Connected Vehicle-based Truck Eco-Driving: A Simulation Study

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Abstract — **While technologies such as adaptive cruise control and platooning can increase energy efficiency of freight trucks on highways, to date less attention has been given to technologies that can improve energy efficient of these trucks during their first-mile/last-mile operations. In this paper, we present a Connected Vehicle-based truck eco-driving system, called Eco-Drive, which uses Signal Phase and Timing (SPaT) information from the upcoming traffic signal along with the information about the equipped vehicle and preceding traffic to determine the most energy-efficient speed trajectory to pass through the intersection. The system is pre-calibrated using real-world acceleration and deceleration profile data to create a graph-based vehicle trajectory planning algorithm. A machine learning algorithm is then developed and trained to enable a fast and accurate determination of optimal vehicle trajectory. During the operation, the system uses real-time information about the host vehicle, SPaT, and preceding traffic to optimize vehicle trajectory for energy while ensuring a safe passage through the intersection. The system evaluation in traffic microsimulation environment shows that the proposed system provides statistically significant energy savings for the host vehicle, while maintaining similar travel time, as a result of reduced number of stops and milder acceleration/deceleration. The results presented are specific to the simulation settings used in this paper. More research is needed to better understand the levels of energy savings that the proposed system could provide under a wide variety of settings.**

I. Introduction

Freight trucks, the dominant mode of goods movement in the U.S., represent the second largest share (21%) of the nation's transportation energy use [1]. They also contribute significantly to greenhouse gas and criteria pollutant emissions from transportation. Truck traffic has been growing nationwide, especially in urban areas, as a result of increased freight demand spurred by international trade and e-commerce. According to the U.S. Energy Information Administration, vehicle miles traveled of freight trucks are expected to increase from 300 billion miles in 2019 to 415 billion miles in 2050 [1]. This will put a lot of pressure on the roadway infrastructure, potentially leading to increased traffic congestion, energy consumption, and emissions. Thus, innovative solutions are needed to address the growing freight demand that outpace the rate of expansion in supporting infrastructure. With the rapid development of advanced vehicle and communication technologies, Connected Vehicles (CVs) have emerged as a prospective solution to a number of transportation problems, as well as brought forward new mobility and energy efficiency opportunities. With wireless communications between vehicles and infrastructure, more efficient vehicle maneuvers have been achieved through information sharing and better cooperation. In urban areas, Eco-Approach and Departure (EAD) have been shown to be one of the most effective CV-based application for energy and emission reductions. The EAD system uses Signal Phase and Timing (SPaT) information from the upcoming traffic signal along with the information about the equipped vehicle and preceding traffic to determine the most energy-efficient speed trajectory to pass through the intersection. Previous studies have shown that with a well-designed speed profile, the vehicle would travel through the intersection in a way that minimizes stops and avoids unnecessary acceleration and deceleration [2-7].

As most connected vehicle and eco-driving technologies to date have been developed for passenger cars, less attention has been given to connected eco-driving technologies for heavy-duty vehicles [8]. In eCoMove project [9], Volvo Group found that driver behavior could affect fuel consumption of commercial trucks by 10-15% based on simulator and on-road experiments. Hao et al. designed a truck EAD application that utilizes SPaT messages from traffic signal controller and road grade information along the path [11]. Numerical experiments were conducted using a hypothetical pre-timed signalized intersection with varying entry times and speeds. The average energy savings compared with a baseline trigonometric EAD algorithm [7] is 11% for level terrain, 6% for uphill, and 20% for downhill. Rodriguez and Fathy developed a dynamic programming based model to explore the fuel saving benefits of heavy-duty truck trajectory optimization, given advanced traffic signal information [12]. Numerical simulations were conducted to evaluate the performance of the proposed method for different arterial corridor configurations, and the results showed 32-72% fuel savings. Wang et al. developed a connected eco-driving system and implemented it on a heavy-duty diesel truck using cellular communications. The system was demonstrated in Carson, California, showing its efficacy in real-world traffic [13]. To the best of the authors' knowledge, there has been little attention given to the customized eco-driving strategies for trucks. There has yet to be studies of CV-based truck eco-driving that use traffic microsimulation as the evaluation approach as well.

