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Real-time Eco-driving of a Connected and Automated Fuel Cell Electric Truck using Approximate Dynamic Programming

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***Abstract*— Eco-driving of Connected and Automated Vehicles (CAVs), in particular with multiple on-board power sources has the potential to significantly improve energy savings in real-world driving conditions. The eco-driving problem seeks to design optimal speed and power usage profiles between origin and destination, based upon route information available from connectivity and advanced mapping features. In this work, the eco-driving problem is solved for a fuel cell electric truck over for a selected real-world route within the Texas Triangle Region. A study on the effect of availability of look-ahead information, such as grade, is brought up and the results are expressed as hydrogen consumption and travel time. The problem is formulated as an optimal control problem (OCP), and solved as a hierarchical model predictive control (MPC) using Approximate Dynamic Programming (ADP). Different levels of driver aggressiveness have been considered in the virtual simulations performed on SIMULINK and the results have been compared against a heuristic-based baseline controller. The improvement coming from the optimized strategy without look-ahead grade information are approximately 3% to 9% depending on the driver aggressiveness, while a substantial and consistent 8% improvement is provided when leveraging look-ahead data.**

I. INTRODUCTION

Heavy-duty long-haul trucks require high power, long range, fast refueling, and high durability (that is, miles travelled over the lifespan of the vehicle). These requirements are not achievable with the limited range and long recharging times of the current battery electric propulsion system [1]. A lot of research is being done in combining electric batteries with sustainable energy sources to reduce range anxiety and improve the energy efficiency over internal combustion engine based powertrains [2]. Efficient decarbonization of the heavy-duty truck industry will not only require a shift from traditional fossil fuels to zero- or low-carbon propulsion systems, but also maximizing the efficiency of the propulsion system with the availability of look-ahead information via connectivity and automation. In this work, a fuel cell electric truck is considered, because it offers high efficiency and zero tailpipe carbon emissions, with short refueling time [3]. However, the efficiency of fuel cells can drop significantly during transient operations and irreversibly degrade over time [4]. For this reason, the typical powertrain architecture of a fuel cell electric vehicle is hybridized with the addition of a battery. With two power sources on-board (that is, the fuel cell and the battery), an optimal control problem can be formulated to determine the best energy management strategy (EMS) to minimize the overall hydrogen consumption [5]. In the literature, different control algorithms are found to solve the energy managament problem. In [6], the authors developed and implemented a fuzzy logic controller to determine the fuel cell power given the driver power demand and the state of charge (SOC), improving both fuel economy and fuel cell life with respect to a rule-based strategy. Ferrara et al. [7] analyzed different strategies in a realistic environment including 1750 hours of real-world data. In [8] and [9], two different evolutionary algorithms (i.e., Particle Swarm Optimization PSO and Genetic Algorithm GA) have been used to develop the control strategies. In the former article, PSO was used to obtain a heuristic controller of a heavy-duty truck in different real-world scenarios, whereas in the latter the authors exploit GA to develop a strategy for a yard truck for port applications. Guo et al. [10] proposed a deep reinforcement learning framework to improve energy efficiency of a fuel cell truck demonstrating similar results as compared to a Dynamic Programming (DP) based algorithm while reducing the computational effort.

Furthermore, information about the upcoming route, such as speed limits, road grade, location of traffic lights and stop signs can become available through connectivity at a limited additional cost [11]. Many studies on passenger cars have shown how these information can be leveraged for planning the vehicle speed throughout the trip in such a way to reduce the energy consumption with minimum increase in total travel time [12], [13], which is commonly referred to as "eco-driving". In [13], the eco-driving problem is formulated as a Receding Horizon Optimal Control Problem (RHOCP), where not only the route information that is known beforehand, but also information that becomes available during the route, such as changing traffic conditions, are used for the speed planning.

