Eco-driving optimization of a signalized route with extended traffic state information

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***Abstract*—Literature suggests that driving style and conditions play a major role in vehicle energy consumption. In this sense, this work focuses on vehicle speed planning using information from the environment, through vehicle-to-infrastructure (V2I), and from nearby vehicles, with vehicle-to vehicle (V2V) information to reduce fuel consumption over a signalized route. By knowing the traffic lights scenario of the route in advance and the current position and speed of the preceding vehicle, the proposed algorithm decides the ego-vehicle speed profile during a given horizon to minimize fuel consumption. The proposed strategy solves the optimal control problem in each prediction horizon through Dynamic Programming (DP) with a simplified model. The scenario and the optimal solution are updated periodically to make up for scenario prediction and modelling uncertainties. Experimental tests were conducted on a test bench to evaluate the fuel consumption of the simulated speed profile when compared to the preceding vehicle. Results show that a reduction of almost 20% in fuel consumption is possible without penalizing travel time while keeping it real-time feasible.**

***Index Terms*—eco-driving, speed planning, DP, traffic lights**

I. Introduction

URBAN mobility is a major player in the current society from both environmental and economic points of views. For instance, it represents up to 40% of the CO_2 emissions of road transport and 70% of the emissions levels. Besides being an energy and health-related problem, urban mobility is also an economic issue once traffic congestion in Europe accounts for an estimated EUR 130 billion annually [1]. To reduce the greenhouse gases (GHG) in the transportation sector, stricter legislations are being proposed. Regarding to 2021 legislation, the aim is to reduce the average fleet CO_2 emissions of new light vehicles by 37.5% in 2030 [2].

Having that in mind, many researchers are searching for approaches to tackle not only the powertrain-related emissions but also managing the driver behavior, which can have a significant impact on GHG depending on the driver's skill, experience, and awareness [3]. New technologies are pushing the implementation of advanced driver assistance systems (ADAS) and the usage of the newly available information from the environment. Intelligent speed adaptation (ISA) came up firstly to deal with traffic accidents and injury-related problems associated with urban mobility. However, not only accidents can be reduced, but also CO_2 emissions can be mitigated through speed advisory [4].

New ADAS technologies can be implemented with the decreased cost of embedded systems, such as GPS on traffic players. Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) can provide data about the environment and route conditions, allowing robust communication and feasible implementation of control strategies. Eco-driving can be regarded as any technique used to smartly route a vehicle to the most efficient path or speed profile. The goal can be minimizing fuel, energy, or even pollutants. Eco-driving can be promoted on different levels, such as making driving decisions that promote higher average speeds, avoiding traffic jams, advising or choosing speed profiles that reduce the need for braking or the time spent idling, or even in cases with enough connectivity, avoid red traffic lights intersections [5] [6]. According to [7], the use of eco-driving techniques can potentially reduce up to 15% the energy usage in a route.

Green Light Optimal Speed Advice (GLOSA) is a well-reviewed algorithm in the eco-driving study that has been investigated by several authors. It relies on creating a cruising speed that avoids reaching an intersection during a red light phase. Authors in [8] review the state-of-the-art in GLOSA applications, proposing a real-time implementation of a vehicle dynamics model to validate its effectiveness over mobility and environmental parameters. Reinforcement Learning (RL) has also been applied by [9] in situations where little information can be accessed by the ego vehicle, obtaining fuel savings when compared to the standard GLOSA algorithm.

Eco-driving can be formulated as an optimal control problem (OCP), taking advantage of a broad set of algorithms and techniques [10]. Predictive cruise control (PCC) has been investigated by [11] using V2V and V2I to mitigate the time spent idling and also the use of brakes by tracking a speed reference calculated based on green phase intervals with model predictive control (MPC). MPC is also used by [12] to predict the deceleration of a leading truck and therefore minimize the fuel consumption of an ego-truck over the predicted horizon. Eco-driving speed planning often relies on other optimization methods such as dynamic programming (DP). In [13] the authors take advantage of this control method to formulate a speed profile that can minimize fuel consumption or NO_x emissions over a real-life daily commute driving cycle. Due to the uncertainties of traffic signals, [14] uses the available probabilistic traffic-signal phase and timing (SPAT) to create a predictive optimal velocity-planning algorithm employing DP, achieving a substantial reduction in fuel consumption.

One of the main advantages of optimal control methods is the capability of including constraints into the problem. For instance, the speed profile optimization in a scenario with traffic lights and DP is possible, as demonstrated by [15] in which fuel or NO_x emissions could be minimized over a signalized route with knowledge in advance of the traffic

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lights pattern. However, DP is computational costly when the problem has too many states, often not being feasible for real-time (RT) implementation. For that reason, [16] implemented a bi-level DP method to solve the RT implementation, using a weighted orientation graph that divides the problem into passable routes for each traffic light interval.

