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Eco-Driving for Connected and Automated Vehicles in Mixed Traffic Urban Environments with Signalized Intersections

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Abstract— **This paper presents a trajectory planning method for connected and automated vehicles (CAVs) operating on a two-lane urban road that includes signalized intersections with a mix of human-driven vehicles (HVs) and CAVs. The proposed approach aims to find the optimal trajectory for CAVs, considering factors such as energy consumption, travel time and passengers' comfort. To achieve this objective, each CAV utilizes data obtained from various sources. Vehicle-to-infrastructure (V2I) communication enables access to information such as traffic light cycle lengths, timings and positions. Vehicle-to-vehicle (V2V) communication allows CAVs to gather information from other CAVs, including their positions, velocities and predicted trajectories. Additionally, on-board sensors can also provide data about surrounding vehicles. Dynamic programming (DP) is employed to predict the velocity profile of the CAVs over a long horizon, incorporating information from traffic lights and the vehicle's specifications. The predicted velocity profile is then fed into a model predictive controller (MPC) to follow the CAV's trajectory. The MPC is capable of handling disturbances encountered during the maneuvers, such as stopping behind a red traffic light or performing lane changes. Extensive simulation studies demonstrate how various objectives in terms of saving in energy consumption and travel time are achieved.**

I. INTRODUCTION

Adaptive cruise control (ACC) is a driver-assistance system that enhances safety and efficiency. However, incorporating vehicle-to-vehicle communication (V2V) and utilizing Cooperative Adaptive Cruise Control (CACC) not only improves safety and efficiency ([1], [2], [3]) but also enhances traffic flow by reducing the headway gap between vehicles ([4], [5]). Vehicle-to-infrastructure (V2I) is another form of communication that enables the sharing of road information with vehicles. In a recent study [6], V2I-enabled eco-driving control was introduced to reduce energy consumption in vehicles by up to 40%. Different control and path planning methods have been employed to find more efficient control strategies by leveraging the data acquired from V2V and V2I. In [7], an accurate and efficient energy consumption approach was presented and used to develop eco-driving systems for electric vehicles. Transition from human-driven vehicles (HVs) to fully automated ones is a gradual process. Authors in [8] proposed a unified multi-class car-following model for a heterogeneous platoon moving in a single lane roadway.

In terms of control, model predictive control (MPC) has become a popular framework that has also been employed for autonomous vehicles. Numerous studies have explored the application of MPC in autonomous driving(see, e.g., [9], [10], [11]). In a recent study (see [12]), an eco-CACC strategy was proposed for CAV platoons driving through successive signalized intersections. The study proposed the use of MPC in follower vehicles to optimize energy efficiency. Another study (see [13]) presented a stochastic energy-efficient adaptive cruise control approach that utilized V2V, V2I and radar information. In [14], a stochastic MPC design was developed specifically for CACC applications in a mixed-autonomy environment with the focus being on considering uncertainties in the behavior of both AVs and HVs. Furthermore, in [15], an eco-driving trajectory planning approach was proposed for heterogeneous connected autonomous vehicles in a single-lane urban environment. The latter study utilized dynamic programming to find the optimal velocity profile for the platoon leader and employed CACC for the followers to track the leader. Existing works mostly focused on single lane roads or highway roads that have no traffic light. However, there has been less emphasis on eco-trajectory planning in a mixed traffic signalized urban roads with multiple lanes, to the best of our knowledge. In this paper, ***an eco-trajectory planning approach is proposed for striking a balance between energy consumption, travel time and passenger comfort in a mixed traffic signalized multi-lane urban road***. The proposed approach utilizes dynamic programming (DP) to predict a long-range velocity profile, while achieving the desired balance between several factors. The predicted velocity profile is then passed to an MPC scheme in order to find the optimal control inputs for the vehicle. To account for any disturbances that may occur along the way, DP would be solved at predefined intervals. This allows the system to adapt and compensate for any changes or unexpected events that may affect the last calculated long-range trajectory.

