Speed Trajectory Generation for Energy Efficient Connected and Automated Vehicles

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***Abstract*— Connected and automated vehicles (CAVs) have real-time knowledge of the immediate driving environment, actions to be taken in the near future and information from the cloud. This knowledge, referred to as preview information, enables CAVs to drive safely, but can also be used to minimize fuel consumption. Such fuel-efficient transportation has the potential to reduce aggregate fuel consumption by billions of gallons of gas every year in the U.S. alone. In this paper, we propose a planning framework for use in CAVs with the goal of generating fuel-efficient vehicle trajectories. By utilizing vehicle-to-infrastructure (V2I) communications and on-board sensor data, we leverage the computational power of CAVs to generate *eco-friendly* vehicle trajectories. The planner uses an *eco-driver* model and a predictive cost-based search to determine the optimal speed profile for use by a CAV. To evaluate the performance of the planner, we introduce a co-simulation environment consisting of a CAV simulator, MATLAB/Simulink and a CAV software platform called the InfoRich Eco-Autonomous Driving (iREAD) system. The planner is evaluated in various traffic scenarios based on real-world road network models provided by the National Renewable Energy Laboratory (NREL). Simulations show a savings of 14.5% in fuel consumption with our approach.**

I. INTRODUCTION

One of the most pressing issues of modern transportation is fuel efficiency. In the United States alone, nearly 143 billion gallons of motor gasoline were consumed in 2018 [1]. Emissions from combustion have adverse effects on the environment [2], while also creating dependence on foreign sources of fuel. As connected and automated vehicle technology improves, their impact on fuel consumption needs to be studied. Fortunately, the computational power, the connectivity, the sensing capabilities and the knowledge of pending near-term actions of CAVs can be proactively used to minimize fuel consumption.

In this paper, we study how the speed profiles of CAVs can be effectively utilized to reduce fuel consumption. We specifically focus on urban environments, where it is common to have high levels of interaction among the CAV, its surrounding vehicles and traffic signals. We propose a *Eco-Planner* framework to generate fuel-efficient driving profiles and define vehicle behavior goals. Multi-objective optimization based on traffic condition and vehicle characteristics is performed in real-time with a speed reference generated and passed to a Short-Term Path Planner, which is further refined before being sent to the actuator controllers. Our iREAD system architecture is shown in Figure 1.

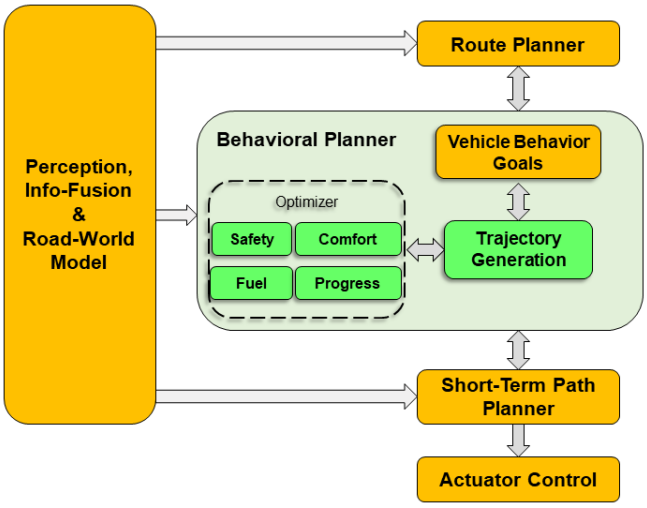

Fig. 1. iREAD System Architecture

Our framework provides the ability to:

1) create vehicle trajectories that emulate what a human driver would do,
2) search through a suitably-sparse space for real-time execution, and
3) reduce a CAV's average fuel consumption in urban environments.

In short, a CAV's on-board communication and computation capabilities are used to predict and optimize the ego vehicle's interaction with its environment.

II. RELATED WORK

The ability for connected and automated vehicles to reduce fuel consumption has been studied in [3]. Michel et al. show that the energy consumption for vehicles decreases, as the level of connectivity increases, especially at lower speeds. Additionally, fuel consumption optimization at signalized intersections are investigated in [4] using speed trajectory generation through closed-form solution as well as numerical solutions. They found that a closed-form solution is sufficient to generate comparable energy savings while significantly reducing computational time, making it practical for use in online optimization.