Therefore, some authors developed optimal speed trajectories by combining DP with other low computational cost control techniques. [17] combines DP with MPC by calculating an optimal speed trajectory offline and applying this reference speed to the host vehicle online through MPC. [18] employ the Pontryagin's Maximum Principle (PMP) to find energy optimal velocity profiles and compares the results to DP to verify the global optimality of the solution. [19] solves a pair of algebraic equations equivalent to an OCP and validates its efficiency in an RT experimental assessment, having close results to the DP solution.

That being said, some studies also rely on the direct method (DM) when complexity is an issue, having a large number of states and controls [20]. Other authors, such [21] make use of sub-optimal approaches that can still provide significant reductions in travel fuel consumption. [22] developed a pruning algorithm that evaluates the feasible paths to cross the traffic lights at a green phase. The comparison between this sub-optimal approach and a DP also demonstrated exciting gains, and it is RT allowable.

This paper addresses a case scenario where a vehicle needs to drive through a given route respecting some boundaries such as the road speed limit, the state of the traffic lights, and avoiding colliding with the preceding vehicle. Vehicle to infrastructure (V2I) such as the traffic lights timing and state is known in advance by the driver. The route characteristics such as elevation, road slope, and position can also be evaluated through GPS information. Vehicle to vehicle (V2V) information is also available from the preceding vehicle, which can provide its current states (position and velocity) at any time. The goal is to find a speed profile that can respect the boundary limits imposed with the minimum fuel consumption during the trip.

Therefore, an optimal speed profile is proposed as a solution through DP, taking advantage of the available information to predict the velocity path that minimizes the fuel consumption. As the future position of the preceding vehicle is not known beforehand, it is assumed to follow a car-following speed profile based on the traffic light policy and the optimization is performed in short-horizon windows to update the solution periodically, improving the estimation errors. Therefore, the algorithm optimizes shorter paths instead of the whole route, solving the problem in a recursive manner.

It is important to mention that although DP is not usually applied to RT scenarios, due to its large computational burden, this paper brings the novelty of proposing an algorithm with a first-order linearization, dealing with only one state (position). Therefore, a receding algorithm can be executed in short windows, updating the information of V2I and V2V in a RT manner, which is further explained in the methodology section.

This study caries out a simulation-based analysis of the fuel consumption of road vehicle when following different speed profiles generated by a recursive DP algorithm. Although not performing any vehicle testing in a road level, the torque demands of the speed profile obtained in simulations has been tested in a fully instrumented engine test-bench.

The article is presented in the following order: The methodology containing the case study, modelling, and control algorithm is explained first. Then, results obtained by simulations and experimental tests are shown, followed by conclusions and discussions about the achieved results.

II. Experimental Setup

The purpose of the described method is to reduce the fuel consumption and hence the emitted CO_2 in a route with partial information. A look-up table of the powertrain, as well as a vehicle model, were used to predict the optimal torque evolution along the route. Experimental tests have been performed on a fully instrumented test bench to obtain the fuel consumption map of the engine and verify the benefits of the proposed strategy.

Table I shows the characteristics of the four-stroke compression ignition (CI) engine used, i.e. a commercial passenger car diesel engine. Measurements of torque and engine speed were acquired with a Horiba DYNAS3 asynchronous dynamometer. The dynamometer was controlled by Horiba SPARC integrated with a HORIBA Automation System STARS. The torque was controlled by the pedal command in order to control the engine operating conditions. Electronic control unit (ECU) parameters, such as pedal position or injected fuel mass, were controlled in real-time through ETK-port with an ETAS ES910 connected to a dSpace prototyping system. All the signals received from sensors, those received by the ECU and those measured at the test bench, e.g. fuel balance or additional sensors, have been acquired and stored with the STARS and the dSpace systems.

TABLE I
Experimental engine specifications.

Parameter	Value
Displaced volume	1499 cm^3
Bore x Stroke	75 x 84.8 mm
Compression ratio	16.4:1
Maximum torque	300 Nm @ 1750 rpm
Maximum power	96 kW @ 3750 rpm
Emissions standard	Euro 6c

III. Methodology

A. Case Study

A case study is chosen to validate and evaluate the performance of the method. Following the benchmark scenario proposed in [23], the selected route of this study consists of a 16 km long commute with 26 traffic lights along the way. Information about the route slope is also provided.

The vehicle must respect the constraints of the route, such as not crashing nor overtaking the preceding vehicle. Also, there is a speed limit of 60 km/h that must be respected. In this study, the preceding vehicle speed profile is taken as a baseline reference to evaluate the achievable reduction in fuel consumption if enough information is available for the vehicle to optimize the speed profile. The state (TL) of any traffic light (i) at a given time (t) is modelled as a boolean depending on a constant policy only depending on time, i.e. red and green periods with constant frequency.

$$TL(t,i) = \begin{cases} 1 & \text{if } red \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where i stands for the number of the traffic light ($i = 1...26$) and t for the time step.