Although eco-driving for passenger vehicles has been extensively researched, there is a noticeable gap in the literature when it comes to fuel cell electric trucks. To the best of the author's knowledge, limited research has been conducted in this specific domain. Most existing studies primarily concentrate on the EMS, neglecting the crucial aspect of speed planning with route information. However, it is worth noting that integrating these two in eco-driving can

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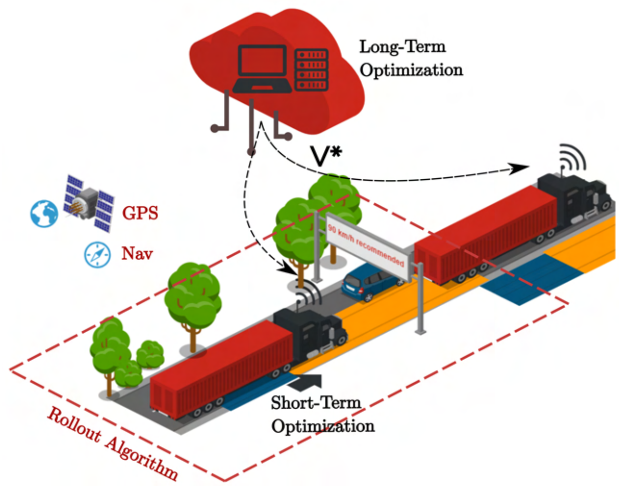

Fig. 1. Qualitative illustration of the proposed control strategy for eco-driving.

potentially yield significant improvements in terms of energy efficiency and safety.

In this study, the eco-driving problem for a fuel cell electric truck is formulated as a RHOCP and solved with Model Predictive Control (MPC). Optimal speed planning is of particular relevance to fuel cell vehicles, as it can smooth the power request to the fuel cell, with subsequent improvement in the system's durability. In addition, in order to develop a flexible and robust real-time implementable controller, different scenarios are tested, in which different information are available for the eco-driving optimization, such as speed limits and road grade.

Figure 1 shows a qualitative illustration of the proposed controller. If the route information is available from a map, a pre-computed solution of the full-route eco-driving optimization can be generated before the start of the trip, for example using cloud computing resources off the truck. This solution is referred to as Long-Term Optimization. Once the truck is on the road, the on-board computational capabilities are used to solve the RHOCP and adapt to dynamic changes in traffic conditions, performing a Short-Term Optimization with a Rollout Algorithm. The novelty of this work is not only limited to formulating the eco-driving problem for a fuel-cell electric truck, but also solving as an MPC with model feedback. A simplified model of the fuel-cell truck is developed for MPC which is then integrated to a high-fidelity plant model. The developed MPC is robust to modeling mismatches and provides approximately 15% energy efficiency improvement over the baseline controller. The rest of this paper is organized as follows: firstly, the model of the fuel cell electric truck is presented with its accompanying equations. Next, the optimal control problem is introduced and a discussion on the baseline controller and the optimized controller is engaged. Lastly, a comprehensive presentation of the simulation results obtained under a real-world route is provided along with the conclusions.

II. FUEL CELL TRUCK MODELLING

The vehicle powertrain model is illustrated with a block diagram in Figure 2(a) and is based on the fuel cell electric truck model provided by the ECCV Control Benchmark competition [14]. The fuel cell stack voltage is determined using a polarization curve which relates the fuel cell voltage to current density. The shape of this curve depends on multiple factors, such as the cathode pressure, p_{ca}, reactants (oxygen and hydrogen) partial pressures, p_{O_2}, p_{H_2} temperature, T_{fc}, and membrane humidity, RH. The dynamic model of the fuel cell considers first-order pressure dynamics for the anode and cathode side of the fuel cell, along with an efficiency-based compressor model. It is important to note that the fuel cell model encompasses numerous additional sub-processes, which are comprehensively documented in [15]. The battery pack is made of Li-ion cells. The cell terminal voltage and state of charge dynamics are obtained using a quasi-linear parameter-varying model and considering a homogeneous battery pack construction for cell-to-pack level scaling. The high-voltage DC bus is modeled considering first-order voltage dynamics along with the power electronics modeled using constant conversion efficiencies. The torque dynamics of the electric motor are modeled by a first-order transfer function along with an efficiency map to calculate the losses. The vehicle is equipped with a 4-speed transmission and a final drive reduction to amplify the torque at the wheels. Additionally, first-order lumped thermal dynamics of the electric motor, the power electronics, and the fuel cell are also considered along with a thermal management system to maintain the respective component temperature within safe limits. This high-fidelity vehicle powertrain model is developed in the MATLAB/SIMULINK simulation environment.