The contributions of the paper are summarized as follows:

- *Eco-trajectory planning for autonomous vehicles while balancing between fuel consumption, travel time and passenger comfort;*
- *Considering mixed traffic in a two-lane signalized urban environment.*
- *Optimizing for lane change and overtake.*
- *Adaptation to road conditions, i.e., human-driven vehicles and any changes in traffic lights timings.*

The remainder of the paper is organized as follows. The system model considered in this study is briefly described in Section II. The proposed DPMPC-based trajectory planning

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approach is discussed in Section III. Simulation results are presented in Section IV, and concluding remarks are provided in Section V.

II. SYSTEM MODEL

A two-lane signalized urban road, with N_{CAV} autonomous vehicles and N_{HV} human-driven vehicles is considered in this paper. Notation $i \in \{1, 2, ..., N_{CAV} + N_{HV}\}$ is used to represent ith vehicle. The distance between vehicle i and its predecessor vehicle on the same lane is defined as $d_i(t) = x_{i-1} - l_{i-1} - x_i$, where x_i is the position of the ith vehicle and l_{i-1} is the length of the front vehicle. In order to mitigate the risk of collisions, a headway gap is maintained between vehicles. Opting for a large gap can lead to traffic congestion, while a small gap increases the likelihood of collisions. The formulation used to calculate the headway gap between the ith vehicle and its predecessor on the same lane, considering different vehicle types, is

$$d_i^*(t) = H_{i-1}\, v_i + d_0 \tag{1}$$

$$H_{i-1} = \begin{cases} C_a & i-1 \in CAV \\ C_a + C_h & i-1 \in HV \end{cases} \tag{2}$$

where d_0 is the standstill distance and H_{i-1} is a function that outputs a constant based on the preceding vehicle. In (2), C_a is the headway constant if the vehicle in front of CAV is autonomous, C_h is the additional headway constant for the case that there is a human-driven vehicle in front of the CAV.

The difference between the current distance of ith vehicle and its predecessor and the desired distance is denoted by Δd_i and defined as

$$\Delta d_i(t) = d_i(t) - d_i^*(t) \tag{3}$$

In this paper, the kinematic bicycle model is used to incorporate the longitudinal and lateral movements of each vehicle. The model we use (see Figure 1) has been well documented in the literature. Interested reader is referred to, e.g., [14], for model description and conversion to a discrete-time state-space model. The final state-space model (as described in [14]) for the ith vehicle is

$$x_i(k+1) = (I + t_s A_i)\, x_i(k) + t_s B_i u_i(k) + t_s C_i v_{i-1}(k), \tag{4}$$

where k is the discrete time instant, x_i is the state vector, u_i is the control input vector, and A_i, B_i and C_i are the state-space matrices of the continuous-time state-space representation (see [14]). Furthermore, I is the identity matrix, and t_s denotes the sampling time. States and control inputs are defined as follows:

$$x_i(k) = [\Delta d_i(k)\ y_i(k)\ \theta_i(k)\ v_i(k)\ a_i(k)]^T, \tag{5}$$

$$u_i(k) = [u_i^a(k)\ u_i^\varphi(k)]^T, \tag{6}$$

where y_i denotes the lateral position of the vehicle, θ_i is the vehicle steering angle with respect to the x-axis (see Figure 1), and v_i and a_i are the velocity and acceleration of the vehicle, respectively. Furthermore, u_i^φ and u_i^a denote the steering rate and the vehicle's acceleration input, respectively.

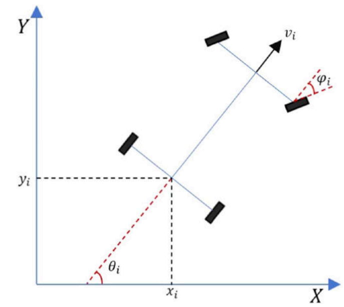

Fig. 1. Linear kinematic bicycle model of a vehicle.

III. DPMPC-BASED TRAJECTORY PLANNING APPROACH

The trajectory planning problem for each vehicle can be approached from three aspects:

- *Energy consumption* that depends not only on the road length and vehicle specifications but also on traffic lights and congestion.
- *Passenger comfort* that focuses on the smoothness of the driving experience, where excessive changes in velocity can cause discomfort for passengers.
- *Travel time* that primarily depends on the road conditions, also the velocity and acceleration. Traffic components such as human-driven vehicles or traffic lights require vehicles to decelerate and accelerate, affecting travel time.

