate vicinity is used to implement and test the Eco-CACC-I controller. The test results demonstrate the controller can effectively reduce stopped delay and energy consumption for ICEV, BEV and HEV in the LA network.

2 Eco-CACC-I CONTROLLER

In this study, the Eco-CACC-I controller uses eco-driving strategy to compute real-time fuel/energy-optimized speed profile for assist vehicles pass signalized intersections. Our previous work developed various Eco-CACC-I systems for vehicles with different engine types, including ICEV, BEV and HEV. In this study, we use the same Eco-CACC-I framework we developed in previous work, and incorporate the energy models of ICEV, BEV and HEV so that the controller can work with different vehicle types in large-scale traffic network.

2.1 Eco-CACC-I Algorithm

The control region is defined as vehicles follow the recommended speed by Eco-CACC-I from a distance upstream of the signalized intersection (defined as d_{up}) to a distance downstream of the intersection (defined as d_{down}), as the Eco-CACC-I algorithm optimizes speed profile for vehicle approaching and leaving signalized intersections. Upon approaching a signalized intersection, the vehicle may accelerate, decelerate, or cruise (maintain a constant speed) based on a number of factors, such as vehicle speed, signal timing and phase, distance to the intersection, road grade, headway distance, etc. Considering that the vehicle may or may not need to decelerate when approaching the traffic signal, two cases are considered to develop the Eco-CACC-I strategies.

Case 1 doesn't require the vehicle to decelerate to pass the signalized intersection. In this case, the cruise speed for the vehicle to approach the intersection during the red indication can be calculated by Equation (1) to maximize the average vehicle speed during the control region.

$$u_c = min\left(\frac{d_{up}}{t_r}, u_f\right) \tag{1}$$

In case 2, the vehicle's energy-optimized speed profile is illustrated in Figure 1. After entering the control region, the vehicle with the initial speed of $u(t_0)$ needs to brake at deceleration level denoted by a, then cruise at a constant speed of u_c to approach the signalized intersection. After passing the stop bar, the vehicle should increase speed to u_f per the vehicle dynamics model, and then cruise at u_f until the vehicle leaves the control region. In this case, The following optimization problem is formulated to compute the optimum vehicle speed profile, and the only unknown variables are the upstream deceleration rate a and the downstream throttle f_p.

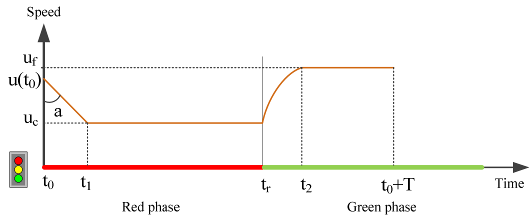

Figure 1: Vehicle optimum speed profile.

Assuming a vehicle enters the Eco-CACC-I control region at time t_0 and leaves the control region at time t_0+T, the objective function entails minimizing the total energy consumption as

$$min \int_{t_0}^{t_0+T} EC(u(t)) \cdot dt \tag{2}$$

where EC denotes the energy consumption at instant t. The energy models for ICEVs, BEVs and HEVs are presented in Equations (5) ~ (10). The constraints to solve the optimization problem can be built according to the relationships between vehicle speed, location, acceleration/deceleration as presented below:

$$u(t): \begin{cases} u(t) = u(t_0) - at & t_0 \le t \le t_1 \\ u(t) = u_c & t_1 < t \le t_r \\ u(t+\Delta t) = u(t) + \frac{F(f_p) - R(u(t))}{m} \Delta t & t_r < t \le t_2 \\ u(t) = u_f & t_2 < t \le t_0 + T \end{cases} \tag{3}$$

$$\begin{gathered} u(t_0) \cdot t - \frac{1}{2} a t^2 + u_c (t_r - t_1) = d_{up} \\ u_c = u(t_0) - a(t_1 - t_0) \\ u \int_{t_r}^{t_2} u(t)\, dt + u_f (t_0 + T - t_2) = d_{down} \\ u(t_2) = u_f \\ a_{min} < a \le a_{max} \\ f_{min} \le f_p \le f_{max} \\ u_c > 0 \end{gathered} \tag{4}$$

