Energy-efficient Speed Planner for Connected and Automated Electric Vehicles on Sloped Roads

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ABSTRACT This paper proposes an energy-efficient speed planning strategy for a connected and automated vehicle (CAV) considering the upcoming traffic and road gradient information, which can be provided by the vehicle-to-everything communication systems. Unlike human drivers, CAV that receives long and short sighted traffic and road geometry information can optimize their speed profile to increase energy efficiency, depending on the powertrain types. In particular, the developed speed planner reducing the battery output power through the energy-efficiency improvement systems in electrified vehicles. Consequently, the CAV that is aware of the existence of the upcoming road gradient increases the speed on the uphill, and decreases the speed on the downhill to minimize the battery output power, which is different from the natural behaviors of human-driven vehicles on sloped roads. To consider the constraints, the model predictive control-based speed planner is developed, and its effectiveness is verified under various driving conditions. Simulation results show that our approach significantly outperforms the alternative speed profiles in terms of battery energy-saving, achieving about 27.21% of the energy efficiency improvement.

INDEX TERMS Connected and automated Vehicle, Model Predictive Control, Electric Vehicle, Energy-efficiency Improvement, and Energy-efficient Driving.

I. INTRODUCTION

Recently, the electric vehicles (EVs) have attracted significant attention of researchers due to their several advantages, and some experts predict that EVs will account for about 28% of the global automotive market in the near future [1].

Although there still remain the technical challenges to more widely spread EVs [2]–[4], compared to the traditional internal combustion engine-based vehicle, EV has shown its ability to reduce the CO₂ emissions significantly [5], save the energy with the eco-driving [6], [7], increase the vehicle dynamic performances [8].

Among them, many automakers emphasized the improvement of energy efficiency of EVs, and combining the connected-and-automated vehicle (CAV) technologies and electrified powertrain has been recently highlighted [9], [10]. The representative CAV technologies such as vehicle-to-everything (V2X) communications allow the vehicle to receive the preview traffic information. This information can be considered when planning the CAV’s future trajectories to minimize energy consumption. In [11], it was revealed that the automated truck could save fuel consumption by approximately 14% on the highway using preview information. Several attempts have been made to optimize the vehicle trajectory planning and control [12]–[16] in a similar manner, which minimizes the energy consumption, on flat road. In addition, several studies demonstrate that the road gradient influences the energy efficiency of the vehicle [17]–[19], but the possibility of the different speed trajectories on sloped roads when the energy-efficiency improvement of the electrified vehicles is included is not explicitly considered.

In this study, when the spatially varying road gradient information is given, the speed profile for EVs is planned to minimize battery power consumption. In particular, reducing the battery output power through the energy-efficiency im-
FIGURE 1: Illustration of the car-following driving scenario while the V2X technologies are available.

The speed trajectory of EV that utilizes the energy-efficiency improvement systems on sloped roads is planned through the trajectory optimization theories (e.g., dynamic programming (DP) [20]). Although DP can find the globally optimized trajectory while satisfying the specified constraints, it requires the entire trip trajectory since the problem is solved from the backward recursion, resulting in a huge computational burden. Therefore, the DP-based trajectory optimization can not be applied to real-time control design, but the result from DP can be used as the benchmark. Meanwhile, the model predictive control (MPC) can be considered, which solves the finite time optimization problem in a receding horizon control manner [21]. Additionally, MPC-based vehicle short-term trajectory planning has confirmed its effectiveness in some literature [22], [23].