In this paper, we present a CV-based truck eco-driving system

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with power-based vehicle trajectory planning as the core algorithm, and the evaluation of the system in traffic microsimulation. Different from field tests, traffic microsimulation can create identical traffic and signal scenarios to fairly compare the performance of the proposed system with the baseline. Traffic microsimulation can also better represent vehicle and traffic behaviors than in numerical simulation. The rest of this paper is organized as follows. In Section II, we introduce the framework and components of the proposed algorithm. We then discuss the simulation-based evaluation results in Section III, followed by concluding remarks in Section IV.

II. Methodology

A. Model Framework

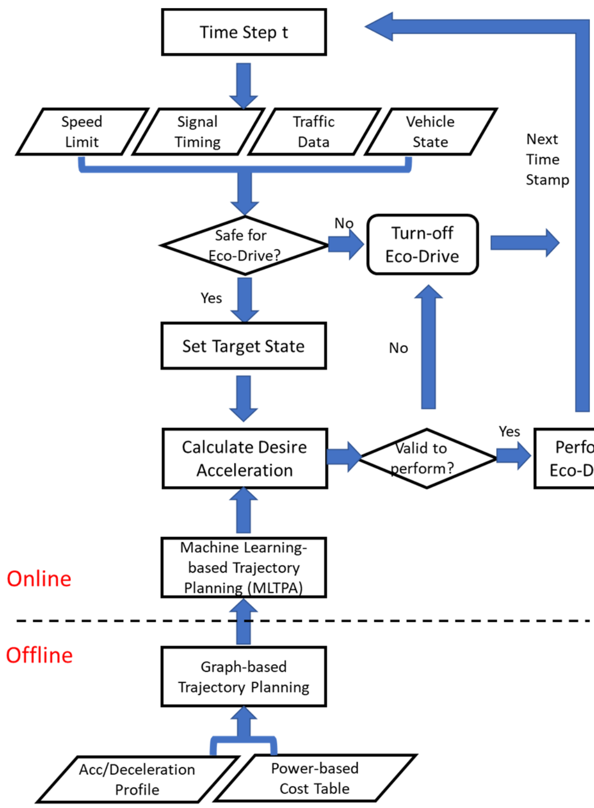

Figure 1. System diagram of the proposed Eco-Drive system

As shown in the system diagram in Fig. 1, the proposed system has both online components and offline components. The online components are implemented in real time. At each time step, the system first collects required data from multiple sources, including SPaT information, activity data from preceding vehicles, dynamic state of the host vehicle, and infrastructure data such as speed limit, road grade, communication range, etc. If the system does not receive all the required data or the situation is not safe enough to perform speed control (e.g., there is another vehicle right in front of the host vehicle), Eco-Drive will be turned off and return the control to the default controller in simulation. Otherwise, Eco-Drive will proceed to conduct trajectory planning and speed control for the virtual host vehicle.

As the key component in the Eco-Drive system, the trajectory planning algorithm designs the optimal speed profile for the vehicle to pass through the intersection with minimum energy consumption without compromising safety and mobility. To address the unique vehicle dynamic and powertrain characteristics of trucks in the algorithm, we first train the algorithm using calibrated acceleration and deceleration profiles and power-based cost table. Those data are fed into the graph-based trajectory planning algorithm first to generate a pool of optimal trajectories for all combinations of starting and ending states. Then, a machine learning-based trajectory planning algorithm (MLTPA) is developed and trained to provide a fast and accurate speed recommendation in real time based on the pool of optimal trajectories. In the following subsections, we discuss the details about each element in the trajectory planning algorithm.

B. Trajectory Planning for Trucks

To design the most energy-efficient trajectory for the host truck to pass through an upcoming intersection while guaranteeing safety and mobility, we define five rules as follows:

1. Driving Rule: The host vehicle can only cross the stop line during the green or yellow time. The vehicle speed must stay within the road speed limit $[0, v_l]$.

2. Gap Keeping Rule: The host vehicle must keep a safe time gap from the preceding vehicle when passing through the intersection.

3. Acceleration/Deceleration Rule: The acceleration and deceleration rates of the host vehicle at a certain speed always stay in a range $[a_{min}(v), a_{max}(v)]$ capped by the dynamic performance of the vehicle and the driving style of the driver.