B. Vehicle Model

Vehicle modelling for control purposes is often regarded in the literature as semi-rigid bodies where only the longitudinal dynamics are considered [24]. This paper uses the longitudinal dynamics for vehicle modelling according to Newton's second law of motion,

$$m\frac{dv(t)}{dt} = F_p - F_r - F_b \tag{2}$$

where m stands for the total mass of the vehicle, $\frac{dv(t)}{dt}$ is the acceleration, $F_p(t)$ is the motion force applied to the vehicle from the powertrain, $F_r(t)$ is equal to the sum of all resistive forces of the vehicle, and F_b stands for the braking force applied. Often called Road Load Forces, F_r can be considered the sum of the aerodynamic force F_a, the friction of the road F_f, and the potential contribution of the gravity F_g:

$$F_r = F_a + F_f + F_g \tag{3}$$

which can be modelled as:

$$F_a = \frac{1}{2}\rho_a C_D A_f v^2 \tag{4}$$
$$F_f = C_r mg\cos\alpha \tag{5}$$
$$F_g = mg\sin\alpha \tag{6}$$

where ρ is the air density, C_D is the aerodynamic drag coefficient, A_f the vehicle's frontal area, the rolling resistance is expressed as C_r, g the gravity acceleration, and α the road slope at the current position. Table II contains the vehicle parameters used in this study.

TABLE II
VEHICLE CHARACTERISTICS.

Parameter	Value
Mass [kg]	1700
Frontal area $[m^2]$	2.239
Wheel Radius [m]	0.3
Air density $[kg/m^3]$	1.2
Drag coefficient $[Ns^2/m^2]$	0.32
Rolling resistance [-]	0.01
Gravity acceleration $[m/s^2]$	9.81

C. Engine Model

A physical model for the engine would have a high computational cost, as it is composed of several complex phenomena, such as combustion. Therefore, one simpler quasi-steady approach is to use experimental operating engine maps to model the powertrain. Figure 1 represents the fuel mass map as a function of both engine speed and demanded torque. This map is computed by experimental data previously collected from an engine on a fully instrumented test cell. In order to calculate the crankshaft torque and engine speed to fulfil the vehicle's motion, a gear ratio law is imposed as a function of the vehicle's speed, so the engine torque can be expressed as:

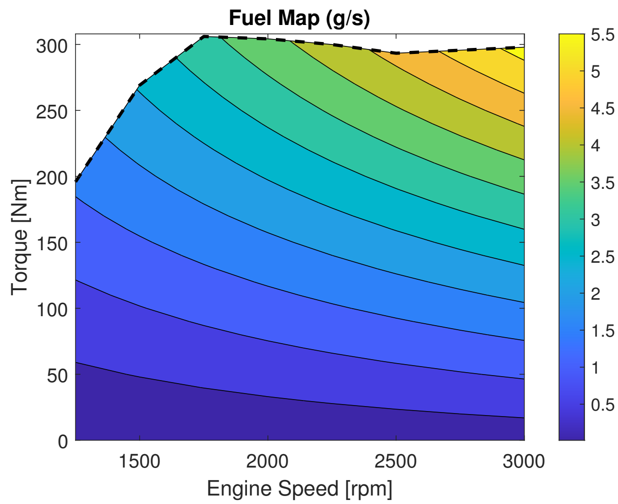

Fig. 1. Fuel map as a function of Torque and Engine Speed acquired from experimental data.

$$T_e = \frac{F_w R_w}{G_r} \tag{7}$$

where R_w stands for the wheel radius and G_r is the ratio between wheel turning speed and engine speed, which follows a predefined gear change policy to maintain efficient operating conditions of the powertrain.

D. Recursive Algorithm

Figure 2 shows a scheme of the method used. The core of the algorithm is the route optimization by defining the optimal speed profile with the information received from the V2V communication about the traffic light scenario and the actual states of the preceding vehicle. Hence, a DP algorithm is run for the next T_H horizon. The method proposes a pre-defined prediction horizon T_H to optimize the trajectory because even for a single state scenario, the prediction of the complete route becomes infeasible for RT applications. Therefore, a shorter prediction horizon T_H is chosen, and the optimal path is recursively updated throughout the route. The optimization is repeated every T_W seconds, so the information is properly updated, and the sub-optimal optimization converges to the optimal solution. The output of the system V_{opt} is translated to a pedal demand to be the input for the vehicle. The control system applies this pedal input to the vehicle and engine model, which updates the states of the ego vehicle.