It is noted that the three aforementioned criteria are conflicting. For example, reducing travel time may result in increased energy consumption and decreased passenger comfort. Similarly, reducing energy consumption may increase travel time and have variable effects on passenger comfort due to the velocity changes. To find the optimal trajectory for each vehicle while balancing the aforementioned factors, dynamic programming (DP) can be employed. DP predicts the best velocity profile for each vehicle over a long distance in the absence of other vehicles while striking a balance between energy consumption, travel time and passenger comfort. In our proposed approach, this optimal profile then serves as a velocity reference for a model predictive controller (MPC) to follow while avoiding collisions, stopping at traffic lights, and performing lane changes. DP solves the problem at predefined distance intervals to account for any disturbances occurring along the way that prevented the MPC from precisely following the velocity profile. This proposed approach is referred to as DPMPC (i.e., combination of dynamic programming and model predictive control).

A. Long-range Velocity Profile Optimization Using DP

The first step in determining the optimal trajectory of a vehicle, involves obtaining the velocity profile along the route. This step assumes an empty road with no other cars present. To achieve this, the specifications and current status of each vehicle along with road information, are utilized.

These data are then used to calculate the following cost along the entire route, resulting in finding the optimal velocity profile for the vehicle from the starting point to the destination:

$$J_{DP} = \sum_{t=t_{st}}^{t_f} \Big(\alpha\, E(t, v(t), v(t{-}1)) + \beta\, (v(t){-}v_d)^2 + \gamma\, a(t)^2\Big). \tag{7}$$

The above cost function consists of three terms as follows:

- Energy consumption: The term $E(t, v(t), v(t-1))$ represents the energy consumption along the way and α is the associated weight.
- Velocity difference: The term $v(t) - v_d$ represents the difference between the velocity of the car $v(t)$ and the desired velocity v_d, and β indicates the influence of the velocity difference on the cost function. If the desired velocity is equal to the speed limit, this term represents the travelling time criterion.
- Passenger comfort: $a(t)$ represents the acceleration of the vehicle, and γ is the associated weight. The last term penalizes large changes in velocity, hence ensuring passenger comfort and smooth driving.

The coefficients α, β and γ are used to balance the influence of energy consumption, travelling time, and passenger comfort, respectively, in the overall cost function. The starting time t_{st} and ending time t_f are used to represent the time equivalents of the starting and final positions, respectively.

1) Energy consumption: To calculate the energy consumption for an *electric vehicle* (EV) at the time instant t, the first step is to calculate the energy at the wheels as

$$\begin{aligned} f_T(v(t)) &= 1/2\, C_d\, A\, \rho_a\, v(t)^2 + \mu_f\, m\, g\, \cos\phi \\ &\quad + m\, g\, \sin\phi, \end{aligned} \tag{8}$$

$$\begin{aligned} E_W(v(t), v(t-1)) &= 1/2\, m\, (v(t)^2 - v(t-1)^2) \\ &\quad + f_T(v(t))\, \Delta x. \end{aligned} \tag{9}$$

To compute the total force applied to the wheel, (8) is used. In this formula, C_d is the drag coefficient, A is the projected frontal area of the vehicle and ρ_a is the air density, μ_f is friction coefficient, m is the mass, g is the gravity and ϕ is the road grade assumed to be zero in this paper. Therefore, the total energy can be calculated as the difference in kinetic energy between two consecutive time samples added to the energy by $f_T(v(t))$ along the distance Δx. Equation (9) shows the calculation of energy on the wheels.

When E_W is positive, it indicates that energy is flowing from the motor to the wheels. On the other hand, when E_W is negative, it indicates that the engine is acting as a generator and hence kinetic energy of the vehicle is converted into electrical energy and stored in the batteries (called regenerative braking).