In Equation (3), $u(t)$ is the velocity at instant t; m is the vehicle mass; $a(t) = dv(t)/dt$ is the acceleration of the vehicle in [m/s^2] ($a(t)$ takes negative values when the vehicle decelerates); function F denotes vehicle tractive force and function R represents all the resistance forces (aerodynamic, rolling, and grade resistance forces). Note that the maximum deceleration is limited by the comfortable threshold felt by average drivers. The throttle value f_p ranges between f_{min} and f_{max}. Dynamic programming (DP) is used to solve the problem by constructing a graph of the solution space by discretizing the combinations of deceleration and throttle values and calculating the corresponding energy consumption levels; the minimum path through the graph computes the energy-efficient trajectory and optimum parameters (Guan & Frey, 2013).

2.2 Energy Consumption Models

The energy consumption models for ICEVs, BEVs and HEVs are the key inputs to the abovementioned objective function to solve the optimization problem. In this study, the fuel/energy consumption models for various vehicle powertrains are selected by considering: (1) speed and grade data are the only required input for the energy models, and vehicle engine data are not required so that the optimization problem can be easily solved; (2) the energy models have been validated and demonstrated to produce good accuracy compared to empirical data; (3) models can be easily calibrated to a specific vehicle type using public data and/or the EPA combined fuel economy data. By considering those factors, the following fuel/energy models for ICEV, BEV and HEV are selected in this study.

The Virginia Tech Comprehensive Power-based Fuel Consumption Model (VT-CPFM) type 1 is selected to estimate the instantaneous fuel consumption rate for ICEV (Park, Rakha, Ahn, & Moran, 2013). The VT-CPFM utilizes instantaneous power as an input variable and can be easily calibrated using publicly available fuel economy data (e.g., Environmental Protection Agency [EPA]-published city and highway gas mileage). The VT-CPFM is formulated as below.

$$FC_{ICEV}(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2 & \forall\, P(t) \ge 0 \\ \alpha_0 & \forall\, P(t) < 0 \end{cases} \tag{5}$$

$$P(t) = (ma(t) + mg \cdot \frac{C_r}{1000}(c_1 u(t) + c_2) + \frac{1}{2}\rho_{Air} A_f C_D u^2(t) + mg\,\theta) u(t) \tag{6}$$

Where $FC_{ICEV}(t)$ is the fuel consumption rate for ICEV; α_0, α_1 and α_2 are the model parameters that can be calibrated for a particular vehicle using public available vehicle specification information from manufacturer; $P(t)$ is the instantaneous total power (kW); g [m/s^2] is the gravitational acceleration; θ is the road grade; C_r, c_1 and c_2 are the rolling resistance parameters that vary as a function of the road surface type, road condition, and vehicle tire type; ρ_{Air} [kg/m^3] is the air mass density; A_f[m^2] is the frontal area of the vehicle, and C_D is the aerodynamic drag coefficient of the vehicle.

This study uses the Virginia Tech Comprehensive Power-based EV Energy consumption Model (VT-CPEM) compute instantaneous energy consumption levels for BEV (Fiori, Ahn, & Rakha, 2016). The VT-CPEM only requires the instantaneous speed and the EV characteristics as input to compute the instantaneous power consumed. One of the major advantages of VT-CPEM is that it captures instantaneous braking energy regeneration, which is not available in most BEV energy models. The VT-CPEM model is summarized as below.