However, in a RT situation, the V2V information only provides the surrounding vehicle's current states. Therefore, an estimation of the preceding vehicle position along the prediction horizon must be done in advance to correctly optimize the

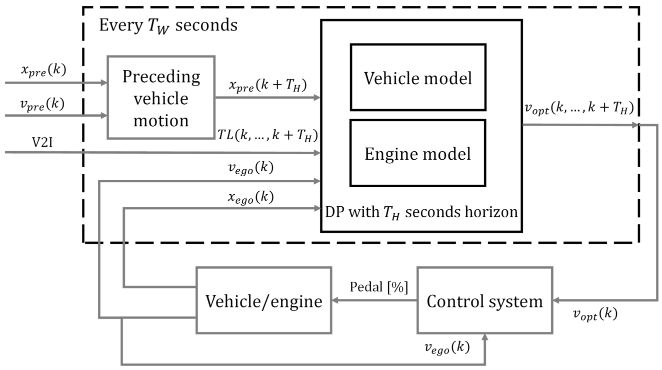

Fig. 2. Scheme of the recursive algorithm proposed

speed profile. The current states (velocity and position) of the preceding vehicle are used to estimate its future states within a T_H horizon, according to the preceding vehicle estimation. In the proposed algorithm, the expected position of the preceding vehicle is assumed to follow a velocity pattern based on the Gipps car-following algorithm [25], which is the core of many commercial software, being a function that arbitrates between a free-flow and a gap-controlled regime. With the actual known states of the preceding vehicle ($x_{pre}(0), v_{pre}(0)$) and with the upcoming traffic lights ($TL(0...T_H, 1...N_{TL})$), an estimation of the path taken by the preceding car can be done over the prediction horizon, such as respecting the next traffic light position (x_{TL}) and speeding to the maximum allowed speed (V_{max}): The algorithm starts by identifying the first

Algorithm 1 Preceding Vehicle Prediction.

Require: $x_{pre}(0), v_{pre}(0), TL(0...T_H, 1...N_{TL})$
Obtain: $x_{pre}(0,\ldots,T_H), v_{pre}(0,\ldots,T_H)$
  for $k = 1 \ldots T_H$, **do**
    $x_{TL} \leftarrow \text{MIN}(TL_{pos}(TL(k,:) == 1) > X_{pre}(k-1))$
    $gap \leftarrow x_{TL}(k) - x_{pre}(k-1)$
    $V_{free} \leftarrow f(v_{pre}(k-1), V_{max})$
    $V_{safe} \leftarrow f(gap, v_{pre}(k-1))$

  $v_{pre}(k) \leftarrow \text{MIN}(V_{safe}, V_{free})$
  $x_{pre}(k) \leftarrow x_{pre}(k-1) + v_{pre}(k)\Delta t$
  end for

next traffic light intersection at time-step k that is closed (red). Then, the calculation proceeds to find a free-flow speed V_{free} and a velocity based on the gap to the expected traffic light V_{safe}, choosing the minimum of both.

It is worth mentioning that the predicted position of the preceding vehicle does not necessarily coincide with the actual one. The bias at the preceding vehicle position can be corrected by updating the optimization more frequently, i.e., reducing T_W.

The core of the algorithm is the optimization of the vehicle speed profile with dynamic programming (DP). DP is a well-established OCP tool for taking the optimal solution from the discretized state and control spaces. However, one of its disadvantages is the so-called "curse of dimensionality", as the computation burden increases exponentially as the number of states increases. DP is the direct application of Bellman's Principle of Optimality. States, control actions, and the time horizon are discretized into discrete steps, splitting the problem into finite smaller sub-problems and solving each one individually, such that:

$$J(x, t_k) = \int_{t_k}^{t_{k+1}} L(x, u, t)dt + J(x, t_{k+1}) \tag{8}$$

where L is the objective to be minimized as a function of the states x, the control policy u, and the time step k. A so-called Cost-to-go function J stands for the cost from step $k+1$ to the end of the problem. By solving step-by-step from the last time step to the beginning, $k = 0$, the model calculates all the possibilities of the sub-problem. Thus, since each step is optimal, the global solution is guaranteed to be optimal.

In the proposed approach, the merit function L to be minimized accounts for the total fuel consumed m_f, which is a function of the current position (slope of the path), the current speed, and the acceleration.

$$L_k = m_f(x_k, v_k, a_k) \tag{9}$$

It can be appreciated from Equation 2 that the total fuel cost depends on the position to estimate the slope influence in the grade and friction forces, on the velocity to estimate the aerodynamic drag, but it also depends directly on the acceleration to estimate the inertial forces, so from the formal point of view, requires two states (speed and position). Nonetheless, the current work proposes a first-order linearization to estimate the acceleration as a function of the optimal velocity profile, being the acceleration:

$$a_k = \frac{v_{k+1} - v_k}{\Delta t} \tag{10}$$

where v_k is the input to optimize the problem, and v_{k+1} is the vehicle speed minimizing the cost-to-go $J(x, t_{k+1})$ obtained recursively from the final timestep, where the terminal vehicle speed is imposed, and hence depends only on the future vehicle position:

$$v_{k+1} = f_{DP}(x_{k+1}) \tag{11}$$

The acceleration demand a_k from Equation 10 is translated to an engine torque demand through the vehicle model equations and the desired vehicle speed v_k is translated to an engine speed since the gear ratio is pre-defined. Therefore, for each time-step, the instantaneous fuel consumption is assessed using the fuel map of Figure 1.