The large count of state variables in the non-linear high-fidelity powertrain model presents a formidable challenge when attempting to employ it as the system dynamics in the optimal control problem formulations due to the curse of dimensionality. This necessitates the development of low-fidelity models for certain powertrain components that significantly reduce complexity while maintaining an acceptable level of accuracy. Hence, a backward-looking approach is used to model the powertrain, as described in the following equations (1a-e). Using the road load equation, the power required at the wheels, P_w, is determined. Then, based on the powertrain efficiency, η_{pt}, and electric machine efficiency, η_{em}, the power of the electric motor, $P_{em,elec}$, is calculated. A map-based approach relating the fuel cell current, I_{fc}, and power, P_{fc}, is developed, assuming the factors influencing the fuel cell polarization curve, f_{fc}, remain in equilibrium at their designated operating conditions $(\bar{T}_{fc}, \bar{p}_{ca}, \bar{p}_{O_2}, \bar{p}_{H_2}, \bar{RH})$. This assumption is upheld during the simulation of the high-fidelity model by fine-tuning the respective reference tracking controllers. A zeroth-order equivalent circuit model of the cells is used for the battery pack to determine the battery current, I_{bat}, based on the power requested to the battery, P_{bat}. Note that the battery open circuit voltage, V_{oc}, and internal resistance, R_0, depend

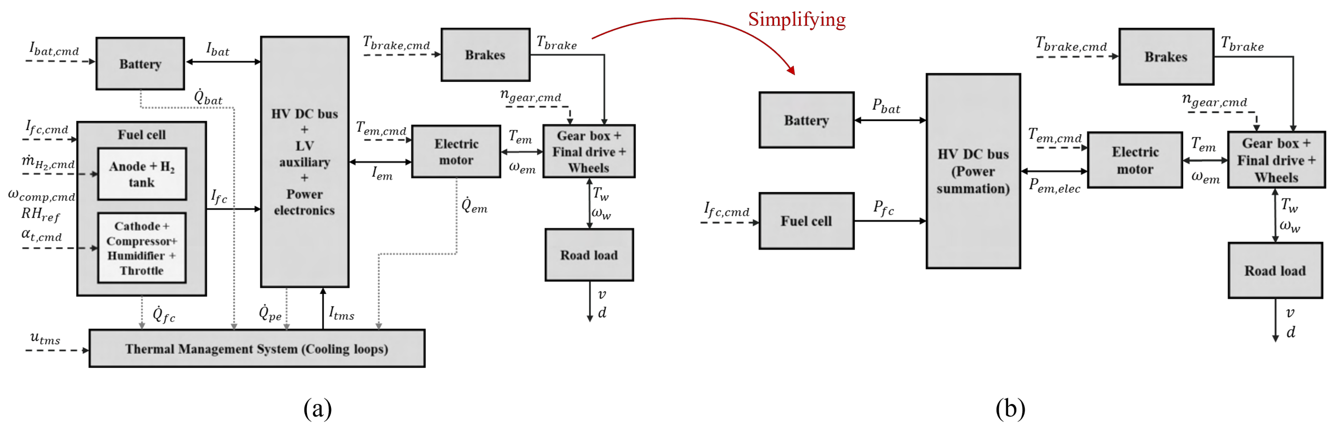

Fig. 2. (a) High-fidelity and (b) low-fidelity fuel cell electric truck powertrain models for vehicle simulation.

on the battery SOC, ξ. Instead of modeling the high-voltage DC bus by its voltage dynamics, it is replaced by a power-summation junction. The fast torque dynamics of the electric motor are neglected. All these modifications result in the design of a powertrain model as depicted in Figure 2(b) that is suitable for the optimal control problem formulation and solution.

$$P_w = \left(F_{\text{aero}} + F_{\text{roll}} + F_{\text{grade}} + M_{eff}\frac{dv}{dt}\right)v \tag{1a}$$

$$P_{em,elec} = P_w \cdot (\eta_{pt}\eta_{em})^{-\beta}\begin{cases}\beta = 1 & P_w \geq 0\\ \beta = -1 & P_w < 0\end{cases} \tag{1b}$$

$$P_{fc} = f_{fc}(I_{fc}; \bar{T}_{fc}, \bar{p}_{ca}, \bar{p}_{O_2}, \bar{p}_{H_2}, \bar{RH}) \tag{1c}$$

$$P_{bat} = P_{em,elec} - P_{fc} \tag{1d}$$

$$I_{bat} = \frac{V_{oc}(\xi) - \sqrt{V_{oc}(\xi)^2 - 4P_{bat}R_0(\xi)}}{2R_0(\xi)} \tag{1e}$$

where F_{aero}, F_{roll}, F_{grade} are the resistive forces (road load) due to aerodynamic drag, rolling resistance, and road grade, respectively.