Required torque form the motor can also be calculated as

$$T(t) = \frac{r}{\epsilon_0\, \eta_{dt}} \times \frac{E_W(t)}{\Delta x}, \tag{10}$$

where r is the wheel radius, ϵ_0 is the gear reduction ratio, and η_{dt} is drive-train system's mechanical efficiency.

To determine the conversion efficiency, one can consult the efficiency map of the vehicle, which provides information on the required torque at the current velocity. According to [7], the efficiency of an electric motor in regenerative mode is calculated as $\eta_r = exp(-0.0411/|a|)$. Using the above definitions, $E(t)$ is calculated as

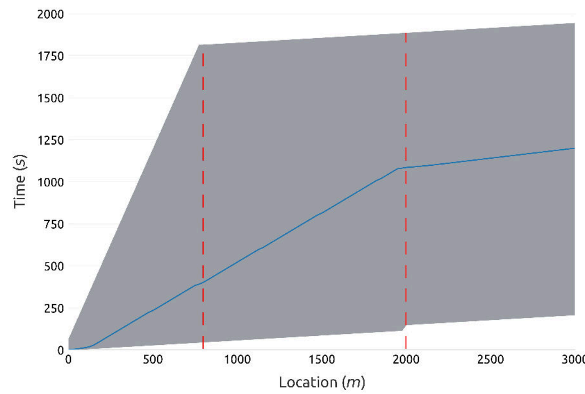

Fig. 2. Example of a vehicle trajectory generated using the predicted velocity profile by DP. The gray-colored area represents the search space, red dashed lines represent the periods during which the traffic lights are red, and blue line represents the trajectory of the vehicle.

$$E(v(t), v(t{-}1)) = \begin{cases} E_W(v(t), v(t-1))\,/\,3600)\,/\,\eta_t; E_W \geqslant 0 \\ E_W(v(t), v(t-1))\,/\,3600)\,/\,\eta_r; E_W < 0 \end{cases} \tag{11}$$

where η_t is the traction efficiency computed using the efficiency map of the vehicle.

2) Cost optimization: In order to minimize the cost function in (7), dynamic programming (DP) is used. Starting from a stationary position, DP calculates the cost in the search space to find a sequence of velocities that minimizes this cost. Searching the entire search space would be computationally cumbersome. To reduce computations, three methods are employed:

- The first approach involves finding upper and lower time bounds at each location. The lower time bound represents the time required for the vehicle to reach the desired point at maximum velocity. By defining these bounds, a time interval is established at each location and valid solutions lie within this interval.
- The second approach entails creating a lookup table for the cost of each time instant. Since velocities are discretized, each vehicle can only have certain velocities at each time step. Consequently, a lookup table can be constructed to store the calculated costs. This results in a matrix V with the dimension of $|v|{\times}|v|$, where each element of the matrix $v_{i,j}$ represents the cost of transitioning from v_i to v_j. Transitions that are impossible due to a limited acceleration are assigned an infinite cost.
- The third approach involves eliminating solutions that result in passing through red traffic lights before reaching the complete solution.

Figure 2 shows an illustrative example of a vehicle trajectory generated using the predicted velocity profile by DP.

B. MPC-based Tracking of the Velocity Profile

The optimal trajectory taking into account the cost function (7) is determined based on the predicted velocity profile by DP. However, achieving this trajectory is only possible if there are no obstacles and no changes in the road condition, as any disturbance could cause deviations from the DP's prediction. To overcome this problem (e.g., mixed traffic), using a low-level controller is necessary. The controller's role is to use the optimal velocity profile generated by DP as a reference and attempt to follow it while maintaining a safe distance from other vehicles. Additionally, the controller should be capable of overtaking slower vehicles in front and stopping behind red traffic lights. We propose to use a model predictive controller (MPC) for that purpose.

To compensate for deviations from reference, DP is solved repeatedly at each predefined distance step.