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Motion planners in autonomous vehicles have typically been implemented as a layer in the vehicle decision-making hierarchy [5]. Wei et al. [6] introduced a prediction-based planning layer, which models interactions between vehicles and focuses on reducing computational cost while preserving planner quality. Optimization using dynamic programming based on travel distance has been explored in [7] and [8]. A drawback to using such a method is the inability to generate a trajectory for a specific timeframe. Trajectory optimization methods have been explored by Kelly [9]. Such methods require solving non-linear programs online, which is undesirable for real-time applications with an emphasis on safety. Compared to prior work, our planner does online energy consumption optimization by taking into account signalized traffic intersections as well as surrounding vehicles, while being practically implementable in CAVs.

III. ECO-PLANNER FRAMEWORK

Our planning framework consists of three steps: (1) candidate generation, (2) prediction, and (3) cost evaluation. In the candidate generation stage, a set of candidate driving strategies is generated based on headway (i.e. a planning horizon). Then, these strategies along with information on surrounding vehicles are sent to the Eco-Driver Model (EDM) with a prediction engine. The EDM next generates a series of forward-simulated speed trajectories for the next prediction horizon (e.g., 15 secs). Finally, the prediction-based optimizer computes the aggregated cost of each candidate speed trajectory and picks the optimal speed profile.

A. Eco-Driver Model

In order to generate a set of candidate trajectories, we employ a modified version of the "Intelligent Driver Model" [10]. The intelligent model, as described by Treiber et al., is a car-following model which is useful when there is a lead vehicle. A similar approach was also studied in [11], which demonstrated improvements in vehicle energy consumption. In order to generalize the model for scenarios that do not include a lead vehicle, we introduce the following driver model:

$$a = \alpha_{max}(v)\left[1 - \left(\frac{V}{\gamma V_{lim}(S)}\right)^{\delta} - \left(\frac{S_{min}(V,V_L)}{S_L}\right)^{2} - \left(\frac{S^*_{min}(V)}{S_{stop}}\right)^{\delta_{stop}}\right] \tag{1}$$

where,

$$S_{min}(V,V_L) = S_0 + V \cdot T_{gap} + V \cdot \frac{V - V_L}{2\sqrt{\alpha_{max}\beta}} \tag{2}$$

$$S^*_{min}(V) = S_{0,stop} + V \cdot T_{gap,stop} + \frac{V^2}{2\sqrt{\alpha_{max}\beta}} \tag{3}$$

The parameters of the Eco-Driver Model are tuned heuristically to obtain the desirable characteristics of fuel-efficient driving, while still maintaining a speed that is acceptable to human-operated vehicles in the ego vehicle's environment. As presented in Equations (1-3), α_{max} is the maximum acceleration, β is the desired deceleration parameter, V is the ego vehicle's speed, T_{gap} is the headway gap between the ego and the lead vehicle, S_L is the distance to the lead vehicle, S_{stop} represents the distance to stop (i.e. intersection) and V_L is the lead vehicle's speed. V_{lim} denotes the speed limit for the particular stretch of road, while γ represents a speed-limit multiplier (eg. 1.1) that allows for some slack in the driver model. S_0 and $S_{0,stop}$ are the minimum distances to keep to the lead vehicle and road intersection, respectively.

The first term of Equation (1) represents the speed regulator. The ego vehicle's speed is normalized by the speed limit, and δ can be viewed as an "aggression" factor. The second term maintains the vehicle-following distance in the presence of a lead vehicle. In the case that there is no lead vehicle present, we choose a suitably large value for S_L, which diminishes the effect of the vehicle-following term. The final term regulates the vehicle deceleration. Analogous to the vehicle-following term, if the Eco-Driver Model predicts that the ego vehicle will enter an intersection during a green phase of the traffic light, S_{stop} will be assigned a large value to prevent it from slowing down unnecessarily[1].

