Can V2X Communication Help Electric Vehicles Save Energy?

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***Abstract*—Battery electric vehicles (BEV) are envisioned to play a significant role in the future of personal mobility. A key challenge in the transition from internal combustion engine (ICE) powered vehicles to BEV is the limited driving range of the latter, which makes an energy-efficient operation essential. In this work, we analyze how vehicle-to-x (V2X) communication, in particular traffic-light-to-vehicle communication (TLVC), can help the drivers of BEVs save energy and thus increase driving range. Furthermore, we analyze factors impacting energy consumption which are relevant to the design of V2X applications for BEV. Our results indicate that TLVC can significantly reduce the energy consumption of BEV, up to 20% in our setup. The actual result, however, is highly dependent on a combination of traffic situation, communication range, auxiliary consumer power demand, road gradient and minimum speed requirement.**

I. Introduction

In the course of the ongoing debate about the limited availability of fossil fuels and the environmental impact of internal combustion engine (ICE) powered vehicles, battery electric vehicles (BEV) have been receiving increasing attention as an eco-friendly alternative. In addition to being able to recoup energy when braking, BEV are known to have a "tank-to-wheels"-efficiency of more than 80%, compared to 20% for ICE powered vehicles [1]. However, even with state-of-the-art battery technology, the amount of energy that can be stored aboard a BEV is severly limited, resulting in driving ranges of about 100 km to 200 km. Therefore, saving energy is directly linked to the usability of BEVs.

Next to the characteristics of the vehicle itself, a significant factor impacting the energy consumption (EC) of vehicles in general is driver behavior, particularly the way of accelerating and decelerating [2]. Upcoming communication technologies, e.g., IEEE 802.11p or LTE, can provide drivers with additional information on the current traffic situation in order to reduce or avoid deceleration and acceleration maneuvers. One use case of such vehicle-to-x (V2X) communication is the transmission of a traffic light's scheduling information to approaching vehicles. Based on such *traffic-light-to-vehicle communication (TLVC)*, future driver assistance systems can provide the driver with speed recommendations in order to pass the traffic light during its green phase. TLVC has been shown to facilitate a significant reduction in fuel consumption and emissions of ICE powered vehicles [2] [3] [4] [5] [6] [7].

Given the different characteristics of the two types of vehicles, the question arises whether or not BEV can benefit from TLVC to a similar extent as ICE powered vehicles. With drivetrains being able to recoup energy when braking and not requiring energy when standing still, are BEV already energy efficient enough to not require guidance by TLVC? Do BEV have different requirements in terms of communication range and optimized trajectory than ICE powered vehicles?

In this paper, we

- introduce a configurable simulation model for BEV,
- analyze factors related to driver behavior which impact the EC of BEV,
- analyze the benefits in EC for an individual BEV using TLVC, including a study on different strategies for approaching a traffic light.

Our results indicate that, while BEV can significantly benefit from V2X communication, it is important to take their special characteristics into account, especially the power demand by auxiliary consumers like air conditioning.

The paper is organized as follows. We review the related work in Section II and introduce our simulation framework in Section III. Then, we analyze important factors impacting the EC of BEV in Section IV and present our findings for TLVC in Section V. We conclude the paper by discussing in Section VI how the results can also be beneficial for the design of other V2X applications for BEV.

II. Related work

TLVC has been analyzed and evaluated by a number of projects and studies. Real-world implementations, e.g., Travolution [3], simTD [8] and ElisaTM [9], have demonstrated its technical feasibility. The authors of [4] present an algorithm which optimizes a vehicle's trajectory for multiple traffic lights. The resulting potential in fuel saving is found to be 12-14%. In [5], the authors conclude that, while an individual vehicle can save more than 20% fuel, the saving potential for a road network can be significantly lower, i.e., in the range of 7-8%. In [2], the authors analyze different TLVC strategies and find that, for an ICE powered vehicle, it is preferable to decelerate quickly in order to maximize vehicle speed when passing the traffic light. The authors of [6] come to a similar conclusion, but emphasize that the optimal trajectory is situation dependent. In [7], an algorithm is introduced which precalculates different potential trajectories based on the traffic light situation and chooses the most fuel efficient one. The authors show that an increased transmission range of traffic light information results in higher fuel savings. However, all of the aforementioned studies refer to ICE powered vehicles. To our knowledge, the impact of TLVC on the EC of BEV has not been studied so far.

In [1], the authors present a study on which battery capacity would be needed to create a BEV with similar dimensions, performance and driving range as modern ICE powered vehicles, concluding that such technology is not yet available. The authors list four groups of factors which influence the power consumption of BEV: Vehicle parameters, driving style and conditions, auxiliary consumer power demand and operating conditions, e.g., lower battery capacity due to cold weather. They present a sensitivity study primarily focusing on vehicle parameters, e.g., coefficient of drag. Our results complement the findings of [1] by focusing on factors related to driver behavior in greater detail.

In [10], a simulation framework is introduced which combines a microscopic traffic simulator with an EC model for BEV and topographic information. The authors study the impact of road gradient on EC and find significant differences in the results of a 2D vs. 3D simulation.

III. Simulation environment

In this work, we use PHEM (Passenger Car and Heavy Duty Emission Model), a longitudinal dynamics model which calculates the EC of a BEV based on its current velocity and the gradient of the road it is driving on. To generate input driving cycles for PHEM, we use Matlab to simulate a single vehicle and traffic light. The vehicle is modeled with a constant deceleration and an acceleration according to the Intelligent Driver Model [11]. According to the results of [5], the communication aspect is modeled as a fixed *information distance* d_i, i.e., the distance at which the vehicle first receives the traffic light's scheduling information. In the following, we introduce PHEM as well as the characteristics of the reference vehicle in greater detail.