III. PROBLEM FORMULATION AND SOLUTION METHODS

The objective of the non-linear dynamic optimization problem, formulated in the spatial domain, is to minimize the hydrogen consumption of the vehicle over an entire itinerary. A key benefit of a spatial trajectory formulation is that it naturally lends itself to the incorporation of route-related information, such as speed limits, road grade, location of traffic lights, and stop signs.

Consider a dynamic control problem discretized in the spatial domain having the form:

$$x_{s+1} = f_s(x_s, u_s), \quad s = 1, \cdots, N-1. \tag{2}$$

where s is the discrete position, $x_s \in \mathcal{X}_s \subseteq \mathbb{R}^p$ and $u_s \in \mathcal{U}_s \subseteq \mathbb{R}^q$ are the state and control action, respectively, and f_s is a function that describes the state dynamics. Note that the dynamic system f is the low-fidelity model shown in figure 2

In this work, the state variables are the vehicle velocity, v_s, and battery SOC , ξ_s. The control actions are the longitudinal acceleration, a_s, and fuel cell current, $I_{\text{fc},s}$:

$$x_s = [v_s, \xi_s]^\intercal \tag{3a}$$

$$u_s = [a_s, I_{\text{fc},s}]^\intercal \tag{3b}$$

The equations describing the state dynamics $f_s(x_s, u_s)$ are:

$$v_{s+1}^2 = v_s^2 + 2\Delta d_s\left(a_s - \frac{F_{\text{RL},s}}{M}\right) \tag{4a}$$

$$\xi_{s+1} = \xi_s - \frac{\Delta d_s}{\bar{v}_s}\cdot\frac{\bar{I}_{\text{bat},s}}{C_{\text{nom}}} \tag{4b}$$

where $F_{\text{RL},s}$ is the road load resistive force, M is the total vehicle mass, C_{nom} is the nominal battery capacity, Δd_s is the discretization step size, and $\bar{v}_s$ is the average velocity over one distance step.

The objective of the long-term eco-driving problem, formulated in the spatial domain, is to minimize the fuel consumed by the vehicle over an entire route consisting of N steps:

$$\min_{\{\mu_s\}_{s=1}^N} \sum_{s=1}^{s=N}\left(\gamma\frac{\dot{m}_{f,s}}{\dot{m}_f^{norm}} + (1-\gamma)\right)\Delta t_s \tag{5}$$

where s is the discrete position, γ is a weighting factor penalizing the travel time, $\dot{m}_{f,s}$ is the fuel flow rate, $\dot{m}_f^{norm}$ is a normalizing factor and $\Delta t_s = \frac{\Delta d_s}{\bar{v}_s}$ is the travel time per step, computed from the distance step (i.e., $\Delta d_s = d_{s+1} - d_s$, with d_s the distance traveled along the route at position s) and average velocity $\bar{v}_s$: $\left(= \frac{v_s + v_{s+1}}{2}\right)$. The state and action space are subject to the constraints as:

$$\begin{aligned} v_s &\in [v_s^{min}, v_s^{max}], \quad \forall s = 1, \cdots, N\\ \xi_s &\in [\xi^{min}, \xi^{max}], \quad \forall s = 1, \cdots, N-1\\ \xi_N &\geq 20\%\\ a_s &\in [a^{min}, a^{max}], \quad \forall s = 1, \cdots, N-1\\ I_{fc,s} &\in [I_{fc}^{min}, I_{fc,s}^{max}], \quad \forall s = 1, \cdots, N-1 \end{aligned} \tag{6}$$

where v_s^{min}, v_s^{max} are the minimum and maximum route speed limits respectively, ξ_s^{min}, ξ_s^{max} are the static limits applied on battery SOC, a^{min}, a^{max} represent the limits imposed on the acceleration for comfort. A terminal constraint $\xi_N \geq 20\%$ is applied to the battery state of charge.