One advantage of this model is the ability to independently select the parameters. A smaller δ value typically leads to less aggressive and more fuel-efficient driving. In the case that the ego vehicle must come to a stop, smaller values of δ_{stop} generate speed profiles that allow for fuel-efficient coast-down. Figure 2 shows the trajectories generated by the driver model for different values of δ while holding all other parameters constant at traffic-free intersections. It can be seen that with increasing values for δ the corresponding acceleration increases and a higher top speed is achieved. Similarly, Figure 3 shows the trajectories generated by the driver model for different values of δ_{stop} under the same driving conditions. Table I shows the parameters used for generating the trajectories in Figure 2 and 3.

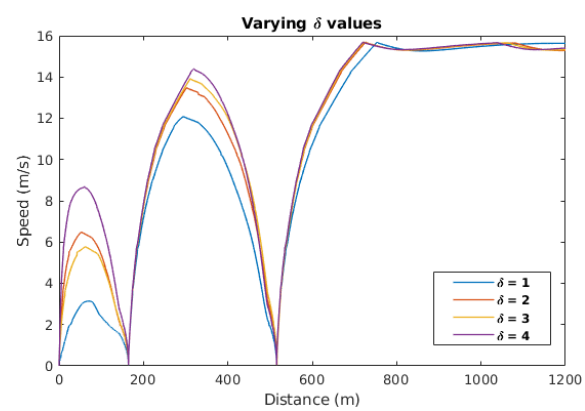

Fig. 2. Trajectories generated by the Eco-Driver Model in traffic-free intersections while varying δ values

B. Headway Search Space

We define headway as the travel time required for the ego vehicle to reach a lead vehicle. A buffer distance is

[1]We make the assumption that signal phase and timing (SPaT) information is available at all intersections controlled by traffic lights

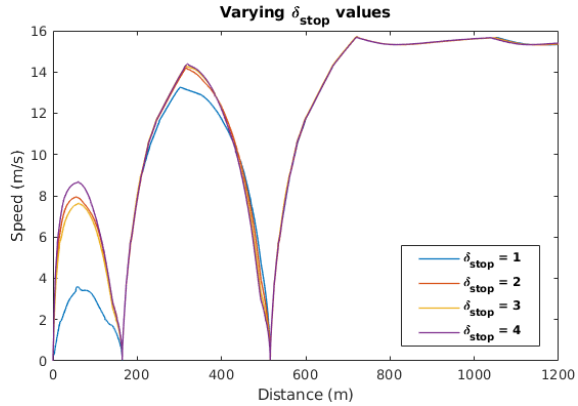

Fig. 3. Trajectories generated by the Eco-Driver Model in traffic-free intersections while varying δ_{stop} values.

TABLE I

PARAMETERS USED FOR FIGURES 4 AND 5

Figure	α_{max}	β	γ	δ	δ_{stop}
4	2	5	1	varies	2
5	2	5	1	5	varies

added to the headway, as depicted in Figure 4, for safety considerations. As shown in Figure 5, for a look-ahead horizon of 15 seconds, the headway search space is generated at 5 second intervals in the prediction horizon, with the headway range being 0.5-5 seconds. This set of headway trajectories is passed to the Eco-Driver Model to be used as T_{gap} in (2), which is then used by the Prediction-Based Optimizer to generate a set of vehicle speed trajectories.

C. Prediction-Based Optimizer

Our prediction-based optimizer searches through candidate trajectories generated based on the headway. Its objective is to forward-simulate the vehicle's trajectory and "observe" its interactions with the lead vehicle and traffic signals. To reduce computational cost, any trajectories which violate the relevant speed limit are discarded and the Prediction-Based Optimizer moves on to the next candidate trajectory in the set. The specific steps of the Eco-Planner are presented in Algorithm 1. The algorithm assumes that the lead vehicle will maintain their speed throughout the prediction horizon. This is unrealistic without knowing the intent of the lead vehicle. In order to address this, we run the Eco-Planner at a rate fast enough such that we only use the trajectory over a period of time that this approximation is valid.
The cost of each candidate trajectory is calculated as follows:

$$Cost = \sum_{t=0}^{Horizon} k_{fuel}C_{fuel,t} + k_{progress}C_{progress,t} + k_{comfort}C_{comfort,t} \tag{4}$$