The driving condition treated in this study is the car-following scenario on a sloped road, assuming the ego and leading cars are connected (See Fig. 1) [24], [25]. It should be noted that this paper focuses on generating the energy-efficient optimal speed profile of the ego vehicle on sloped roads while the speed prediction of preceding cars are not considered, which is challenging due to the uncertainties in the behaviors of the human-drivers [26], [27]. As shown in Fig. 1, the vehicle connectivity enables the ego car to access the historical position and speed trajectories of the leading car, which can drop a hint how the human-driven cars in front behave in the future [28]. That is, based on the rational behaviors of all vehicles, the short-term future behaviors of the preceding human-driven cars are assumed to be predicted using the vehicle connectivity information. By exploiting this, the safe and energy-efficient speed trajectory of the ego car can be generated at each control cycle. Specifically, the different speed trajectory that is not generally planned by the human-driver could be generated on sloped roads, increasing energy efficiency, which is the main distinguishing feature of our approach.

The main contributions of this study are as follows.

1) The vehicle speed trajectory that minimize the battery output power through the energy-efficiency improvement systems in the EV is generated on sloped roads, which cannot be realized by human-driver due to its lack of preview road gradient information.

2) The finite time nonlinear optimization problem is solved in real-time based on the MPC manner, reflecting the change in the driving environment at every control cycle. Since no lane changing is assumed in our developed simulation environment, the state constraints (i.e., the future behaviors of vicinity vehicles of the ego vehicle) can be rationally specified. Thus, enabling the ego vehicle to generate a safe and energy-efficient speed profile.

3) The effectiveness of the developed speed planner in terms of energy-saving is tested in various driving environments. The results are compared with the alternative car-following speed profiles. The comparisons show that our approach could save 7% to 27% battery energy consumption, depending on the driving cycles. Additionally, our approach is the most effective in urban driving.

The remainder of the paper is organized as follows. The treated driving environment and the principle of how the CAV generates the speed profile on a sloped road are described in Section II. The vehicle and battery systems are modeled in Section III. The infinite time optimal control problem is solved in Section IV. The effectiveness of the developed speed planner is compared with alternative methods in Section V. Finally, Section VI presents the
II. PROBLEM FORMULATION

A. CAR-FOLLOWING SCENARIO

In this section, we formulate the treated problem, and the car-following driving scenario in the single lane is described. As shown in Fig 1, the ego and leading cars are connected, so they can communicate. Additionally, multiple human-driven vehicles drive in the same lane between ego and leading cars.

We assume that the ego car can receive real-time position-and-speed information of the leading car to predict short-term speed profile of the front human-driven car of the ego car under the assumption that all vehicles behave rationally. In other words, the monitored leading car’s speed and position drop a hint to predict the front car’s behaviors. Additionally, through the V2X technologies, other useful preview information, including the road slope, is known to ego car before planning its trajectory. Based on this information, the ego car plans its optimized speed profile to improve energy efficiency, while maintaining the appropriate distance. We design a speed controller that minimize the battery output power during braking events on the downhill, resulting in different speed profiles compared to the human-driven car.

From the ego car’s perspective in Fig. 1, the following assumptions are made. 1) All vehicles follow their front vehicle based on the collision-free car-following model (e.g., intelligent driver model), and lane-change is not considered. 2) Short-term future position-and-speed trajectory of the leader car can be predicted, and it is known to the ego car. 3) Major state variables in the vehicle and electrified powertrain, i.e., battery state-of-charge (SOC), vehicle position and speed, battery pack temperature, can be measured accurately.

B. MAXIMIZATION OF THE AMOUNT OF ENERGY RECUPERATION

The road gradient information is a fixed value, and it can be obtained from navigation systems. Using this predefined road gradient, the electrified CAV can plan its speed profile in a way that minimize the battery output power, resulting in increased energy efficiency [29], [30].

As shown at the top of Fig. 2, the human driver can slightly increase the vehicle speed on the uphill. They usually use the brake on the downhill as little as possible. It should be noted that described human-driven vehicle (HV) speed profile is an example, so that it does not mean that all human drivers behave the same. However, since no road gradient information is known to human drivers, at least, they are likely to maintain their speed on a sloped road, while keeping an appropriate safe distance with the front vehicle [31]. In contrast, CAV with road gradient information in advance behaves differently on the sloped road, as described at the bottom of Fig. 2. It means that the functionality of the energy-efficiency improvement of the electrified vehicle can be used when planning the speed profile. The CAV can accelerate on the uphill, and then the regenerative braking force is applied to the vehicle on the downhill, minimize the battery output power.