System constraints over an MPC prediction horizon for the ith vehicle are as follows:

$$\begin{aligned} v_{min} \le v_i(k) \le v_{max}, &\quad a_{min} \le a_i(k) \le a_{max}, \\ \theta_{min} \le \theta_i(k) \le \theta_{max}, &\quad d_i(k) > 0. \end{aligned} \tag{12}$$

Furthermore, the MPC cost is assumed to be

$$\begin{aligned} J_{MPC} = \sum_{k=0}^{N_h} \Big[& c_1\,(v_i(k) - v_i^{DP}(k))^2 + c_2\, a_i(k)^2 \\ & + c_3\,(y_i(k) - y_i^r)^2 + c_4\, \theta_i(k)^2 \\ & + R_i(x_i(0), x_{i-1}(0), v_i(0)) \\ & \times \left[c_5\, \Delta d_i(k)^2 + c_6\,(v_i(k) - v_{i-1}(k))^2\right] \Big] \end{aligned} \tag{13}$$

where

$$R_i(x_i(0), x_{i-1}(0), v_i(0)) = \max\{0, -w_1\,(x_{i-1}(0) - l_{i-1} - x_i(0)) + w_2\, v_i(0)\}.$$

MPC optimizes the vehicles' control inputs over a prediction horizon of length N_h by minimizing objective function (13) subject to the constraints (4) and (12). The MPC cost in (13) consists of the following ingredients:

- To follow the DP velocity profile, $(v_i(k) - v_i^{DP}(k))^2$ represents matching the vehicle velocity v_i with the predicted velocity profile v_i^{DP}.
- To ensure passenger comfort, $a_i(k)^2$ is added to penalize large acceleration and deceleration.
- To follow the reference lane, $(y_i(k) - y_i^r)^2$ is used to represent following the lateral reference, in other words, the lane that the vehicle should be in. The reference lane (y_i^r) would be given to the MPC at each iteration as described in Section III-C.
- To penalize steering, $\theta_i(k)^2$ is added to represent minimizing lateral movements or steering.
- To allows velocity and distance matching, $c_5\, \Delta d_i(k)^2 + c_6\,(v_i(k) - v_{i-1}(k))^2$ represents maintaining the desired distance and matching velocity with the predecessor, in the close distance defined by function $R_i(x_i(0), x_{i-1}(0), v_i(0))$.

C. Lane Change

Given different conditions, each vehicle may have a different reference velocity to follow. If the front vehicle has a smaller velocity reference, it can disrupt the trajectory of the vehicles behind. This situation may occur when the front vehicle is a heavy-duty connected automated vehicle (CAV) or even a human-driven vehicle. To ensure that the predicted trajectory is followed in such cases, a lane change may be necessary. To determine the need for a lane change, the average of the difference between the vehicle's velocity and the predicted velocity over the past T_c samples is calculated as

$$L(k) = \sum_{t=k-T_c}^{k} (v(k) - v_r(k))^2, \tag{14}$$

where $v_r(k)$ represents the reference velocity at time instant k. To initiate a lane change, several conditions must be met:

- The average velocity difference should be greater than a predefined threshold.
- The speed in the adjacent lane should be higher than that of the front vehicle.
- There should be a safe distance between the vehicles in the adjacent lane.

The last two conditions can be evaluated using onboard sensors. When all the conditions are met, the lateral reference of the ith vehicle (y_i^r) is adjusted so that the controller can initiate the lane change. This parameter would be given to the MPC as the reference lane to be followed. Figure 3 illustrates the control diagram of each autonomous vehicle, and the proposed control algorithm is also shown in Algorithm 1.

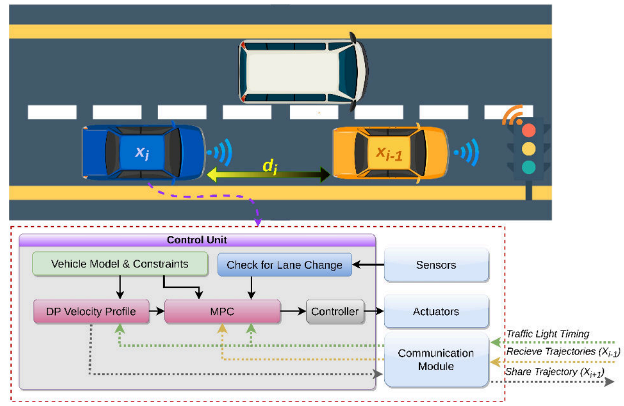

Fig. 3. Configuration of the proposed control structure.