On the one hand, this implementation has a significant drawback: it defines the optimal velocity profile associated with the possible positions at each time-lapse but does not consider the initial speed. But on the other hand, it reduces the number of states, alleviating the computational cost of the algorithm. DP suits the addressed problem once it is restricted to deal with a single state, position $x(k)$, and a single input $v(k)$. In this way, the DP is feasible for RT purposes within a window of reasonable size. Hence, the evolution of the state can be expressed as:

$$x_{k+1} = x_k + v_k\Delta t \tag{12}$$

Although having a single state $x(k)$, the algorithm evaluates the effect of velocity and acceleration by storing the optimal path. This information is used backward to calculate the cost associated with increasing or decreasing the velocity, thus minimizing the fuel spent on accelerations while taking advantage of the route slope. However, because the acceleration is only based on the future conditions and does not consider the initial speed when the DP is initiated, the vehicle needs to reach the optimal position and speed, which might lead to unwanted sharp accelerations. To avoid such undesired behaviour an additional term is lumped into the function to penalize this variation between the DP matrices, such that m'_f is the fuel associated with the acceleration required a'_k to reach the desired speed from the initial conditions, following:

$$a'_k = \frac{(v_k - v_0)}{k\ \Delta t} \tag{13}$$

where v_0 is the initial speed. Note that the time step k on the denominator makes the penalty harder on the initial positions, where the discrepancies start, while it has an almost negligible effect at T_H. Another additional cost L_{res} is proposed to consider the physical restrictions. The hard constraints imposed are the following:

- The vehicle should never overpass the preceding car position with a predefined margin, i.e. in this work a margin M of 10 meters is used

$$x_k \leq x_{k,pre} - M \tag{14}$$

- The vehicle should always respect the traffic lights:

$$\text{if} \quad x_{TL} > x_k \quad \text{then} \quad x_{TL} \geq x_k + v_k \Delta t \tag{15}$$

- The vehicle cannot exceed the maximum allowed speed, and neither achieve a negative speed (going backwards)

$$0 \leq v_k \leq v_{max} \tag{16}$$

- The maximum braking, as well as the maximum acceleration are limited

$$-a_{brake} \leq a_k \leq a_{max} \tag{17}$$

Note that this is an essential condition to assure solution feasibility since the vehicle speed is used as model input. In addition, if any of these restrictions are broken, a cost of $J_\infty = 10^5$ mg is added.

Also, a final condition is imposed to maintain the desired distance to the preceding car, giving an advantage to the final positions that end within the space between M and $2M$, where no cost is added. If the vehicle ends up at the expected preceding vehicle position or if it does not move, $x(T_H) = x(0)$, a cost of J_∞ is assigned. When the vehicle achieves intermediate positions, a linear function is used. Figure 3 shows the final cost associated where no cost is associated if the end position of the ego vehicle is between M and $2M$ from the final preceding vehicle position. The final cost function is composed of the fuel consumption, a term representing the fuel consumed at the initial acceleration required to achieve the optimal path m'_f, and an additional cost L_{res} if any restriction is not met.

$$L_k = m_f(x_k, v_k, a_k) + \beta\ m'_f + L_{res} \tag{18}$$

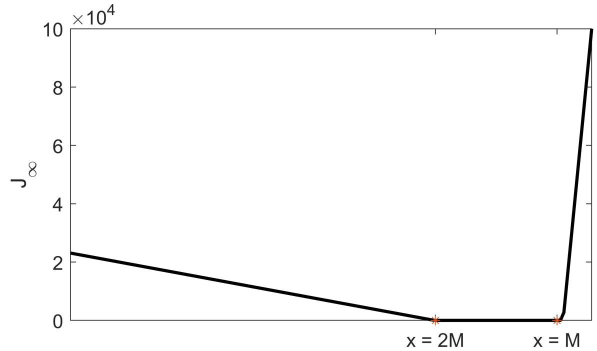

Fig. 3. Cost associated to the final position

where β stands for a tuning parameter.

It is worth mentioning that as the prediction horizon T_H is updated every T_W seconds, the model might face unexpected situations during this interval, as the constraints of the route i.e., the deceleration of the preceding vehicle, can change due to a hard braking maneuver. Therefore, to avoid crashing, a condition is imposed when the gap between the ego vehicle and the preceding vehicle is less than M. It consists in applying the same Gipps car-following algorithm used for the preceding vehicle estimation, arbitrating over a free-flow speed and a gap-controlled regime.