This speed planning strategy is possible because the road gradient and predicted short-term speed of the front vehicle are given using the V2X technologies. Additionally, electric vehicle equipped with electric motors with a function of minimization of battery output power generates a different optimized speed trajectory on sloped roads.

III. SYSTEM MODELING

A. VEHICLE LONGITUDINAL DYNAMICS

The considered vehicle longitudinal dynamics model in this study is as follows.

\[ \dot{s} = v, \]  
\[ \dot{v} = \frac{T_w}{m r_w} - \frac{1}{2 m} \rho A_f \frac{C_d v^2}{2} - g \sin \theta - f g \cos \theta. \]  

where \( s \) is the vehicle travel distance, \( v \) is the vehicle speed, \( m \) is the effective vehicle mass, \( T_w \) is the applied wheel torque, \( r_w \) is the tire radius, \( \rho \) is the air density, \( A_f \) is the frontal area of the vehicle, \( C_d \) is the aerodynamic drag coefficient, \( \theta \) is the road slope, \( g \) is the gravitational constant, \( f \) is the rolling resistance coefficient.

The system control input \( T_m \) (motor torque) is computed using the wheel torque \( T_w \) and the final gear ratio \( i_0 \).

\[ T_m = \frac{T_w + T_b}{i_0} \approx \frac{T_w}{i_0}. \]

where \( T_b \leq 0 \) is the friction brake torque.

In this study, we assume the all required braking torques are covered only by the electric motor, so the \( T_b \) that is only needed when the maximum motor torque is insufficient is assumed to be zero.

Now, the vehicle dynamics is discretized using Euler method:

\[ x_{i+1}^v = x_i^v + f(v_i^v, u_i^v)T_s \]  

where \( T_s \) is the sampling time interval, \( x_i^v = [s_i, v_i] \) is the vehicle state variable, and \( u_i^v = T_{m,i} \) is the control input at time instant \( i \).
B. BATTERY DYNAMICS

The battery SOC is expressed as follows.

$$S_{OC}(t) = -\frac{I_b(t)}{C}$$  \hspace{0.5cm} (5)

where $I_b$ is the battery current, and $C$ is the battery maximum capacity.

The battery current $I_b$ is computed by

$$I_b(t) = \frac{V_c(t) - \sqrt{V_c^2(t) - 4R_b(t)P_b(t)}}{2R_b(t)}$$  \hspace{0.5cm} (6)

where $V_c$ is the open-circuit voltage, $P_b$ is the battery output power, and $R_b$ is the battery resistance.

To find $V_c$ and $P_b$ according to the battery SOC, we use the predefined look up tables in Fig 3. The battery output power is described as follows.

$$P_b = \begin{cases} P_m c_b, & P_m < 0 \\ \frac{P_m}{e_b}, & P_m \geq 0 \end{cases}$$  \hspace{0.5cm} (7)

where $P_m$ is the motor output power that has a negative value during battery recharging and has a positive value during battery discharging, and $e_b$ is the battery efficiency that is assumed to be constant.

The motor output power is as follows.

$$P_m = \begin{cases} \omega_m T_m e_m, & T_m < 0 \\ \frac{\omega_m T_m}{e_m}, & T_m \geq 0 \end{cases}$$  \hspace{0.5cm} (8)

where $\omega_m = \frac{\omega}{T}$ is the angular speed of motor, $e_m$ is the motor efficiency determined by the motor operating points, i.e., $e_m(\omega_m, T_m)$. The predefined motor efficiency map is described in Fig. 4. Similar to (7), the vehicle recovers battery SOC when the negative $T_m$ is applied, and uses the battery SOC during the propulsion.