IV. SIMULATION RESULTS

We demonstrate the advantages of fusing DP and MPC, where DP is used for predicting the optimal velocity profile and subsequently MPC to follow that profile (DPMPC approach); a comparison is also made against solely using MPC following a desired constant velocity. The simulation scenario involves a 2km, two-lane urban road with three traffic lights positioned at 775m, 975m, and 1175m. On the first lane, there are seven CAVs with an initial gap of 25 meters. Additionally, there are two human-driven vehicles; one at 195m and the other at 345m, both traveling at a constant velocity of 5m/s. The first vehicle is on the first lane, while the second vehicle is on the second lane. Figure 4 shows the simulation setup. In both approaches, the CAVs are required to maintain a safe distance with their preceding vehicle, change lanes to overtake the human-driven vehicles, and come to a stop behind the traffic lights during the red signal period. In DPMPC, DP is used to make long-range planning for

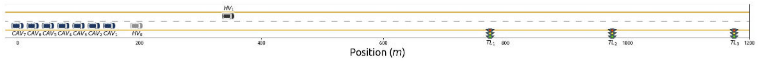

Fig. 4. Simulation setup for comparison purposes.

Algorithm 1: Control Algorithm

Data: Traffic lights position and timing, front CAV trajectory, immediate cars positions and velocities

Result: Reaching destination safely and efficiently

```
x ← 0 ;                      // longitudinal Position
y ← 1 ;                      // Lateral Position
v ← 0 ;                      // Velocity
v_d[] ← 0.0 ;                // Array of Size T_c
i ← 0 ;                      // Iteration Counter
v_profile ← Solve MPC (minimize (13) subject to (4) and (12));
while x ≠ x_destination do
    i ← i + 1;
    u ← Solve MPC (minimize (13) subject to (4) and (12));
    v ← Current velocity;
    v_f ← Front vehicle speed;
    v_d[i MOD T_c] ← v − v_profile;
    if (x MOD Δd_dp) == 0 then
        v_profile ← Solve DP (see Section III-A);
    end
    if Average(v_d) > v_threshold then
        v_a ← Adjacent lane speed;
        d_a ← Adjacent lane vehicle distance;
        if v_a > v_f and d_a > Safe Distance then
            Change lane reference
        end
    end
end
0
```

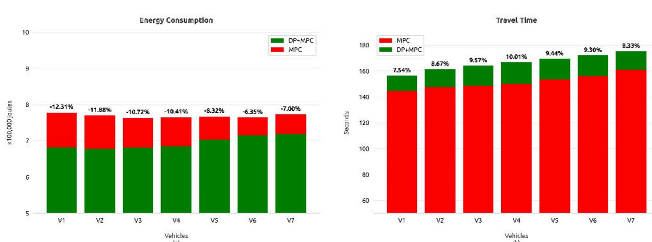

Fig. 5. Simulation results showing: (a) energy consumption, and (b) travel time

the CAV, where the optimized profile is then utilized as the reference velocity v_i^{DP} in the MPC cost (13). In contrast, the second approach solely relies on MPC, where instead of using the velocity profile predicted by DP, a constant speed is used. This constant velocity is the road speed limit assumed to be 15m/s. The simulation results in Figure 5 show a comparison between the two approaches. Here is a summary of our findings:

- Energy consumption: The proposed approach reduces energy consumption by 9.57% on average compared to the MPC (only) approach. This indicates that employing DP to predict the best velocity profile can lead to more efficient energy usage.
- Travel time: On the other hand, the proposed approach exhibits an average increase of 8.98% in travel time compared to the MPC (only) approach. This implies that following the predicted velocity profile from DP may result in slightly longer travel times.

The above findings highlight the trade-off between energy consumption and travel time when considering the use of DP for velocity profile prediction in coordination with MPC. While energy efficiency improves, travel time increases, and this is expected. Those factors can be balanced based on the specific goals and priorities of the system in question.