At the beginning of the route, only limited information such as speed limits, position of stop signs and traffic lights can be known a priori. To account for route variabilities such as Signal Phase and Timing (SPaT) information and traffic, the long-term eco-driving optimization problem is formulated as a receding horizon optimal control problem (RHOCP) or a short-term optimization problem where the full route of N steps is solved over a reduced horizon $N_H (<< N)$. At any given position $s = 1, \dots, N - N_H$, the optimization problem is formulated as:

$$\mathcal{J}^*(x_s) = \min_{\{\mu_k\}_{k=s}^{s+N_H-1}} \sum_{k=s}^{s+N_H-1} c(x_k, \mu_k(x_k)) + c_{\mathrm{T}}(x_{s+N_H}),$$
$$c(x_k, \mu_k(x_k)) = \left(\gamma \cdot \frac{\dot{m}_{\mathrm{f},k}(x_k, \mu_k(x_k))}{\dot{m}_f^{norm}} + (1-\gamma) \right) \cdot \Delta t_k \tag{7}$$

where $\mu_k : \mathcal{X} \to \mathcal{U}$ is the admissible control policy of the controller at the step k in the prediction horizon; $c : \mathcal{X} \times \mathcal{U} \to \mathbb{R}$ is the stage cost function defined as the weighted average of the hydrogen consumption and travel time; $c_{\mathrm{T}} : \mathcal{X} \to \mathbb{R}$ is the terminal cost function.

The problem is solved using the Rollout algorithm developed in [13], [16], which uses Approximate Dynamic Programming (ADP).

IV. SIMULATION RESULTS

Simulations were run over a real-world route extracted using Open Street Maps (OSM). Figure 3 shows the route in the Texas Triangle Region on OSM with the markers representing the origin and destination. This particular route selection aligns with the U.S. Department of Energy's H2LA (Houston to Los Angeles) initiative, which aims to establish an extensive hydrogen fueling infrastructure and promote zero-emission heavy-duty freight transportation growth, particularly within the Texas Triangle Region [17]. Additionally, the U.S. Department of Transportation Federal Highway Administration's Texas Connected Freight Corridors project complements these efforts by implementing and making the vehicle-to-vehicle and vehicle-to-infrastructure technologies available in this region, which will help in reducing fuel consumption among freight trucks [18]. Origin-destination pairs can be used to generate trips on the OpenStreetMaps API, which is then used to extract route information, such as speed limits, grade, and position of stop signs and traffic lights in SUMO [19]. The obtained speed limits and altitude information as a function of distance for the selected route are shown in Figure 4.

The route is used to evaluate the benefits of the ADP-based MPC presented in the previous Section III against a baseline controller. As shown in Figure 5, the baseline controller is integrated with the high-fidelity plant model presented in

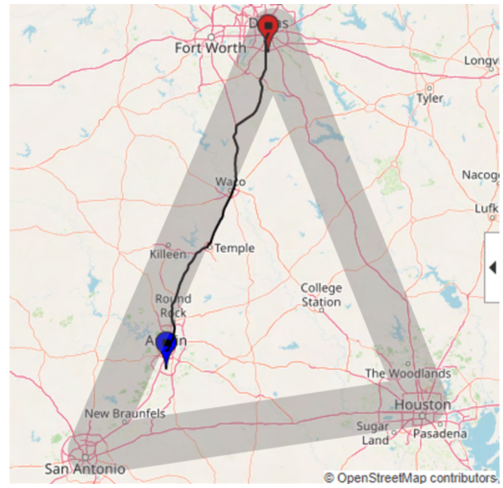

Fig. 3. Considered route on OpenStreetMaps (blue marker: origin and red marker: destination) and the Texas Triangle Region.