Now, similar to previous subsection, the nonlinear discrete-time battery dynamics can be represented as follows.

$$x_{i+1}^s = x_i^s + f(x_i^s, u_i^s)T_s$$  \hspace{0.5cm} (9)

where $x_i^s$ is the SOC$_i$. 

C. INTEGRATED MODEL

To design the model-based optimal control, the vehicle and battery dynamic models are integrated as follows.

$$X_{i+1} = X_i + g(X_i, u_i^s)T_s.$$  \hspace{0.5cm} (10)

where $X_i = [x_i^s, x_i^v]$, $u_i^s = T_m,i$, and $g(\cdot) = [f^v(\cdot), f^s(\cdot)]'$.

Based on these integrated model, the optimization problem will be formulated in the following section.

IV. OPTIMIZATION PROBLEM FOR MINIMIZATION OF BATTERY OUTPUT POWER

The finite-time optimal control problem is formulated in the receding horizon control approach as follows, which aims to minimize the battery output power for $N$-steps.
\[ \min J_i(X_i, U') = \sum_{k=0}^{N-1} P_b(X_{k|i}, u'_{k|i}) \quad (11a) \]

subject to

\[ X_{k+1|i} = X_{k|i} + g(X_{k|i}, u'_{k|i})T_s, \quad (11b) \]

\[ X_{0|i} \text{ is given}, \quad (11c) \]

\[ T_{\min} < u'_{k|i} < T_{\max} \quad (11d) \]

\[ \Delta s_{k+1|i} < \Delta s_{k+1|i} < \Delta s_{\max} \quad (11e) \]

\[ \dot{v}_{k+1|i} < v_{k+1|i} < \eta \cdot \hat{v}_{f}^{+1|i} \quad (11f) \]

where \( \Delta s_{k|i} = s_{k|i} - s_{f}^{+1|i} \) is the relative distance between ego and front cars \((s_{f}^{+1|i})\) at time step \( i + k \) made at time instant \( i \), \([T_{\min} : T_{\max}]\) is the acceptable range of the motor torque, \([\Delta s_{\min} : \Delta s_{\max}]\) is the specified range of safe distance between ego and front vehicles, \( X_{0|i} \) is the state variables at time instant \( i \), \( v_{\min} = 0 \) is the minimum vehicle speed, \( \eta \) is the constant tuning parameter, and \( \hat{v}_{f}^{+1|i} \) is the predicted front vehicle's speed for the infinite time horizon length.

A. CAR-FOLLOWING MODEL – IDM

In this subsection, we introduce an alternative speed planner, i.e., IDM, to construct the simulation environments. IDM is a widely used conventional collision-free car-following model.

We assume that all vehicles, except for ego and leading cars are driven based on IDM, generating the collision-free speed profiles of the series of HVs [34]:

\[ \dot{v}(t) = a \left[ 1 - \left( \frac{v(t)}{v_0} \right)^\delta - \left( \frac{d^+(v, \Delta v)}{d(t)} \right)^2 \right]. \quad (12) \]

where \( a \) is the maximum acceleration, \( v_0 \) is the desired velocity, \( d^+(v, \Delta v) \) is the desired gap between vehicle.

| Parameters                  | Urban | Highway |
|-----------------------------|-------|---------|
| Maximum acceleration \( a \) [m/s²] | 1.43  | 3.76    |
| Desired velocity \( v_0 \) [m/s] | 40    | 40      |
| Acceleration exponent \( \delta \) [-] | 4     | 4       |
| Jam distance \( d_0 \) [m] | 2     | 2       |
| Jam distance \( d_1 \) [m] | 0     | 0       |
| Safe time headway \( T_h \) [s] | 2     | 2       |
| Comfortable deceleration \( b \) [m/s²] | 1.4   | 2       |

The desired gap between two vehicles is defined as follows.

\[ d^+(v, \Delta v) = d_0 + d_1 \sqrt{\frac{v}{v_0} + T_h v + \frac{v \Delta v}{2 \sqrt{ab}}}. \quad (13) \]

where \( d_0 \) and \( d_1 \) are the jam distance, \( T_h \) is the time headway, and \( b \) is the comfortable deceleration.