4. Mobility Rule: Under Rules 1-3, the host vehicle aims to minimize the travel time to reach a target location (usually the stop line) with a reasonable speed.

5. Energy-Saving Rule: Under Rules 1-4, the host vehicle aims to minimize the total amount of energy consumed in the eco-driving process from the current state to the target state.

Considering Rules 1-4, the host vehicle will attempt to safely pass the stop line at the earliest possible time. Then, the target state in Rule 5 is defined as the expected time, location (i.e., the stop line), and speed at which the vehicle fulfills this goal. Assuming that the vehicle first accelerates with $a_{max}(v)$, and then keep the speed once it reaches the speed limit v_l, the earliest possible time it can reach the stop line (defined as t_e) can be calculated based on kinematic equations. As t_e is the earliest time the vehicle can reach the stop line if ignoring the traffic signal, it can be used to identify the target state. If t_e falls within the green phase, it can be directly considered as the target time of the vehicle. The target speed is then the maximum speed the vehicle can reach at that time. If t_e falls within the red or yellow phase, the target time will be switched to the beginning of the next green phase, plus a buffer time for the preceding vehicle queue to clear. In Section II-D, we provide more details on the estimation of the buffer time. The target speed is set to be a predefined value v_t.

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Given the current state and the target state, we develop a graph-based algorithm to solve the trajectory planning problem with constraints on total travel time T, total travel distance X, and target speed v_t at the stop line [11]. To formulate this graph problem, we discretize the time and space into fixed time step Δt and distance grid Δx. The vehicle speed domain is therefore discretized with $\frac{\Delta x}{\Delta t}$ as the step. At each node of the proposed directed graph, we assign a unique 3-D coordinate (t, x, v) to describe the dynamic state of the vehicle, where $t \in (0, T]$ is time (in second), $x \in [0, X]$ is distance to the intersection (in meter), and $v \in [0, v_l]$ is vehicle speed (in m/s). There is an edge from V_1 (t_1, x_1, v_1) to V_2 (t_2, x_2, v_2) if and only if the following rules are satisfied:

1) Time at V_2 is consecutive with time at V_1: $t_2 = t_1 + \Delta t$;

2) Consistency in the distance and speed relationship: $x_2 = x_1 + v_1 \Delta t$;

3) Speed constraints: $v_2 = v_1 + a\Delta t$ and $0 \le v_2 \le v_l$;

4) Acceleration/deceleration constraint: $a_{min}(v_1) \le a \le a_{max}(v_1)$, where $a_{min}(v_1)$ and $a_{max}(v_1)$ are the maximum deceleration and maximum acceleration rates at speed v_1 for the host truck, respectively. The acceleration/deceleration range in this paper are calibrated in the real-world truck data.

We further define the cost on edge $V_1 \to V_2$ as the tractive power during this state transition process. At this point, the trajectory planning problem for energy minimization is converted into a problem to find the shortest path from the source node $V_s(0, X, v_s)$ to the destination node V_d (T, 0, v_t) in the directed graph. We apply the Dijkstra's algorithm [14] to solve this single-source shortest path problem with non-negative cost.

C. Power-based Cost Function

In this paper, the cost of the graph is defined as the tractive power of the truck at certain speed and acceleration rate. Assume that road grade is zero, the coasting acceleration rate is a function of speed as follows:

$$a_{coast} = -\mu g - \frac{1}{2m} C_D \rho_a A v_i^2 \quad (1)$$

When the truck is in a coasting or braking mode, i.e. $a \le a_{coast}$, we assume that the tractive power is 0. When the truck is in a traction mode ($a > a_{coast}$), the tractive power is calculated as:

$$P = Fv = \left(ma + \mu mg + \frac{1}{2} C_D \rho_a A v_i^2\right) v \quad (2)$$

We calibrate the function using real-world data collected from trucks, so the tractive power can be a reasonable indicator of the fuel consumption rate of the truck. Fig. 2 shows the contour map of tractive power as a function of instant speed and acceleration rate.