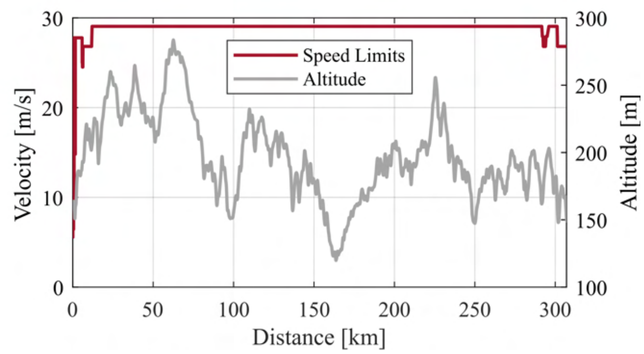

Fig. 4. Speed limits and altitude information of the considered route.

Section II. In the same figure, the enhanced driver model (EDM), as developed in [20], is a parametric driver model that can be calibrated with different driver aggressiveness levels, using the route speed limit and route marker information as inputs. The EDM is used as a reference velocity generator in the baseline vehicle simulator. A simplified charge-depleting/charge-sustaining heuristic energy management strategy [21] is developed to split the power demand at wheels between the electric battery and the fuel-cell.

The effect of availability of route information on the energy consumption is evaluated for both the baseline and ADP-based MPC controllers by performing a full sweep of the weighting factor γ in equation 5. For the baseline simulations, three values of aggressiveness are chosen for the EDM, based on [22], representing aggressive, normal, and relaxed driving.

Figure 7 shows the comparison of the fuel consumption and travel time for both controllers. In addition, for the ADP-based MPC controller, two cases are considered, depending on the availability of the grade information. When compared against the baseline, the optimizer without grade preview reduces the fuel consumption by approximately 3-9% depending upon the driving aggressiveness of the baseline driver. It is noteworthy that the grade preview enables a

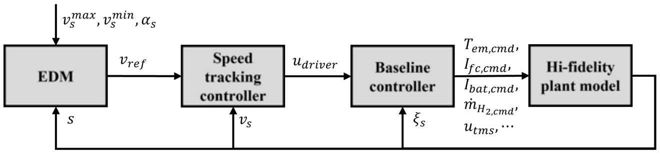

Fig. 5. Block-diagram of the baseline vehicle simulator.

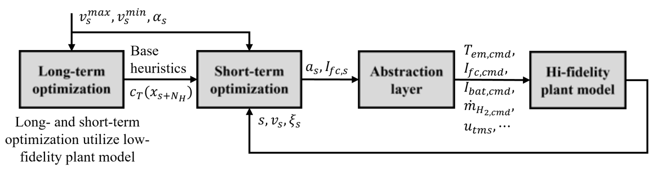

Fig. 6. Block-diagram of the ADP-based MPC controller vehicle simulator.

consistent additional 8% fuel consumption reduction over the eco-driving without grade preview. This signifies the high sensitivity of the fuel consumption to the elevation information and how this information can help in optimally using the power sources in a hybrid truck where the payload is high.

Finally, Figure 8 shows the optimal state trajectories for the considered route. In presence of grade, the ADP-based MPC anticipates the uphill and downhill and will adjust the velocity profile to avoid unnecessary power demands to the powertrain. As shown, the proposed controller will accept lower velocity when going uphill and let the velocity increase when going downhill in order to save energy. On the other hand, the reactive baseline controller takes instantaneous decision and regardless of the road grade conditions will keep the vehicle speed fixed at an almost constant value. This will cause unnecessary high power demands when traveling up a slope and need for braking when going downhill. As compared to the optimized controller without grade information, the ADP-based MPC with grade anticipation not only provides additional energy savings, but at the same time improves the safety by preventing over-speeding in aggressive downhills, as shown in the detailed window in Figure 8.

V. CONCLUSIONS

Leveraging route information when controlling heavy-duty trucks is of crucial importance to improve energy efficiency and durability of the system components. The eco-driving problem seeks the optimal speed and power flow using data coming from connectivity and advanced mapping features. In this study, the eco-driving problem for a fuel cell electric truck has been solved in a receding horizon optimal control problem formulation, that is robust to sudden changes including traffic and/or possible rerouting. To demonstrate the potential of such method, virtual simulations over a real-world route from the Texas Triangle Region identified by the US DOE Houston to Los Angeles initiative have been performed. To provide a comparison with a benchmark solution a baseline controller has been developed based on a driver model with different levels of aggressiveness.