Table 1 presents constant parameter values of IDM used in this study, depending on the driving cycles (i.e., urban driving...
FIGURE 6: Road slope profile, reproduced from the road gradient data along the Beijing city 3rd ring road [33].

FIGURE 7: Schematic of the developed speed planner.

and highway drivings).

B. OVERALL ARCHITECTURE OF THE DEVELOPED MPC-BASED SPEED PLANNER

By solving (11), the following optimal control sequence can be obtained, and only first element $u^{v_0}_{Ki}$ is applied to the vehicle at time instant $i$.  

$$U^{v,*} = \{u^{v_0}_{Ki}, \ldots, u^{v_N}_{N-1|i}\}. \quad (14)$$

At the next time step $i + 1$, based on the updated preview traffic information, a new optimal control sequence is computed, and this procedure is repeated at every time instant.

C. SIMULATION

The proposed MPC-based speed optimization is tested in the car-following scenario where only ego and front vehicles drive on the relatively simple sloped road (See Fig. 5(a)).

In this verification, our approach is compared with the conventional car-following model-based speed planner, i.e., intelligent driver model (IDM). IDM-based speed profile is very similar to that of the front vehicle since it maintains the almost same distance with the front vehicle, as shown in Fig. 5(d). In other words, the IDM-based speed profile is to mimic the behavior of the human driver with a short-sighted view. In contrast, MPC-based speed planner adjusts the distance between front vehicles actively, while satisfying the safe constraints, i.e., $\Delta s_{\text{min}}, \Delta s_{\text{max}}$, as illustrated in Fig. 5(d).

As expected, the MPC-based controlled vehicle maintains or increases its speed on the uphill and decreases its speed on the downhill, as shown in Figs. 5(a) and (b), which is different from that of IDM, improving the energy efficiency in terms of the battery $SOC$ consumption in Fig. 5(c). This is because MPC-based speed planner reduce the battery output power through the energy-efficiency improvement systems on the downhill, given to CAV in advance [35].

However, our approach sometimes shows unintended results. For example, the vehicle decelerates on the uphill, which is the conflicting result of Fig. 2. Since the priority is placed on the satisfaction of the safe distance constraint with the leader car, the appropriate control input is applied to

| Table 2: Parameter values |
|---------------------------|
| Description               | Symbol | Value   |
| Mass of the vehicle       | $m$    | 1.445 [kg] |
| Wheel radius              | $r$    | 0.3166 [m]  |
| Ratio for single reduction gear | $i_0$ | 7.2 [-]     |
| Gravitational constant    | $g$    | 9.81 [m/s$^2$] |
| Coefficient of rolling resistance | $f$   | 0.00863 [-] |
| Air density               | $\rho$ | 1.2 [kg/m$^3$] |
| Vehicle frontal area      | $A_f$  | 2.52 [m$^2$] |
| Drag coefficient          | $C_d$  | 0.28 [-]    |
| Assumed battery efficiency| $e_b$  | 0.9 [-]     |
| Battery maximum capacity  | $C$    | 198,000 [A · s] |
| Sampling time             | $T_s$  | 1 [s]      |
| Min/max relative distances | $\Delta s_{\text{min, max}}$ | 10, 80 [m] |
| Min/max motor torques     | $T_{\text{m, min, max}}$ | $-220, 220$ [N·m] |
| Tuning parameter for $v_{\text{max}}$ | $\eta$ | 1.5 [-]     |
| Prediction and control horizon | $N$  | 20 [s]      |
the vehicle regardless of the level of road slope to keep the safety. Although the vehicle speed decreases in this region, this is not the energy-efficiency improvement operation area. Indeed, with a small amount of motor torque, the vehicle does not overcome the resistive forces such as the gravity due to the inclined road, aero drag, and rolling resistance, and slows down slightly.