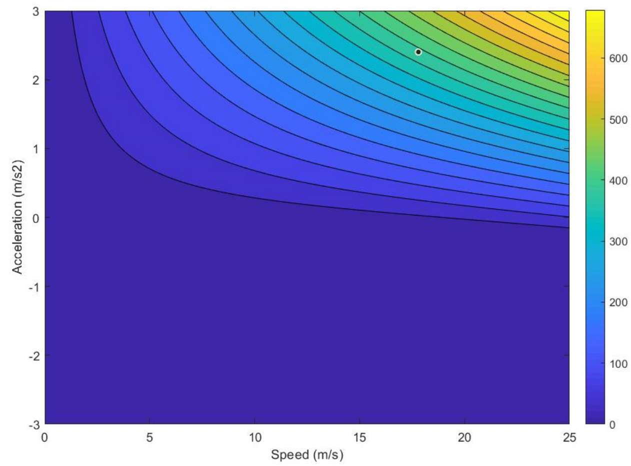

Figure 2. Contour map of tractive power vs. instant speed and acceleration rate

D. Eco-Drive with Preceding Queues

In Eco-Drive algorithm design, it is a challenge to develop an energy-efficient vehicle trajectory in traffic, considering the existence of preceding vehicle queues. If there is no queue in front, the target time can be set as the beginning of the next green phase. If there is a queue, however, the host vehicle has to keep a safe time gap from the preceding vehicle by adding a buffer time for the queue. As shown in Fig. 3, the buffer time consists of 4 parts:

1. Shockwave time: The elapsed time for the queue discharging shockwave to propagate to the preceding vehicle, i.e., the additional green time the preceding vehicle needs to wait before it can start moving.

2. Acceleration time: The time needed for the preceding vehicle to reach the stop line in its acceleration process.

3. Time compensation for speed difference: As Eco-Drive usually plans a non-stop trajectory, the speed of the host vehicle at the stop line would be higher than the typical speed when the preceding vehicle passes the stop line. This time compensation is added to the buffer time to avoid a potential crash when the host vehicle gets closer to the preceding vehicle after passing the stop line.

4. Safe headway: The time headway the host vehicle needs to keep to safely follow the preceding vehicle in the traffic.

The buffer time, as the sum of the four terms above, can be formulated based on kinematic equations as follows:

$$\tau = \frac{L}{v_{sw}} + \frac{v_t}{a_p} - \left(\frac{v_t}{2a_p} - \frac{L}{v_t}\right) + \tau_h = \left(\frac{1}{v_{sw}} + \frac{1}{v_t}\right) L + \frac{v_t}{2a_p} + \tau_h \quad (3)$$

where L is the queue length, i.e., the distance between the stop line and the stop location of the preceding vehicle, v_{sw} is the shockwave speed, a_p is the average acceleration rate of the preceding vehicle, and τ_h is the safe headway. According to Equation (3), the buffer time is linear to the preceding queue length. As v_{sw} and a_p are specific to the geometry and vehicle composition (e.g. truck/car ratio) of the intersection, the parameters in the equation have to be calibrated using onsite data.

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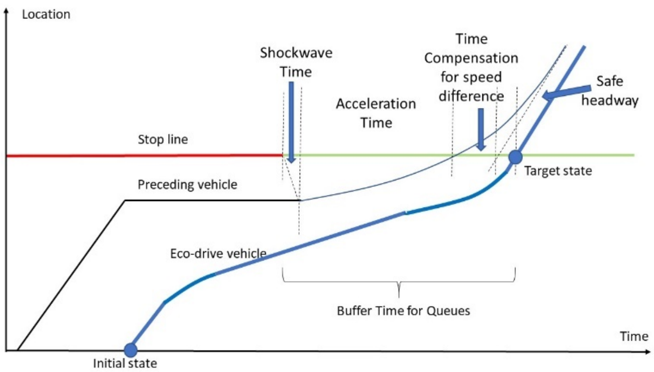

Figure 3. Buffer time for the queue considered by Eco-Drive

E. Machine Learning-based Trajectory Planning

The trajectory planning algorithm described above improves the computation efficiency over conventional optimization techniques by introducing dynamic programming framework. However, we can further reduce the computation time using an innovative algorithm, named Machine Learning-based Trajectory Planning Algorithm (MLTPA) [15]. In contrast to the end-to-end model, MLTPA uses training data generated by Graph-Based Trajectory Planning Algorithm (GBTPA) on a range of representative unique inputs. Using the GBTPA-generated data, MLTPA is trained to predict the next target state for the host vehicle. We compare the prediction accuracy of five types of machine learning techniques, including linear regression, k-nearest-neighbors, decision tree, random forest, and multi-layer perceptron neural network. The random forest method has the best performance in terms of root mean square error (RMSE). After being trained offline, MLTPA is then applied in Eco-Drive online to yield both computation efficiency for the system and energy efficiency for the host vehicle.