$$EC_{BEV}(t) = \int P_B(t) \cdot dt \tag{7}$$

$$P_B(t) = \begin{cases} \dfrac{P_W(t)}{\eta_D \cdot \eta_M \cdot \eta_B} + P_{Aux} & \forall\, P_W(t) \geq 0 \\ P_W(t) \cdot \eta_D \cdot \eta_M \cdot \eta_B \cdot \eta_{rb} + P_{Aux} & \forall\, P_W(t) < 0 \end{cases} \tag{8}$$

$$\eta_{rb}(t) = \left[e^{\left(\frac{0.0411}{|a(t)|}\right)} \right]^{-1} \tag{9}$$

where EC_{BEV} represents the energy consumption for BEV; P_B is the power consumed by (regenerated to) the electric motor; Pw denotes the power at the wheels computed in Equation (6); P_{Aux} is the power consumed by the auxiliary systems; η_D and η_M are the driveline efficiency and the efficiency of the electric motor, respectively; η_B denotes the efficiency from battery to electric motor; η_{rb} represents the regenerative braking energy efficiency, which can be computed using Equation (9).

An HEV energy consumption model developed in (Ahn & Rakha, 2019) is selected to compute instantaneous energy consumption levels for HEVs. The model was developed after analyzing field data and HEV energy consumption behaviors. First, the amount of fuel consumed is proportionally related to both the vehicle power and speed; second, the HEV operates in EV mode when the power is less than 0; third, the HEV utilizes only an electric mode when the speed is lower than an EV mode speed (u_a) and the required power is lower than a specific power (P_a). This model only requires instantaneous speed as input and can be easily calibrated with high accuracy to match field data. The HEV energy consumption model is formulated as below.

$$FC_{HEV}(t) = \begin{cases} FC_{EV_{mode}} & \text{for } \begin{cases} P \leq 0 \\ u < u_a \text{ and } P < P_a \end{cases} \\ a + b * u(t) + c * P(t) + d * P(t)^2 & \text{for } \begin{cases} P > 0 \text{ and } u \geq u_a \\ u < u_a \text{ and } P \geq P_a \end{cases} \end{cases} \tag{10}$$

where $FC_{HEV}(t)$ is the fuel consumption rate for HEV, and FC_{EV_mode} is the fuel consumption rate in EV mode and estimated as average fuel consumption in EV mode; $P(t)$ is the instantaneous total power and can be computed using Equation (6); and u is the instantaneous vehicle speed. Statistical analysis of the empirical data found that the optimum values for v_a and P_a are 32 km/h, and 10 kW, respectively (Ahn & Rakha, 2019).

3 CASE STUDY

3.1 The Simulated Traffic Network

In this study, INTEGRATION was used as the simulation tool to simulate the traffic network in the Greater Los Angeles Area including the downtown LA and the immediate vicinity. INTEGRATION is an integrated simulation and traffic assignment model that creates individual vehicle trip departures based on an aggregated time-varying O-D matrix. In consideration of traffic control devices and gap acceptance, INTEGRATION moves vehicles along the network in accordance with embedded preset traffic assignment models and the Rakha-Pasumarthy-Adjerid (RPA) car-following model. A more-detailed description of INTEGRATION is provided in the literature (Aerde & Rakha, 2007a, 2007b).

Different data sources are used to build the microscopic network, including NavTeq for generating nodes and links, OpenStreetMap for creating intersection traffic control information, and Google Maps for validating road attributes – the number of lanes, one-way streets, speed limits, bus lane locations, etc. The simulated traffic network in LA includes 1625 nodes, 3561 links and 457 signals. A static O-D demand file was generated using QueensOD (Rakha & Lucic, 2002), a software application developed by VTTI researchers. QueensOD estimates the most-likely time-dependent static O-D using observed link traffic flows, observed link turning movement counts, link travel times, and a seed matrix. QueensOD iteratively minimizes the error between the observed link volumes and estimated link flow to generate a most-likely O-D matrix that is as close as possible to the seed matrix.

In this study, the median of the traffic count data for ten randomly selected Tuesdays and Wednesdays in 2014, which were provided by the Caltrans Performance Measurement System (PEMS), were used as the input observed link flow data for QueensOD.

The simulation results were compared against the traffic count data from PEMS and the corresponding R values were computed. The statistical analysis demonstrated that the simulated network is highly accurate by comparing to the field data collected in LA. More detailed information of the simulated LA traffic network can be found in (Du, Rakha, Elbery, & Klenk, 2018; Elbery, Devorak, Du, Rakha, & Klenk, 2019).