The individual cost terms are:

$$C_{fuel,t} = table_{fuel}(V_t, a_t) \tag{5}$$

$$C_{progress,t} = \frac{t}{max(\sum_{i=0}^{t} V_i \Delta T, \varepsilon)} \tag{6}$$

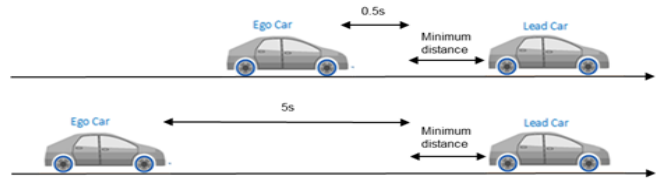

Fig. 4. Vehicle Headway

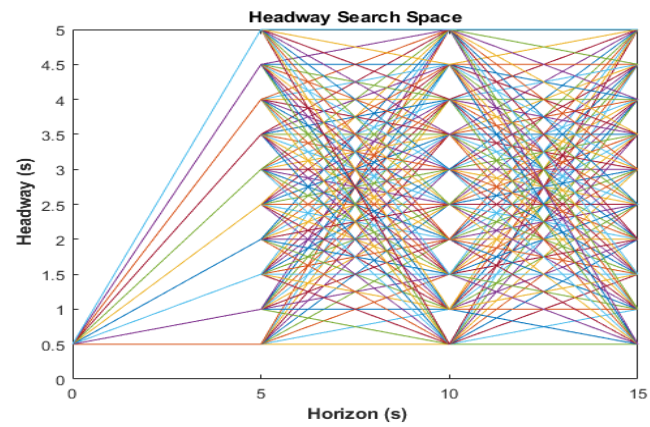

Fig. 5. Headway Search Space

$$C_{comfort,t} = table_{jerk}(J_t) \tag{7}$$

where ε is a small value so that $C_{progress}$ is bounded.

The fuel cost is a lookup table shown in Figure 6. Figure 7 shows the lookup table for the comfort cost. Jerk was chosen as a comfort cost due to the desire to generate trajectories which do not rapidly accelerate or decelerate. Progress cost is chosen as the travel time divided distance traveled, The idea here is that shorter distance traveled over a period of time is penalized. The relative importance of the cost factors is adjusted with their respective weights: k_{fuel}, $k_{progress}$, and $k_{comfort}$.

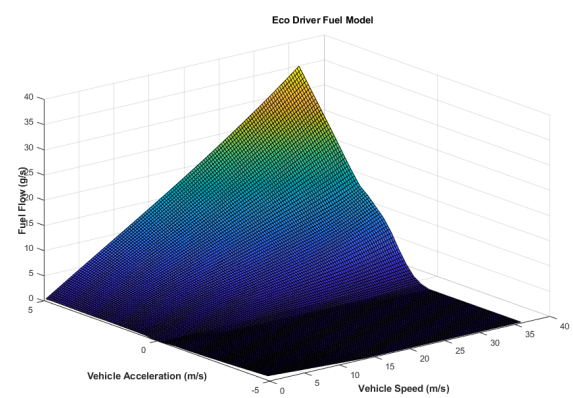

Fig. 6. Fuel cost lookup table

IV. TEST ENVIRONMENT

To validate our approach, we built a test environment consisting of a 3D-environment simulator (Vires VTD), a MAT-

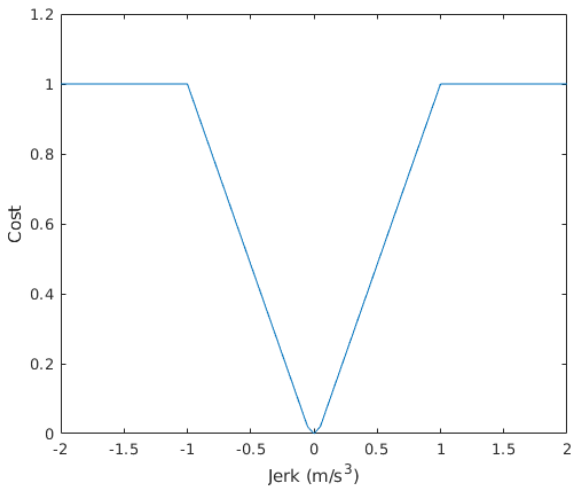

Fig. 7. Comfort cost lookup table

Algorithm 1: Prediction-Based Eco-Planner

Input : $V_{lead}, V_{ego}, S_{lead}, S_{end}, V_{lim}, T(trajectory\ set)$
Output: Vehicle Trajectory V_{pred}