Fig. 7 shows the overall schematic of the developed MPC-based speed planner. Through the V2X technologies, the front vehicle’s speed is predicted and road gradient information is given for the specified time horizon length, and the optimization problem is solved at every time step, resulting in the optimal control sequence, which aims to minimize battery output power consumption.

As the new traffic information is updated, the above procedure is repeated at every time instant. Here, since the upcoming road gradient $\theta$ has a fixed value, the energy-efficiency improvement event is easily planned once the front vehicle’s behavior is given, which gives the safety constraints.

V. CASE STUDIES

In the previous section, we verified that the developed speed planner operates as intended on sloped roads. In this section, we will validate the effectiveness of our approach under various driving conditions.

A. SIMULATION ENVIRONMENT

Table 2 presents the vehicle parameter values offered from the high-fidelity vehicle model in ADVISOR [32], and specified parameters to formulate the MPC problem. The road slope profile in the spatial domain is described in Fig. 6. The leading vehicle’s speed profile is assumed to be the various driving cycles in urban and highway driving conditions.

The closed-loop simulations were performed in Windows 10 operating system with Intel(R) Core(TM) i5-9500, 16GB RAM memory, and MATLAB command \texttt{fmincon()}. The sequential quadratic programming (SQP) method that is the state of the art in nonlinear programming method is employed to solve the problem efficiently, and the maximum number of iteration and the termination tolerance for the function values are specified $1e+3$ and $1e-6$, respectively.

B. TEST RESULTS IN URBAN DRIVING PATTERN

In this section, we verify the performance of the developed speed planner in the urban driving pattern. In other words, the leading car is assumed to follow the urban driving cycle (i.e., UDDS), whereas other HVs follow the leading car based on IDM.

Fig. 8 shows the test results in the spatial domain when all vehicles drive on the flat road. As shown in Fig. 8(a), the least amount of the battery SOC consumption is observed when CAV is controlled by the developed MPC-based speed planner compared with the IDM and human driver (leading car) [36]. This is because our approach optimizes the speed profile to minimize battery power consumption in (11) while keeping the safety even at the flat road. Compared with the other two speed profiles, battery power consumption is actively reduced through the energy-efficiency improvement (see Fig. 8(b)).

Fig. 8(c) shows the relative distance between CAV and front car, and the specified minimum and maximum constraints (i.e., $s_{\text{min}}$ and $s_{\text{max}}$) are satisfied at all times using the MPC-based control. The significant fluctuations of the relative distance between ego and leader cars are observed since the formulated problem in (11) lacks the ability to attenuate these fluctuations by specifying constant values of $s_{\text{min}}$ and $s_{\text{max}}$. Therefore, the results of Fig. 8(c) demonstrates that the MPC-based speed planner faithfully performs its given task. However, by specifying varying constraints (i.e., $\Delta s_{\text{min}}(t)$, $\Delta s_{\text{max}}(t)$), the relative distances can be easily attenuated if necessary.
In contrast, the IDM-based speed profile that follows the front vehicle in a similar pattern sometimes approaches the front vehicle too closely, especially at low speeds. The constraint violation is also observed without the functionality to handle the constraints. Although no collisions are observed with IDM-based speed profile, further safety margin in terms of the relative distance between two vehicles should be considered to cope with the unexpected sudden braking events of the front vehicles.

As shown in Fig. 9, speed profiles on the sloped road shows similar results to Fig. 8, although all cases consume more battery energy due to the road slope. The MPC-based speed planner outperforms the other two alternative speed profiles in terms of energy consumption. In this case, the road gradient information is also considered when solving the optimization problem in (11). Thus, we can observe MPC-based speed planner decelerates appropriately to minimize the usage of battery power as much as possible on the downhill while satisfying the constraints (see Fig. 9(d)), and it reaches the upper and lower limits of the safe distance constraints (i.e., $\Delta s^{\text{max}}$, $\Delta s^{\text{min}}$) in Fig. 9(b).