3.2 Test the Eco-CACC-I Controller

The Eco-CACC-I controller was implemented into the simulated LA network using the INTEGRATION software. The Eco-CACC-I controller was enabled on all the 457 signalized intersections in the LA network. In particular, 1,606 arterial links (including both upstream and downstream links) that are controlled by traffic signals for vehicle entering or existing are selected to implement the Eco-CACC-I controller. An experiment design was conducted to test the performances of the LA network in two scenarios (base case, Eco-CACC-I), under the combinations of vehicle type (ICEV, BEV and HEV), traffic demand (no congestion - 25% demand, mild congestion - 50% demand and heavy congestion - 100% demand), and level of market penetration (LMP) rate of the controlled vehicles (1%, 2%, 5%, 10%, 20%, 25%, 50%, 75% and 100%). It should be noted that 100% demand was calibrated by one-hour real traffic data under weekday morning peak traffic conditions, which represents heavy traffic congestion. Note that the Eco-CACC-I controllers are disabled in the base case, and the controllers are enabled on the selected 1,606 arterial links in the Eco-CACC-I case. Each scenario was simulated using 10 different random number seeds to address the stochastic characteristics of real-world traffic conditions, we should point out that all results reported below are averages across the 10 runs. The comparisons of the test results in two scenarios are presented as below.

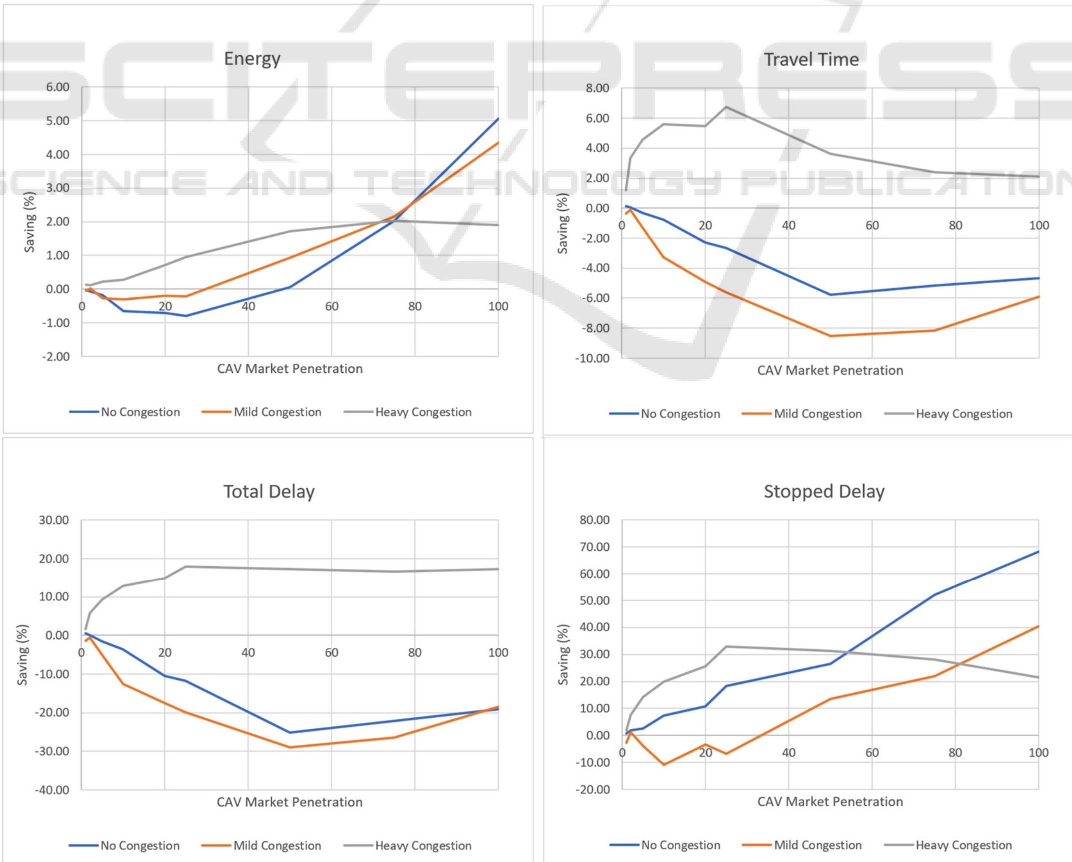

Figure 2: The savings of Eco-CACC-I vs. base for BEV under different CAV market penetration and congestion levels.