for i = *1 ... N* $\in T$ **do**
  for $t = 0 \rightarrow prediction\ horizon$ **do**
    Calculate S_{min}, S^*_{min} *as in (2) and (3)*
    Calculate $a_{i,t}$ *as in (1)*
    $J_{i,t} = (a_{i,t} - a_{i,t-1})/\Delta T$ *(Jerk)*
    $V_{i,t} = V_{i,t-1} + (a_{i,t-1}\Delta T)$ *(Vehicle Speed)*
    $P_{i,t} = P_{i,t-1} + (V_{i,t}\Delta T)$ *(Progress)*
    $F_{i,t} = Fuel\ Table(V_{i,t}, a_{i,t})\Delta T$ *(Fuel)*
    Calculate $Cost_{i,t}$ *as in (4)*
    if $V_{i,t} > V_{lim}$ **then**
      go to 1
    end
  end
  if $Cost_i < Cost_{min}$ **then**
    $Cost_{min} \leftarrow Cost_i$
    $V_{pred} \leftarrow V_i$
  end
end

LAB/Simulink model for vehicle dynamics and fuel consumption, and our CAV platform. Our Eco-Planner framework is then tested and evaluated within this environment.

A. The InfoRich Eco-Autonomous Driving System (iREAD)

The iREAD system is our CAV platform that the Eco-Planner is built upon. The operation of the iREAD system is shown in Figure 9. Given a map and a set of waypoints to traverse, the route planner determines the path of travel. The behavioral layer generates a set of intermediate goals which are used by the Eco-Planner to generate a reference plan. The Eco-Planner optimizes the reference plan for multiple objectives: safety, fuel efficiency, comfort, and progress. The optimized trajectory is then sent to the Short-Term Path Planner for further refinement and to obtain a desired speed for the actuator controller. A PID controller is used to control the throttle position of the engine in the vehicle model, which provides vehicle state feedback. The iREAD system is a real-time system that is extensible to fully autonomous on-road operation, as well as vehicle-in-the-loop (VIL) testing on a dynamometer.

B. VIRES Virtual Test Drive

VIRES VTD [12] provides a virtual environment to test interactions among the ego vehicle and the surrounding traffic, traffic signals as well as the road network. VIRES enables testing our planning framework under different driving conditions. Adjustable parameters, including traffic density, traffic light signal phase and timing (SPaT) and the driver characteristics of surrounding vehicles, allow for the emulation of urban and rural driving scenarios. Using the number of surrounding vehicles per unit distance, we took an average separation distance of <10m per vehicle as heavy traffic congestion (traffic jam), and 30-50m per vehicle as moderate traffic. Traffic surrounding the ego vehicle at an intersection is visualized in Figure 10. Furthermore, "virtual sensors" provide real-time data such as SPaT and surrounding vehicles' state to the iREAD CAV platform.

C. Vehicle Model

A high-fidelity model of our ego vehicle's powertrain was constructed using Simulink's Simscape Driveline platform. The vehicle model consists of a 3.6-liter V6 engine, torque converter, 8-speed automatic transmission, and vehicle chassis. A custom powertrain model was built using the Simscape language, whose input signals include throttle position, deceleration fuel cut off (DFCO), engine shut off, and cylinder deactivation. Engine parameters include torque-speed tables, engine inertia, fuel consumption tables and idle reference speed.

While typically an engine's control unit (ECU) will take more inputs such as ambient temperature, coolant temperature and air flow rate, our simplified model uses only the engine speed along with the throttle position sensor (TPS) input to capture the engine dynamics and fuel consumption. The assumption of the model is that the engine is already at operating temperature (i.e. hot start). Vehicle data from General Motors LLC (GM) were used to create the torque and fuel-rate lookup table. Samples between data points were linearly interpolated and sample points outside the range of data points were assigned the value of the nearest data point.