In Fig. 8(c) and Fig. 9(c), the fluctuation of the relative distance profiles are observed when employing our approach since the MPC-based speed planner utilizes the energy-efficiency improvement system as much as possible to reduce the battery output power. Since the major objective of the developed approach is to increase the energy efficiency, the speed and relative distance profiles are generated as intended.

C. TEST RESULTS IN HIGHWAY DRIVING PATTERN

Figs. 10 and 11 show the simulation results tested in the highway driving pattern (i.e., US06 that is the supplemental federal test procedure (FTP) schedule). The results are similar to those performed on the urban driving cycle. However, in the highway driving environment, to follow
TABLE 3: Simulation results on various driving cycles.

| Driving Cycle | Baseline | IDM | MPC | Improvement (%) | Baseline | IDM | MPC | Improvement (%) |
|---------------|----------|-----|-----|-----------------|----------|-----|-----|-----------------|
| UDDS         | 6.93     | 6.42| 5.17| 25.4            | 8.56     | 8.08| 7.17| 16.24           |
| US06         | 12.74    | 11.24|10.53| 17.35           | 14.43    | 12.97|12.43| 13.86           |
| WLTC         | 17.01    | 15.64|14.23| 16.34           | 43.68    | 42.46|40.52| 7.23            |
| LA92         | 11.98    | 10.37| 8.72| 27.21           | 13.98    | 12.4 |10.82| 22.6            |

D. RESULTS SUMMARY

The simulation results in various driving cycles are compared in terms of the battery $SOC$ consumption in Table 3, comparing the results in UDDS, US06, WLTC, and LA92, where the same road gradient in the spatial domain in Fig. 6 is considered. Here, the baseline denotes the speed profile of the human driver (i.e., original driving cycles). The battery $SOC$ consumption from MPC and IDM are compared to those from the baseline.

Similar to the results in the previous sections, all cases show that EV consumes more energy on sloped roads than flat roads. Additionally, the MPC-based speed planner outperforms the other two approaches for all driving cycles. For example, our approach achieves the 25.4% and 16.24% improvement of energy efficiency on the flat and sloped roads respectively. These trends are similar in other urban driving environments (i.e., LA92). In contrast, relatively small improvements are observed in the driving environment where many high speed sectors are included such as the US06 and WLTC. This is because the energy recuperation does not operate as much as in the urban driving environment cases due to the rare braking events.

In addition, the control operating point and cumulative battery power consumption of test results of Fig. 9 are described in Fig. 12. We can observe that negative motor torque is generally applied actively when employing the MPC to recover the energy, as shown in the gray shaded area of Fig. 12(a). As a result, in case of MPC-based
speed planner, the significant less battery power is consumed compared to other approaches (See Fig. 12(b)).

Therefore, we can conclude that the developed speed planner is effective in any driving environments. Moreover, the benefit is maximized in the urban driving patterns where many braking events are inevitable.

VI. CONCLUSION

This paper presents an optimal speed planning strategy for connected and automated EVs in various driving environments when vehicles utilize preview traffic and road gradient information. The MPC-based speed planner is developed under the assumption that CAV may behave differently with the human driver by optimizing its speed profile to minimize the energy consumption. In particular, different speed profiles between CAV and human driver could be planned on sloped roads. For example, unlike the human driver, who is likely to maintain the vehicle speed to keep the appropriate relative distance with the front vehicle regardless of the road slope, CAV can accelerate on the uphill. Then, the energy-efficiency improvement system is operated on the downhill to minimize the usage of battery power, which is possible because our target vehicle is the electrified one.

The effectiveness of our approach is verified through the simulations under various driving conditions. Compared with alternative speed planners, our approach shows the least amount of energy consumption in any driving situation. In particular, we could observe an increase in energy efficiency of about 27.21% in urban driving compared to the human driver. However, the ride quality of the driver will be considered by adding the vehicle acceleration and jerk terms in the objective function of the optimization problem, which is left to our future work.

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