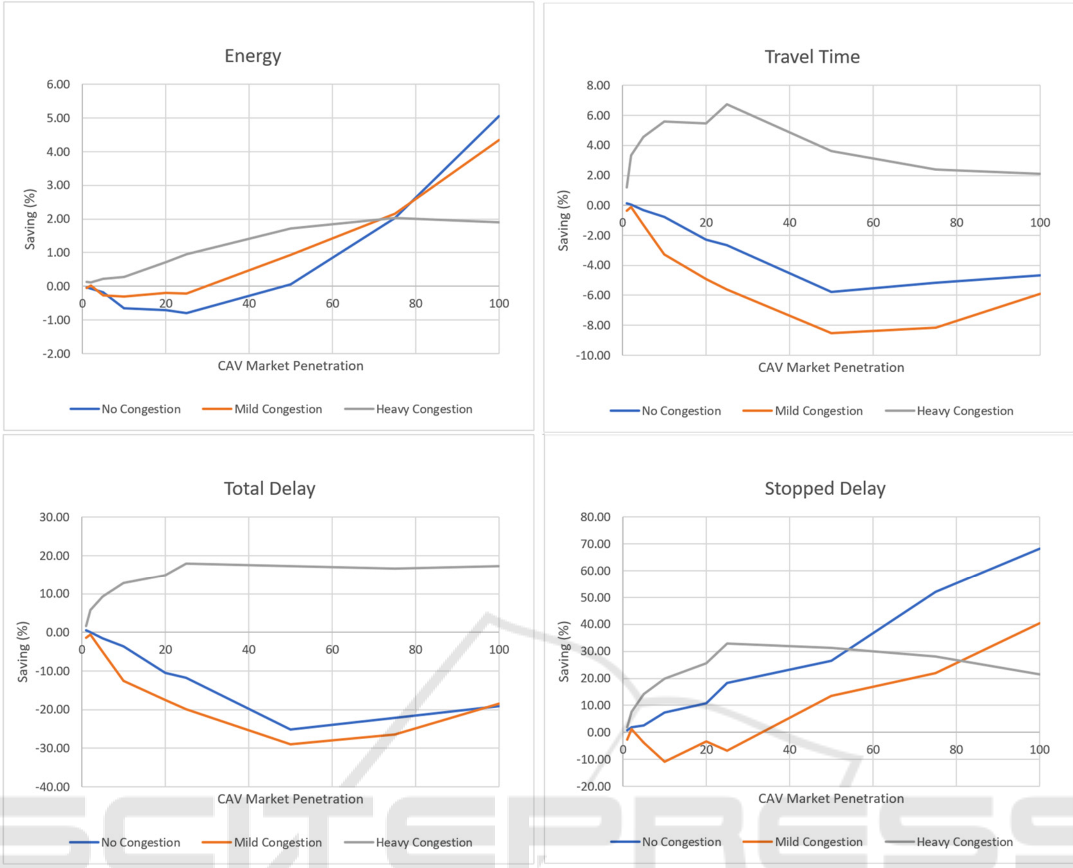

Figure 3: The savings of Eco-CACC-I vs. base for BEV under different CAV market penetration and congestion levels.