The proposed MLTPA enables the Eco-Drive system to work in real time, in both traffic microsimulation real-world environment. In this paper, use PTV Vissim as the traffic microsimulation platform for validating the Eco-Drive system, as discussed in the next section.

III. VALIDATION

A. Simulation Setup

To validate the proposed system, we implement a truck Eco-Drive API into Vissim, and test it in a calibrated simulation network of the Alameda St corridor in Carson, California, as shown in Fig. 4. The corridor is a 3-mile segment with 2-3 lanes per direction. The speed limit is 45 mph. There are six signalized intersections in the segment where five of them are connected. Eco-Drive can receive SPaT from and perform vehicle trajectory planning only at the connected intersections. The network is calibrated using signal timing data and traffic data provided by the local agencies.

When activated, the truck Eco-Drive API replaces the inherent driving behavior model in Vissim with a user-defined behavior model embedded in the vehicle dynamics control module written in C++. During a simulation run, the API calls the External Driver Model DLL code for the host truck in each simulation time step, obtains the current vehicle state, determines its next optimal speed, and then passes this updated vehicle state back to Vissim. The MLTPA is applied to perform real-time vehicle trajectory optimization during this process.

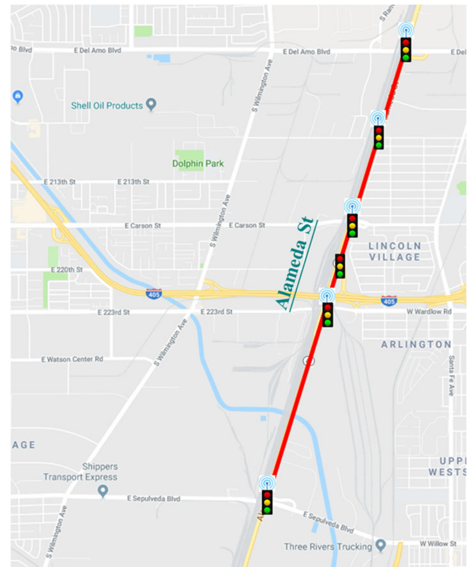

Figure 4. Simulation corridor in Carson, CA

In Vissim, profiles of desired acceleration vs. speed, along with information about the vehicle's surrounding environment are used to determine each vehicle's acceleration at every time step [16]. The same applies for deceleration. Every vehicle type in Vissim (e.g., light-duty vehicle, bus, truck) has desired acceleration and deceleration profiles, especially for trucks which have diverse size, weight, and power. Using real world data, we calibrated those parameters before running simulation to address their significant impact on truck mobility, energy, and emissions.

B. Simulation Results

The simulation of a heavy-duty truck without and with Eco-Drive is conducted in each direction of the signalized corridor in the calibrated simulation network. For each direction, 350 simulation runs are made using different seed numbers in order for the truck to encounter a large variety of traffic situations. The same set of seed numbers is used for the cases without Eco-Drive (baseline) and with Eco-Drive.

Since the primary benefit of Eco-Drive is that the host vehicle would save energy without significantly sacrificing travel time by reducing unnecessary acceleration/deceleration when approaching and departing signalized intersections, we calculate the differences in travel time, travel delay, number of stops, cumulative acceleration, cumulative deceleration, and energy consumption between the baseline and Eco-Drive scenarios, along with their statistical significance, as shown in Table I. A stop is defined as the vehicle speed being zero for more than 3 seconds, and the travel delay is defined as the total time of stops. The results for each study segment are discussed below.