IV. Results

Regarding the recursive DP algorithm, the chosen horizon, i.e., how far the future states are estimated, directly impacts the optimization performance and its computational burden. For that reason, an analysis of the impact of the horizon T_H is done, which is presented in Figure 4a. In all the simulations proposed, the updating time T_W is set to 10s, and only the time horizon is varied. The fuel savings are referred to the fuel consumed by the preceding vehicle.

Until a prediction of 100 seconds ahead, the fuel savings increase sharply. It can be attributed to the fact that the traffic lights in this study have a constant phase duration of 60 seconds. Therefore, in the cases where the horizon T_H is shorter or too close to this value, the algorithm might not be able to adapt the speed profile in such a way that stopping at the next intersection can be avoided. In addition, a further increase in T_H did not bring enough benefit compared with the increased computational time.

The influence of the updating period on the performance of the algorithm is evaluated in Figure 4b. The updating period T_W is varied from 5 to 40 seconds interval, maintaining a prediction horizon T_H of 100 seconds. It can be stated that from an updating period of 20 seconds onwards, the fuel savings decrease primarily due to the lack of accuracy of the predictions of the preceding vehicle position. This is explained due to the nature of the algorithm, once updating is mandatory to keep track of the preceding vehicle position. When applying more than 20 seconds of updating period, the ego vehicle could not follow the speed-planning trajectory since it must actuate to avoid crashing due to deviations in the estimations of the preceding car. Although an updating

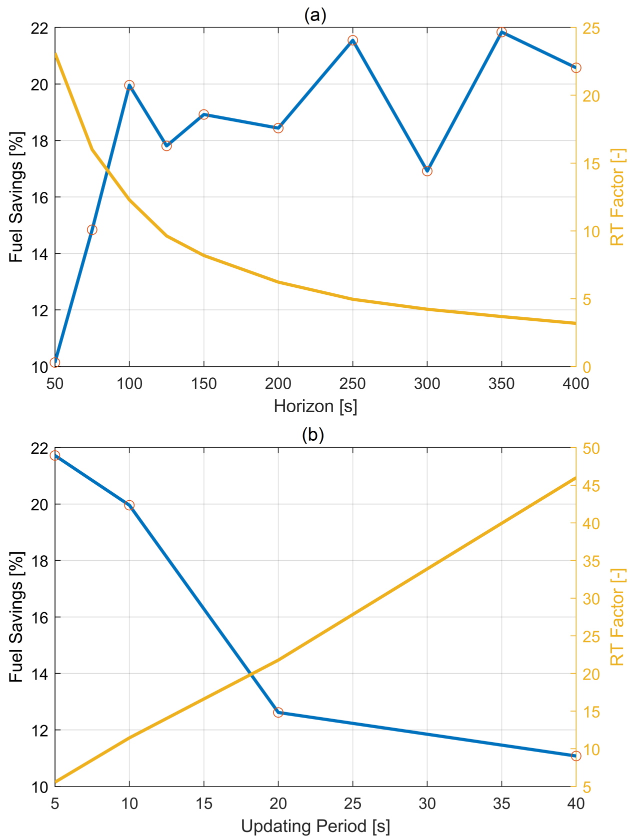

Fig. 4. (a) Influence of the prediction horizon T_H on the fuel consumption and on the computational time and (b) influence of the updating period T_W on the fuel consumption and on the computational time.

period of 5 seconds improves fuel savings, it penalizes the RT factor, doubling the time to accomplish the route. Therefore, for the rest of the analysis, a prediction horizon T_H of 100 seconds and an updating period T_W of 10 seconds are chosen by offering good fuel consumption reduction with acceptable computational time, operating in an RT scenario.

TABLE III
FUEL COMPARISON BETWEEN METHODS

Method	Fuel consumption [g]	Fuel savings [%]
Preceding Vehicle (Car-following Model)	609	0.0 (baseline)
Ego Vehicle (Recursive DP)	487	-19.96%
Ego Vehicle (Offline DP)	468	-23.02%
Ego Vehicle (2 States Recursive DP)	447	-26.60%

To evaluate the potential of the proposed strategy, i.e., recursive solution of DP in a moving window, its performance is compared with three cases: the preceding vehicle, based on the car-following model, the DP computed offline to the complete route and another recursive DP with two states. In this sense, Figure 5 shows the paths taken in the four cases. It can be noticed that the offline DP, which cannot be applied for RT purposes since it relies on knowing the total future information of the preceding vehicle in advance, takes a different trajectory.