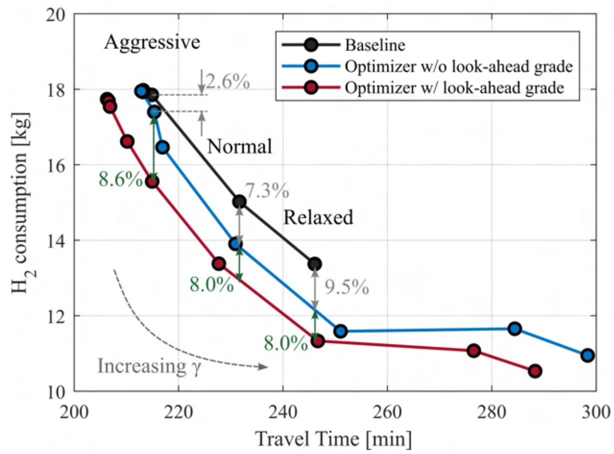

Fig. 7. Pareto Front showing the comparison of hydrogen consumption and travel time for baseline, MPC with and without grade look-ahead information.

Furthermore, the effect of the availability of look-ahead route information has been studied, mainly focusing on the road slope availability. Results show a reduction in hydrogen consumption in the range 3% to 9% when comparing the baseline controller with the optimizer without grade preview, where the lowest improvement is achieved for an aggressive driver. The optimized strategy with the complete information on road slope consistently delivered an additional 8% improvement across all driver aggressiveness compared to the optimizer with no grade preview. This outcome confirms the advantages of incorporating such data into the eco-driving problem, especially for heavy-duty trucks with substantial payload, thus inertia. Future studies will include the implementation of such optimizer on a Rapid Prototyping System to analyze the real-time feasibility.

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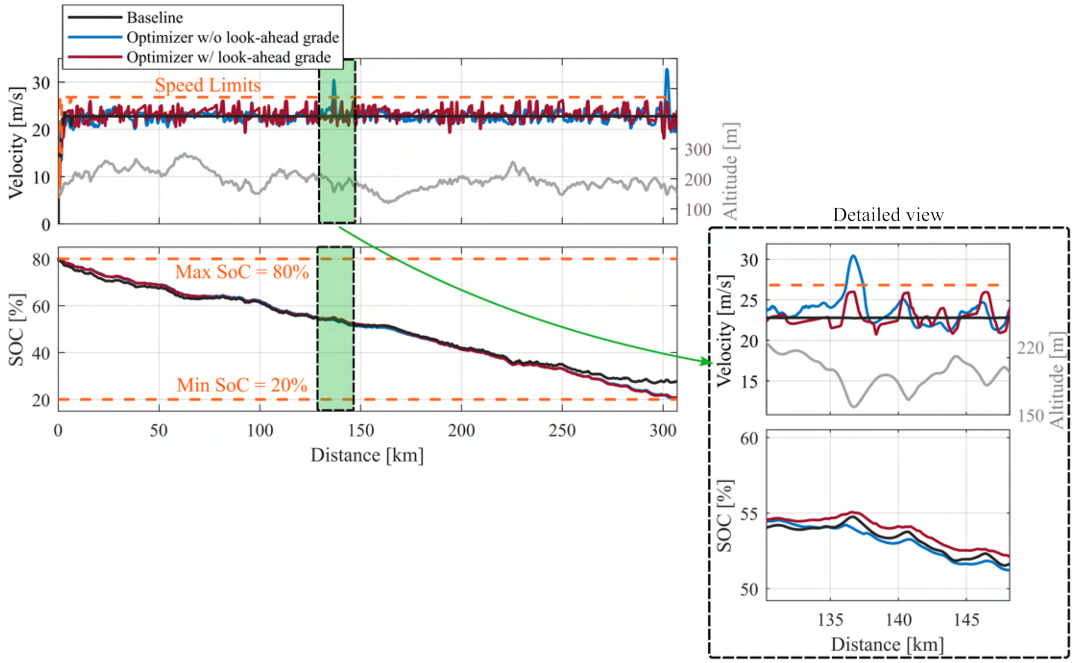

Fig. 8. Speed profiles and SOC trends of the three controllers with a detailed view of a case of steep downhill.

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