Figure 2 illustrates the savings in fuel, travel time, total delay and stopped delay associated with the application of the Eco-CACC-I controller for ICEV. The test results indicate that the Eco-CACC-I controller reduced the fuel consumption of ICEVs by up to 6.4%, travel time by up to 8.7%, total delay by up to 21.5%, stopped delay by up to 68.5%. We performed t-tests and found the results to be statistically significant. Figure 2 also demonstrates that the Eco-CACC-I controller effectively improves the fuel efficiency of ICEVs in heavily congested conditions, but the controller increases fuel consumption by up to 4% when the congestion levels are low. This is due to the fact that the entire network uses dynamic vehicle routing and an adaptive traffic signal controller that continuously changes the traffic signal timings, which makes the control of the vehicle very challenging given the continuous stochastic changes in the system. In addition, the study found that the Eco-CACC-I controller is most effective for ICEVs on fuel consumption, travel time, and total delay when the CAV MPR is 25% and the roads are heavily congested. The results also indicate that the Eco-CACC-I controller can effectively reduce ICEV stopped delay in various congestion levels. The savings of stopped delay are generally increased with higher MPRs when the congestion levels are low. The maximal savings of stopped delay are 68% and 41% for no congestion and mild congestion levels for a 100% MPR.

Figure 3 illustrates the savings in energy, travel time, total delay and stopped delay associated with using the Eco-CACC-I controller for BEV. The simulation results demonstrate that the Eco-CACC-I controller produces energy savings of BEVs up to 5.05% (p-value < 0.01) on the LA network. The energy consumption savings increase as the CAV MPR increases for all congestion levels. The study found that the BEV energy savings for no congestion and mild congestion cases are greater than those of heavy congestion cases when the CAV MPR is 100%. Figure 3 also demonstrates that the Eco-CACC-I controller reduces BEV travel times and the total delays in the heavily congested cases. In particular, the controller produces savings in travel time by up to 6.8% (p-value < 0.01) and total delay by up to 17.9% (p-value < 0.01) at a 25% CAV MPR in heavily congested conditions. However, Figure 3 also