Figure 6 shows the velocity profile for vehicles 1, 3 and 7. The subplots on the top correspond to the proposed DPMPC approach and the bottom plots are the results of using MPC only. The red line in the top subplots shows the predicted velocity profile by DP that keeps updating every 25 meters. The green line is the actual velocity of the vehicle along the way. The difference between these two lines is due to other HVs and CAVs and also traffic light timing. As observed, for the first CAV, this discrepancy is less than the 7th CAV, since there would be no CAV in front of the first one. The bottom subplots show the results corresponding to MPC approach in which the controller tries to follow a constant speed. In this case, there would be higher acceleration and deceleration since MPC controller takes into account neither energy consumption nor the passenger comfort. As can be seen, for the first and second CAVs, there would be a hard braking at 750m due to the red traffic light.

Finally, Figure 7 illustrates the steering angle θ for vehicles 1, 3 and 7. As observed, each vehicle overtakes two HVs. Upon examining the plots, it is evident that the initial lane change occurs at a nearly identical position in both approaches (MPC and DPMPC). However, the second overtake happens at a closer location to the first one in the MPC approach. This discrepancy is attributed to the fact that the average speed of the vehicle in the MPC approach is higher compared to the DPMPC approach.

V. CONCLUDING REMARKS

In this paper, a new trajectory planning method was developed by combining the benefits of dynamic programming and model predictive control. Dynamic programming was used to optimize the velocity profile for each vehicle over a long distance, and then, this profile was fed into MPC as a reference to follow while avoiding collisions and passing red traffic lights. Simulation results demonstrated the viability of the proposed control design approach and trade-off between energy efficiency and travel time when comparing the proposed method with MPC only. Our results

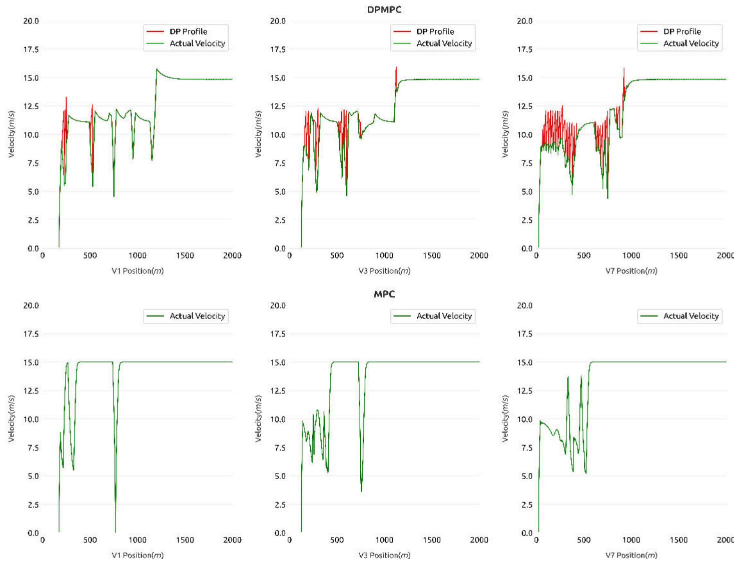

Fig. 6. Simulation results showing position-velocity profiles for vehicles 1, 3 and 7. The red plots are the results of DPMPC and the green ones are MPC (only) results.

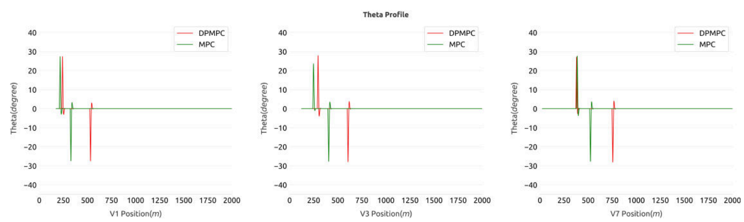

Fig. 7. Simulation results showing the steering angle. The subplots display θ w.r.t. the vehicle's position for vehicles 1, 3, and 7. The red graph is the DPMPC result, while the green one shows the MPC (only) result.

suggest that using the predicted velocity profile by DP is beneficial in decreasing the energy consumption while also slightly increasing the travel time. Other benefits of this work include its scalability (due to the computations done at individual vehicle's level) and straightforward extension to non-electric vehicles.

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