TABLE IV
COMPUTATIONAL TIME COMPARISON BETWEEN METHODS

Method	Computational Time [s]	Real-time Factor
Preceding Vehicle (Car-following Model)	-	-
Ego Vehicle (Recursive DP)	174.6	11.5
Ego Vehicle (Offline DP)	79.3	25.2
Ego Vehicle (2 States Recursive DP)	4890.4	0.41

Table III presents the compared fuel reduction between the methods, and Table IV shows the computation time taken for each algorithm. Using an offline DP benefit the total fuel consumption by 3%. However, it would not apply to a real-time scenario once the V2V and V2I information is loaded beforehand. Therefore, the traffic scenario prediction is impossible since it demands to be updated to have correct predictions.

For the sake of the analysis, another algorithm uses two states (position and velocity) and one control action (pedal position). It uses the same constraints and the same V2V and V2I information. Using two states improves the fuel consumption since it has the smoothest trajectory, cruising in an overall longer constant speed profile. This can be attributed to the fact that by having the velocity as a state, the final time-step velocity is known, minimizing sudden changes in velocity. Although showing a considerable reduction in fuel consumption, Table IV shows that using two states on a recursive algorithm approach is not possible for RT purposes once the time taken to run the simulations are much higher than the real time of the route.

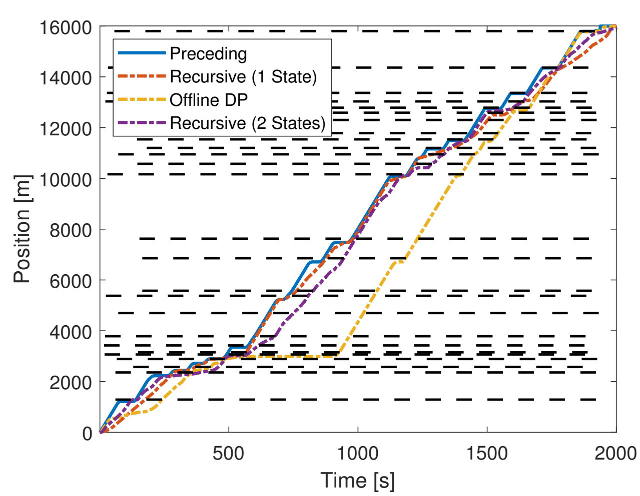

Fig. 5. Paths taken by the different speed profiles.

Figure 6 presents the data of torque, engine speed, and fuel consumption for both the modelled and the experimental data, respectively. In addition to the smaller velocity oscillations, the overall torque amplitudes are also lower in the proposed recursive DP algorithm. Results for the cycle average engine

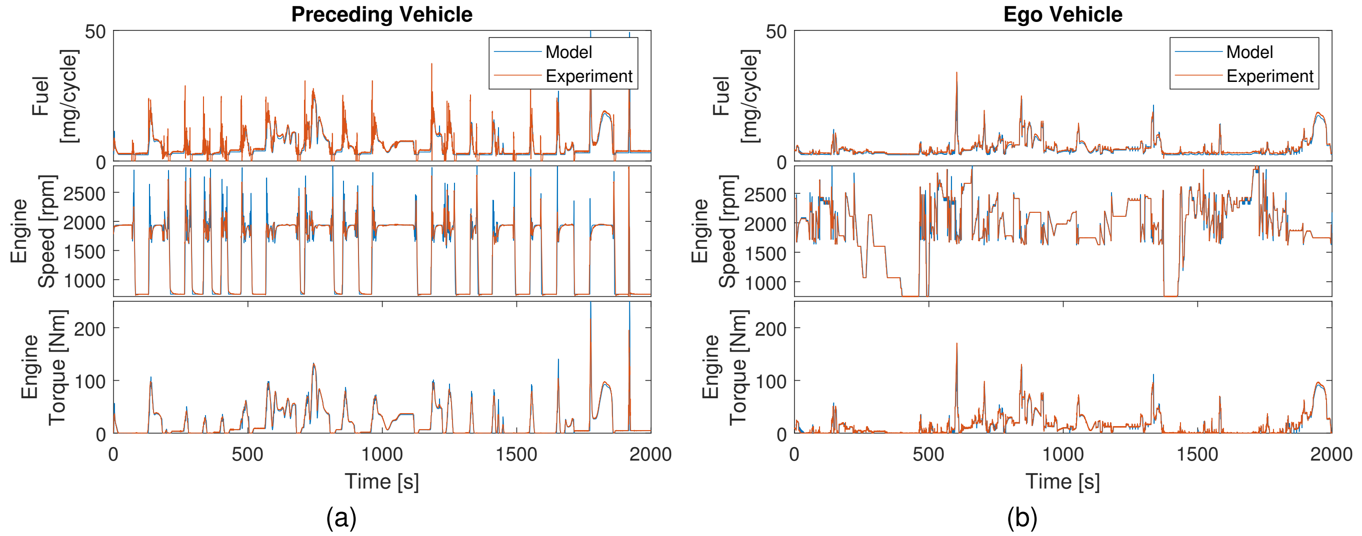

Fig. 6. Comparison of engine torque, engine speed and instantaneous fuel consumption between model and experiment for (a) Preceding vehicle. (b) Ego vehicle.

power are 35.2% less than the cycle average engine power of the preceding vehicle.