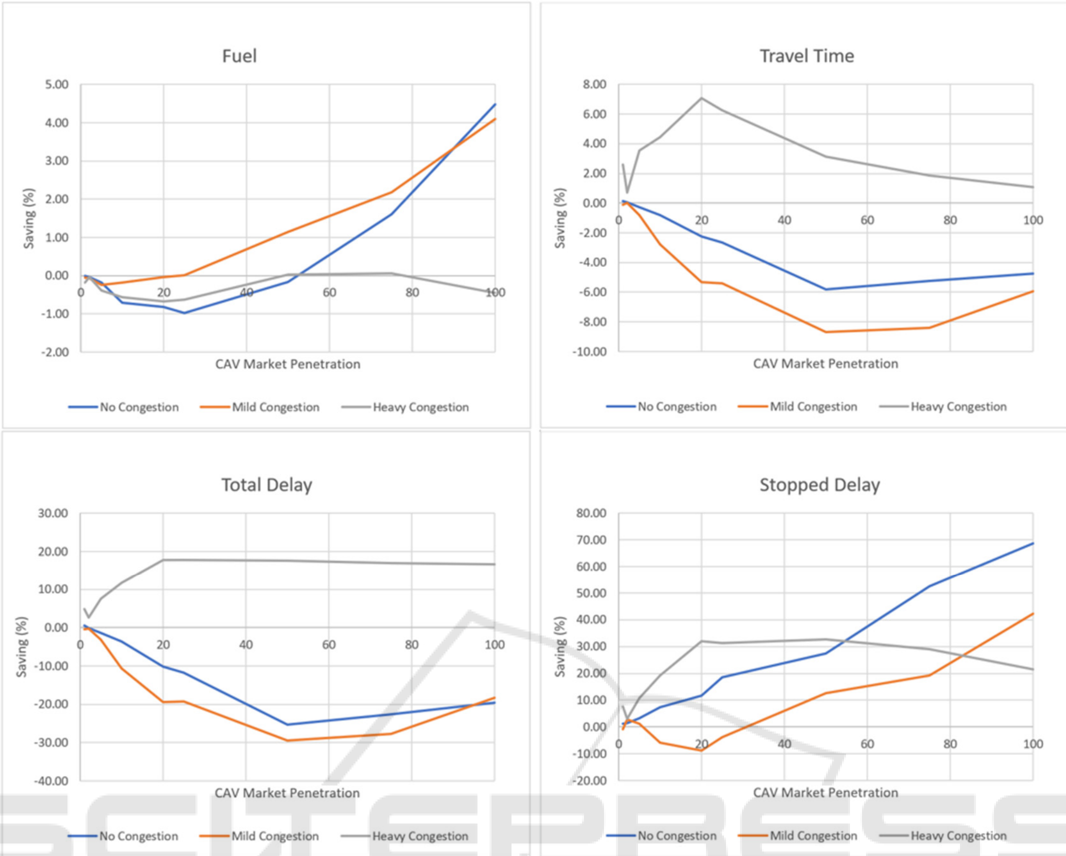

Figure 4: The savings of Eco-CACC-I vs. base for HEV under different CAV market penetration and congestion levels.

demonstrates that the Eco-CACC-I increases both travel time and total delay in the no congestion and mild congestion cases when BEV powertrains are considered. The simulation results indicate that the BEV Eco-CACC-I controller can effectively reduce stopped delay under various congestion levels. The savings in stopped delay generally increase with higher CAV MPRs for no and mild congestion conditions. The study found that the Eco-CACC-I produced savings in BEV stopped delay by up to 68.2% (p-value < 0.01) with a 100% CAV MPR and no congested conditions.

Figure 4 illustrates the savings in fuel, travel time, total delay and stopped delay by using the Eco-CACC-I controller for HEV. The simulation study found that the Eco-CACC-I controller reduced the fuel consumption of HEVs by up to 4.5% (p-value $<$ 0.01) when the CAV MPR is 100% with no congestion in the LA network. The study found that Eco-CACC-I increased the fuel consumption of HEVs for most cases. However, Eco-CACC-I reduced the fuel consumption of HEVs for high CAV MPR cases (75% and 100%) in no congestion and mild congestion cases. Figure 4 also demonstrates that the Eco-CACC-I reduces the travel time by up to 7.1% (p-value < 0.01) and total delay by up to 17.8% (p-value < 0.01), and stopped delay by up to 32.8% (p-value < 0.01). The study found that Eco-CACC-I is most effective on travel time, total delay, and stopped delay for HEVs when CAV MPRs are between 20% and 50% and when roadways are heavily congested. However, Eco-CACC-I is not effective when the roads are not congested or are mildly congested. The results also indicate that the Eco-CACC-I controller can effectively reduce stopped delay under various congestion levels. The savings in stopped delay generally increase with higher CAV MPRs in low to mild traffic congestion.

4 CONCLUSIONS

This study implements and tests an Eco-CACC-I system on a large-scale metropolitan network to quantify the system-level impact considering different vehicle powertrains, CAV market penetration rates and congestion levels. Specifically, three powertrains are considered in this study, including ICEVs, BEVs and HEVs. This study integrates the Eco-CACC-I controller with different fuel/energy consumption models, so that the controller can compute energy-optimized solutions to assist ICEVs, BEVs and HEVs traverse signalized intersections. A simulated traffic network in the Greater Los Angeles Area including the downtown LA and the immediate vicinity is used to implement and test the Eco-CACC-I controller. The test results demonstrate that the controller has positive impacts on reducing fuel/energy consumption, travel time, total and stopped delay, for ICEVs, BEVs and HEVs for different combinations of CAV market penetration and congestion levels. More data analysis on links with or without Eco-CACC-I controllers, and the further tests to combine Eco-CACC-I with other controllers (such as freeway speed harmonization, platooning, eco-routing, etc.) will be considered in the future work.

ACKNOWLEDGEMENTS

This work was funded by the Department of Energy through the Office of Energy Efficiency and Renewable Energy (EERE), Vehicle Technologies Office, Energy Efficient Mobility Systems Program under award number DE-EE0008209.