The Simscape model of the vehicle body, shown in Figure 8, consists of the vehicle's longitudinal dynamics, tire model, brakes and all-wheel drive system with the transfer case, as well as front and rear differentials. The vehicle body parameters include frontal area, drag coefficient, vehicle mass, wheel/tire radius, wheel inertia and final drive gear were obtained through GM's proprietary high-fidelity vehicle model. The gain for the braking force was tuned using the transmission output torque from the GM model to match the

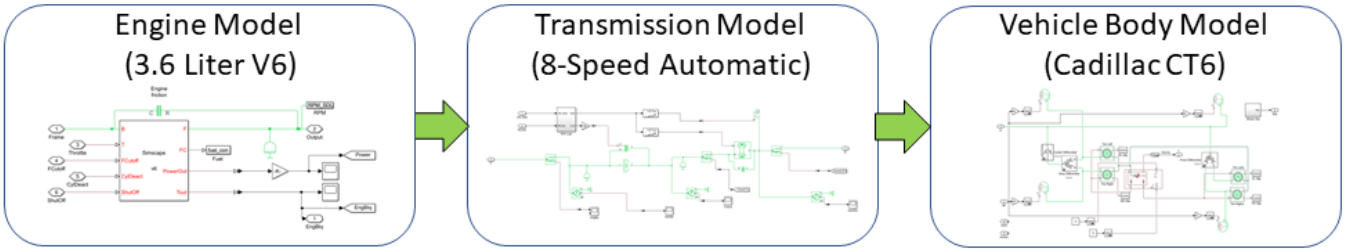

Fig. 8. Vehicle Powertrain Model

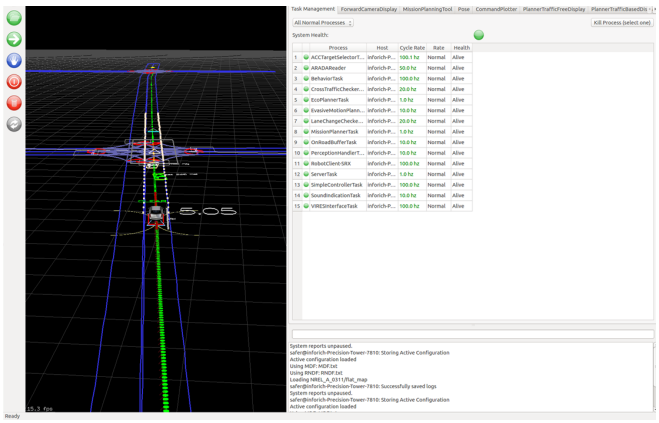

Fig. 9. InfoRich Eco-Autonomous Driving System (iREAD).

Fig. 10. The VIRES simulation environment with traffic surrounding the ego vehicle.

speed profile for the FTP-75 [13] test cycle used by the U.S. Environmental Protection Agency for emissions testing.

V. RESULTS

To validate the approach we created a set of real-world driving scenarios in VIRES using NREL's Transportation Secure Data Center (TSDC) database. The NREL TSDC routes represent different roads, ranging from highways to urban settings. They are representative of typical routes that a commuter would take in the U.S. In-depth simulations were conducted on 16 different routes. They consisted of 9 short (∼1.7 km) and 7 long (∼15 km) routes. The routes

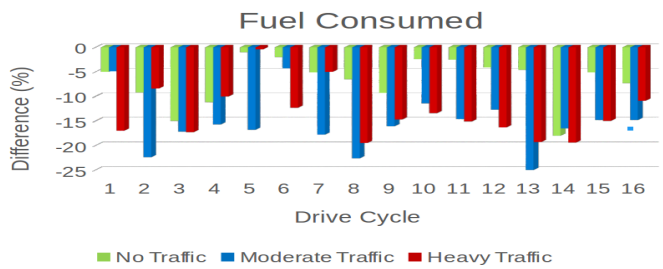

Fig. 11. Simulated Fuel Consumption of Drive Cycles

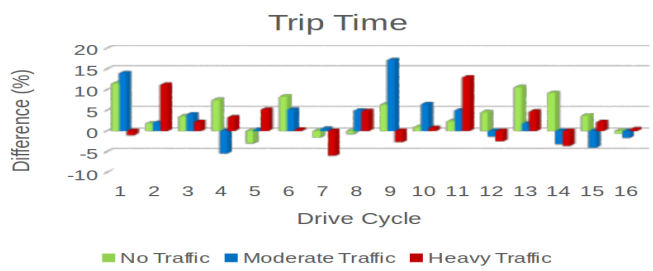

Fig. 12. Simulation Completion Time of Drive Cycles

represented a total of 742 kilometers of simulated travel distance. When compared to the baseline driver, the Eco-Driver is able to achieve an average of 14.5% fuel savings with a modest increase in travel time of 2%.