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Table I Benefit evaluation results from simulation

	Alameda St NB	Alameda St SB
Travel time (s/mi)	-0.6%	1.2%
Travel delay (s/mi)	-26.5%*	-13.5%*
No. of stops per mile	-24.5%*	-3.0%
Positive Energy consumption (kWh/mi)	-6.1%*	-7.3%*
Cumulative acc (mph)	-11.1%*	-3.1%*
Cumulative dec (mph)	-11.1%*	-2.1%*

**Statistically significant at 5% significance level*

Alameda St Northbound

As shown in Table I, the energy consumption for the truck in the Eco-Drive case is 6.1% less than in the baseline case, with statistical significance at 5% significance level. The travel delay and number of stops are reduced by 26.5% and 24.5%, respectively. And the cumulative acceleration and cumulative deceleration are both reduced by 11.1%. These decreases are as expected since Eco-Drive helps the truck avoid unnecessary stops, acceleration, and deceleration around the connected intersections on the segment. These also result in 0.6% less travel time as compared with the baseline. To visually present how the Eco-Drive truck saves energy while keeping a similar travel time, we plot the speed profiles of the truck in the baseline and Eco-Drive cases in Fig. 5(a) and Fig. 5(b), respectively. In Fig. 5(a), the truck without Eco-Drive makes a harder brake to stop before the red light at the connected intersections. When equipped with Eco-Drive, the truck starts to adjust its speed far ahead of the connected intersections, often avoiding stops at those intersections and producing smoother trajectories in Fig. 5(b). Another benefit of Eco-Drive is the improvement in driving comfort and traffic smoothing as evident by the acceleration histograms in Fig. 6. With Eco-Drive, the truck spends a lot more time coasting and a lot less time accelerating/decelerating, which makes it more comfortable and energy-efficient. The milder acceleration/deceleration would likely result in lower noise pollution around the intersections as well.

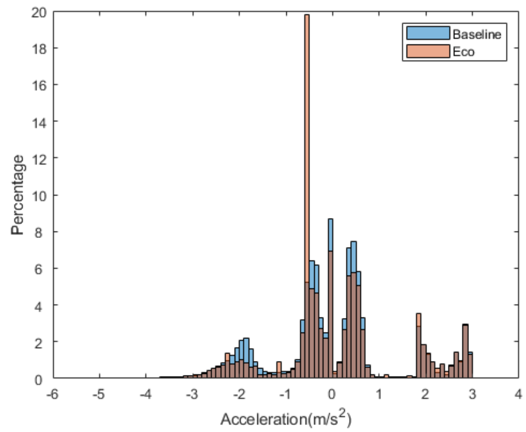
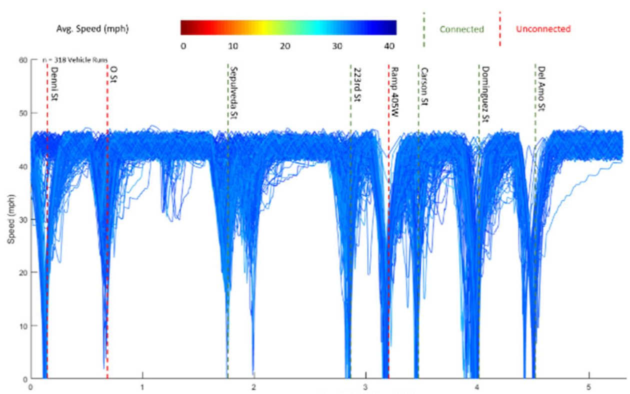


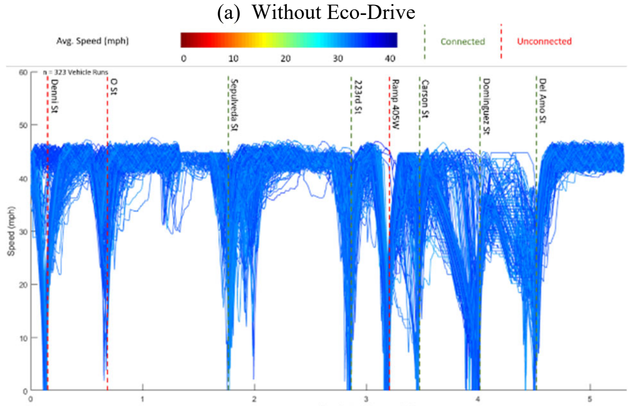
Figure 6. Histograms of acceleration rate of the truck along Alameda St NB without and with Eco-Drive