REFERENCES

Aerde, M. V., & Rakha, H. (2007a). INTEGRATION © Release 2.30 for Windows: User's Guide – Volume I: Fundamental Model Features. M. Van Aerde & Assoc., Ltd., Blacksburg.

Aerde, M. V., & Rakha, H. (2007b). INTEGRATION © Release 2.30 for Windows: User's Guide – Volume II: Advanced Model Features. M. Van Aerde & Assoc., Ltd., Blacksburg.

Ahn, K., & Rakha, H. A. (2019). A Simple Hybrid Electric Vehicle Fuel Consumption Model for Transportation Applications Electric and Hybrid Vehicles.

Almannaa, M. H., Chen, H., Rakha, H. A., Loulizi, A., & El-Shawarby, I. (2019). Field implementation and testing of an automated eco-cooperative adaptive cruise control system in the vicinity of signalized intersections. Transportation Research Part D: Transport and Environment, 67, 244-262.

Barth, M., & Boriboonsomsin, K. (2008). Real-world carbon dioxide impacts of traffic congestion. Transportation Research Record: Journal of the Transportation Research Board(2058), 163-171.

Chen, H., & Rakha, H. A. (2020). Battery Electric Vehicle Eco-Cooperative Adaptive Cruise Control in the Vicinity of Signalized Intersections. Energies, 13(10), 2433.

Chen, H., & Rakha, H. A. (2021). Developing a Hybrid Electric Vehicle Eco-Cooperative Adaptive Cruise Control System at Signalized Intersections. Retrieved from

Du, J., Rakha, H. A., Elbery, A., & Klenk, M. (2018). Microscopic simulation and calibration of a large-scale metropolitan network: Issues and proposed solutions. Retrieved from

Elbery, A., Devorak, F., Du, J., Rakha, H. A., & Klenk, M. (2019). Large-scale Agent-based Multi-modal Modeling of Transportation Networks.

Fiori, C., Ahn, K., & Rakha, H. A. (2016). Power-based electric vehicle energy consumption model: Model development and validation. Applied Energy, 168, 257-268.

Guan, T., & Frey, C. W. (2013). Predictive fuel efficiency optimization using traffic light timings and fuel consumption model. Paper presented at the Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on.

Kamalanathsharma, R., & Rakha, H. (2014). Agent-Based Simulation of Ecospeed-Controlled Vehicles at Signalized Intersections. Transportation Research Record: Journal of the Transportation Research Board(2427), 1-12.

Malakorn, K. J., & Park, B. (2010). Assessment of mobility, energy, and environment impacts of IntelliDrive-based Cooperative Adaptive Cruise Control and Intelligent Traffic Signal control. Paper presented at the Sustainable Systems and Technology (ISSST), 2010 IEEE International Symposium on.

Miyatake, M., Kuriyama, M., & Takeda, Y. (2011). Theoretical study on eco-driving technique for an electric vehicle considering traffic signals. Paper presented at the Power Electronics and Drive Systems (PEDS), 2011 IEEE Ninth International Conference on.

Park, S., Rakha, H., Ahn, K., & Moran, K. (2013). Virginia tech comprehensive power-based fuel consumption model (VT-CPFM): model validation and calibration considerations. International Journal of Transportation Science and Technology, 2(4), 317-336.

Qi, X., Barth, M. J., Wu, G., Boriboonsomsin, K., & Wang, P. (2018). Energy Impact of Connected Eco-driving on Electric Vehicles Road Vehicle Automation 4 (pp. 97-111): Springer.

Rakha, H., & Lucic, I. (2002). Variable power vehicle dynamics model for estimating truck accelerations. Journal of transportation engineering, 128(5), 412-419.

Saboohi, Y., & Farzaneh, H. (2008). Model for optimizing energy efficiency through controlling speed and gear ratio. Energy Efficiency, 1(1), 65-76.

Zhang, R., & Yao, E. (2015). Eco-driving at signalised intersections for electric vehicles. IET Intelligent Transport Systems, 9(5), 488-497.