We compared the Eco-Driver model to a baseline driver as outlined in Table II under no traffic, moderate traffic (50m/vehicle), and heavy traffic (20m/vehicle) conditions. The baseline driver is modeled after how an average person would drive on a road with traffic [14]. Compared to the baseline, the Eco-Driver has a longer preview window. We make these assumptions based on a CAV's sensing and communication capabilities. Additionally, the baseline driver is a constant headway follower while the Eco-Driver performs online headway optimization. The EDM was also tuned so that acceleration is not as "aggressive" and increased coasting by lowering the values of δ and δ_{stop}

Two drive cycles from the results shown in Figures 11 and 12 are particularly interesting. Drive Cycles 13 and 14 show a large difference in fuel savings when there is no traffic. The two road networks turn out to be very different. Figure 13 (Drive Cycle 13) shows a typical highway-driving scenario where there are only a few stop-and-go instances. Since this is a stretch of highway where there is no traffic, the Eco-

TABLE II

BASELINE DRIVER VS. ECO-DRIVER

Comparison	Baseline Driver	Eco-Driver
Preview Distance	Lead Vehicle: 60m Traffic Light and Stop Sign: 60m	Lead Vehicle: 200m Traffic Light and Stop Sign: 300m
Car Following Headway (T_{gap})	2s	1-5s (Headway search space)
Aggression Factor (δ)	4 (Average human driver aggression)	2 (Lower aggression level for Eco-Driver)
Braking Factor (δ_{stop})	2 (Average human braking factor)	0.5 (More coasting for Eco-Driver)

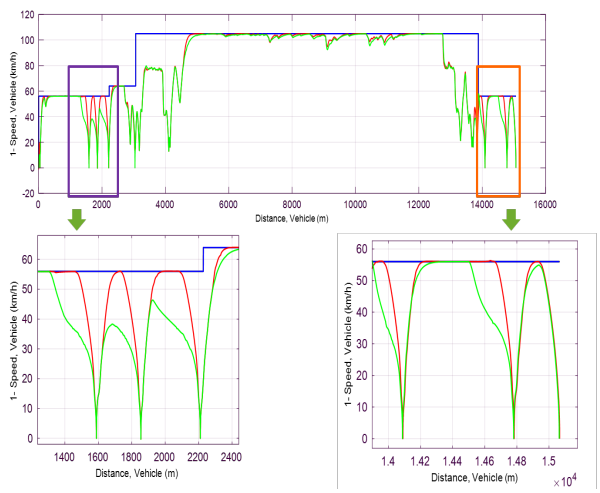

Fig. 13. Drive cycle 13 with no traffic (Baseline: Red, Eco: Green, Speed Limit: Blue)

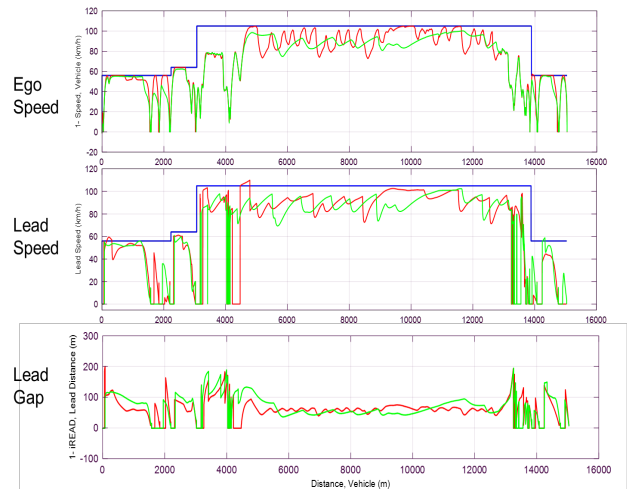

Fig. 14. Drive cycle 13 with moderate traffic (Baseline: Red, Eco: Green, Speed Limit: Blue)

Driver tracks the speed limit and we see limited improvements in fuel consumption. The same highway route, but now populated with moderate traffic, is depicted in Figure 14. The baseline driver follows the lead vehicle with a constant headway. With moderate traffic, as the lead vehicle's speed fluctuates, so does the ego vehicle's speed. When compared with the Eco-Driver, the headway optimization generates a trajectory that results in reduced fuel consumption.