It is expected that high accelerations oscillation requires high torque demands from the powertrain, thus being a scenario to be avoided. Therefore, maintaining a constant speed by avoiding stopping at the traffic lights is a sensible suboptimal strategy to be applied once the inertial term is minimized. In addition, by keeping a constant velocity, energy dissipation is reduced when the braking effort is diminished.

Figure 7 shows the accumulated fuel in the simulations and the test bench for the speed profile of the preceding vehicle, for the proposed algorithm, and the DP computed offline. Estimating the preceding vehicle's position within a moving window horizon and its recursive solution allows to strongly improve the fuel consumption of the preceding vehicle and approximate the offline DP. Of course, the offline DP has a better fuel consumption, providing a fuel reduction of 23% since it exploits the full knowledge of the route in advance.

Nevertheless, using several DPs on smaller horizons has proved advantageous since almost all the traffic lights could be avoided at the red phase, cruising in a so-called "green wave". The results from the experimental setup demonstrate minimal deviation from the torque and engine speed inputs. Furthermore, the results present a good correlation when comparing the mass fuel injected with the modelled one. The difference in fuel consumption between the simulated preceding vehicle and that obtained by applying the recursive proposed algorithm with a single state is 19.96%, and the difference to the experimental results is 17.47%. Little difference can be noticed, mainly due to the transient aspects of the engine, which could not be included in this study since the fuel consumption simulated is based on steady-state look-up tables from experimental data.

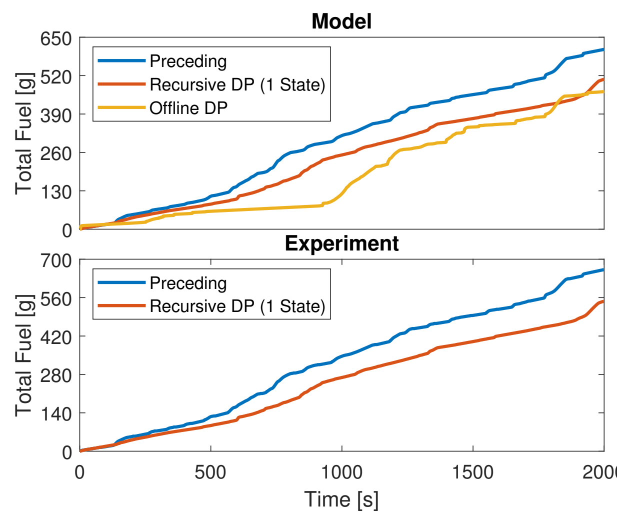

Fig. 7. Accumulated fuel consumption for the model and experimental setup.

V. Conclusions

This work presented a speed planning algorithm to minimize fuel consumption over a signalized route with several traffic lights and a preceding vehicle by taking advantage of traffic information from the nearby vehicles (preceding vehicle) and also information from the infrastructure, such as the traffic lights phase and timing and GPS information like road slope.

The approach consisted of using an optimal control problem tool such as DP, but in order to be able to predict the behaviour of the preceding vehicle, i.e., maintain a safe distance and avoid crashing, the problem was addressed as a sub-optimal approach. Splitting the horizon into several smaller horizons and thus running a recursive DP algorithm, the method can predict the preceding vehicle position by implementing an estimation algorithm based on a known car-following model and recursively updating it to keep track of the actual position of the preceding car. Therefore, it would not be possible for a RT case to use a standard DP approach since the disturbances should be known in advance.

Even though being a sub-optimal approach, a significant improvement in fuel consumption could be achieved. In the case study, the proposed algorithm improves the fuel economy of the previous vehicle by 17.47%, leading to a simulated 3% penalty with regard to the offline DP that cannot be applied in a real scenario. In addition, using a real-life traffic scenario with several nearby vehicles, lanes and intersections would be an interesting study to further prove the potential of the approach.

Future works using real-life traffic scenarios can be investigated. For instance, applying a recursive optimization algorithm in a multi-lane route, with several vehicles and intersections, would be an interesting study to further prove the potential of the approach. Furthermore, different kinds of predictions models can be applied. Instead of using a deterministic traffic prediction, other models using traffic probability and machine learning might be an interesting alternative to improve the traffic prediction.

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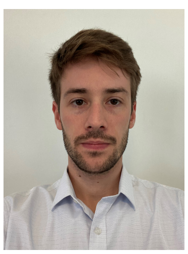

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