Alameda St Southbound

This direction of traffic is more congested than in the NB direction, with vehicles often experiencing long queues at the intersections with 223rd St, Sepulveda St, and O St. This

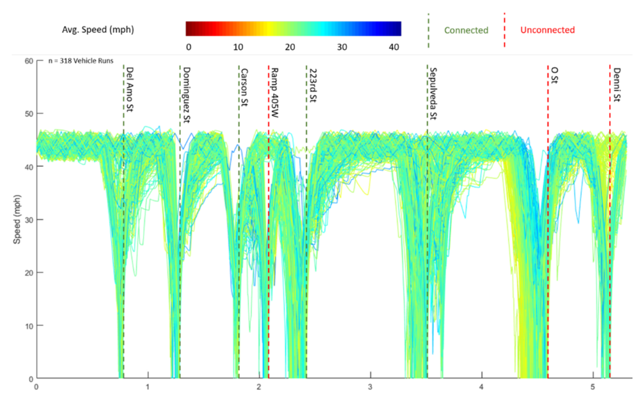


(a) Without Eco-Drive

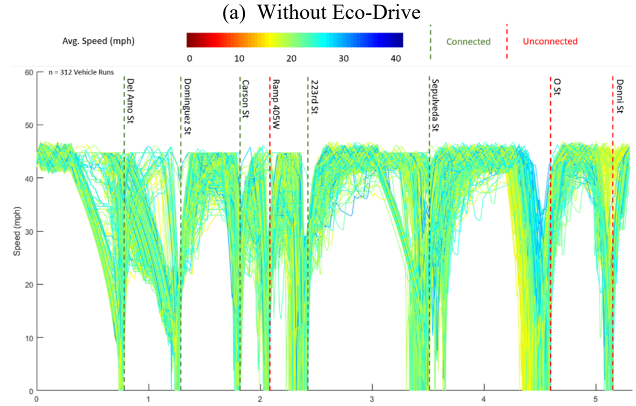


(b) With Eco-Drive

Figure 5. Speed profiles of the truck along Alameda St NB



(a) Without Eco-Drive



(b) With Eco-Drive

Figure 7. Speed profiles of the truck along Alameda St SB

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results in lower average speeds as indicated by the color of the trajectories in Fig. 7, which limits Eco-Drive's ability to help the truck avoid stopping at these intersections. Nevertheless, the truck energy consumption in the Eco-Drive case is 7.3% less than in the baseline case, with statistical significance at 5% significance level. The travel delay and number of stops are reduced by 13.5% and 3.0%, respectively. And the cumulative acceleration and cumulative deceleration are reduced by 3.1% and 2.1%, respectively. The truck travel time in the Eco-Drive case is 1.2% higher than in the baseline case, but it is not statistically significant.

IV. Conclusions

In this paper, we present a connected vehicle-based truck eco-driving system to minimize energy consumption at signalized intersections. The system is pre-calibrated for the host vehicle using real-world acceleration/deceleration profiles from the vehicle to create a graph-based trajectory planning algorithm. A machine learning-based trajectory planning algorithm is then developed and trained to enable a fast and accurate determination of optimal vehicle trajectory. During the operation, the system uses real time information about the host vehicle, traffic signal phase and timing, and preceding traffic to optimize vehicle trajectory for energy while ensuring a safe passage through the intersection. The simulation-based system evaluation on a signalized urban freight corridor in Carson, California, shows that the proposed system provides statistically significant energy savings for the host vehicle, while maintaining similar travel time, due to fewer number of stops and milder acceleration/deceleration.

It should be noted that the results presented are specific to the simulation settings used in this research. The results could vary by a number of factors, such as corridor characteristics (number of signalized intersections, intersection spacing, how many of the intersections are connected, terrain, etc.), vehicle characteristics (body type, weight, etc.), traffic conditions (congestion level, signal timing plan, vehicle composition, etc.), among others. This is evidenced by the differences in the impact of the proposed system between the NB and the SB directions of the test corridor shown in this paper. With many factors at play, it is challenging to generalize the benefits of the proposed system. More research is needed to better understand the levels of energy savings that the proposed system could provide under a variety of settings.

V. Acknowledgement

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