In contrast, an urban scenario is shown in Drive Cycle 14 (Figure 15). In this scenario, there are plenty of instances of stop-and-go at intersections. In such cases, we observed much greater fuel savings as the Eco-Driver generated less aggressive acceleration profiles while increasing the duration of coasting during deceleration events. Since the speed of travel is dictated more by the stop-and-go intersections and less by the traffic, we also see that there is less variance in fuel consumption due to traffic density.

As demonstrated by these two drive cycles, the Eco-Driver model is able to show significant fuel savings in stop-and-go traffic regardless of traffic densities by utilizing the SPaT information from traffic signals and the available preview of upcoming stops at intersections. In highway driving, when there is moderate traffic, the Eco-Driver is also able to outperform the baseline driver by choosing the most fuel-efficient trajectory generated by the Eco-Driver using the online optimization based on the headway search space. In traffic-free highway driving, the fuel benefits obtained from the Eco-Driver are diminished as both the baseline and Eco-Driver attempt to drive at or near the speed limit constantly.

VI. CONCLUSIONS

In this paper, we addressed the efficiency of fuel consumption using the preview information available to CAVs. We proposed an Eco-Planner framework that utilizes an Eco-Driver Model with heuristically-tuned parameters to enable fuel-efficient driving. The Eco-Driver Model explores the headway search space to generate candidate speed trajectories. Using real-world drive cycles, we re-created road networks with various different traffic densities. Virtual sensors were utilized to simulate the connectivity capabilities of CAVs. The complete Eco-Planner framework has been implemented on our iREAD CAV platform, a real-time system that can be realized on a real vehicle. We showed that the iREAD system with the Eco-Planner is able to reduce fuel consumption by an average of $\sim 14.5\%$ with only slight increases in the travel time of only $\sim 2\%$. The fuel savings is more significant in scenarios where the ego vehicle has greater interactions with the environment, such as lead vehicles, traffic lights, and stop signs. The results suggest that the iREAD system with the Eco-Planner is suitable for use in urban and highway settings, where there are increased interactions between the ego vehicle and its surroundings. Some aspects of energy consumption optimization we would like to explore in the future include: 1) replacing the PID

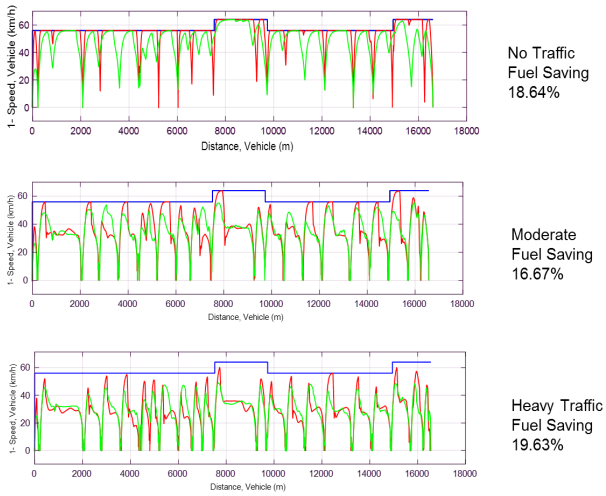

Fig. 15. Drive cycle 14 (Baseline: Red, Eco: Green, Speed Limit: Blue)

controller with a Model-Predictive Controller to fully utilize the "preview" trajectory from our Eco-Planner, 2) integrating road curvature and grade information into the Eco-Planner to more accurately predict fuel consumption in the presence of external disturbances, and 3) Implement a "discount factor" as in Markov Decision Processes which will place more weight on the cost at the beginning of the prediction horizon.

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