A. Energy consumption (EC) model

PHEM is a microscale emission model developed at the Institute of Internal Combustion Engines and Thermodynamics of the Graz University of Technology (TUG). It calculates the engine speed and power in steps of 1 Hz using the backwards longitudinal dynamics approach (wheel-to-engine) as described below. Fuel consumption and pollutant emissions are calculated from engine power/speed maps. PHEM is used in various applications ranging from R&D projects on specific vehicles to emission factor calculations of multiple vehicle categories and fleets or in combination with traffic flow simulation software [12] [13] [14].

In recent years, PHEM has been further developed to meet the requirements of (hybrid) electric vehicles. A battery model which was developed at the TUG Institute of Fundamentals and Theory in Electrical Engineering was implemented to calculate the battery's efficiency and state of charge (SOC). It is based on a common electric circuit model and uses analytical functions to describe the general battery characteristics [15]. For the application described in this paper, the battery model was configured as temperature-independent as no reliable data regarding temperature effects was available.

TABLE I
Aux. consumer configurations and impact on NEDC result

Parameter/ NEDC result	Configuration		
	Spring	Summer	Winter
Ambient Temperature [°C]	18	28	-7
Relative humidity [%]	50	40	80
Sun intensity [W/m^2]	320	500	200
Fan speed [m/s]	0.54	1.53	2.73
Climate regulation power demand [kW]	0.1	1.17	3.45
Total electrical power demand [kW]	0.14	1.21	3.79
NEDC energy consumption [kWh/km]	0.15	0.19	0.27
NEDC ΔSOC [%]	-12.2	-14.9	-21.5
NEDC driving range [km]	59	48	33

In BEV mode, PHEM calculates the following parameters for each second of the driving cycle in the following order:

1) P_{Wheel} [kW]: Required power to overcome the driving resistances (roll and air resistances, acceleration and road gradient). Forces to overcome roll and air resistances are defined using a second order polynomial function of the vehicle speed.
2) P_{eEM} [kW]: Effective mechanical power output of the electric machine; calculated from P_{Wheel} by adding the power train losses. PHEM uses empirical power and speed dependent functions to calculate losses in the gear box and the axle transmission.
3) P_{eBat} [kW]: Effective electrical power output of the battery; equals P_{eEM} plus internal losses of the electric machine and power electronics (taken from a predefined power/speed dependent efficiency map) and auxiliary consumers like air conditioning.
4) SOC, U [V], I [A]: The battery model calculates the battery's current (I), voltage (U) and state-of-charge (SOC) as well as the losses due to internal resistance.
5) P_{iBat} [kW]: Equals P_{eBat} plus battery-internal losses.
6) EC [kWh/km]: Energy consumption; calculated as the normalized average P_{iBat}.

To calculate the power needed for cabin air conditioning and heating, a separate air conditioning model is used. Depending on ambient conditions (temperature, humidity and solar radiation) as well as climate control settings (cabin temperature and fan speed), it calculates the required electrical power of compressor, blower and heater necessary to keep the heat balance in the thermodynamic refrigeration cycle [16]. The resulting power consumption is used as an input parameter for PHEM, which models auxiliary consumers as a constant power drain on the battery. In this paper, three exemplary auxiliary consumer configurations were used as shown in Table I.

B. Reference vehicle configuration

The reference BEV used in this paper represents a compact car which is loosely based on Opel's E-Meriva, an electric prototype version of the conventional Meriva. It has a kerb

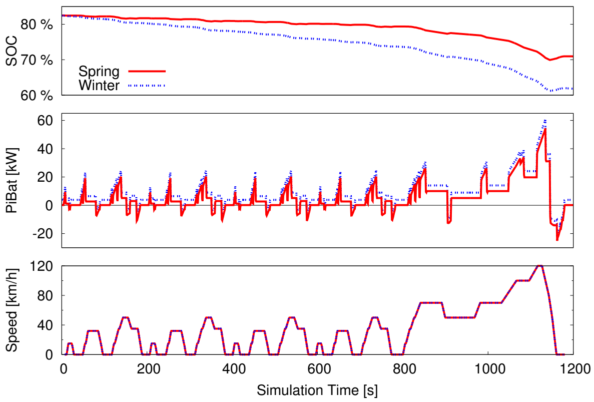


Fig. 1. Instantaneous speed, energy consumption and state of charge of the reference vehicle in the NEDC

weight of 1590 kg, a rated power of 60 kW, a 3-speed transmission and a battery capacity of 16 kWh with a usable SOC range of 65%. That is, the battery is used between 20% and 85% of its capacity in order to extend its life span.

EC and other performance indicators are typically compared using standardized driving cycles such as the New European Driving Cycle (NEDC). Figure 1 illustrates the instantaneous EC and SOC of our reference vehicle in the NEDC as calculated by PHEM. The average EC and projected driving distance for the different auxiliary consumer configurations are shown in the lower part of Table I. Note that the driving range is decreased by 44% for configuration *Winter* when compared to *Spring*.Without auxiliary consumers, the resulting EC is 0.146 kWh/km, ΔSOC is 11.5% and driving range is 62 km in the NEDC (compared to 64 km as specified by Opel).

IV. Influencing factors on energy consumption

In this section, we study the impact of vehicle speed, road gradient and acceleration/deceleration on the EC of our reference BEV, each with respect to the auxiliary consumer configurations listed in Table I. All of these factors can (at least to some degree) be influenced by the driver and are therefore relevant for the design of V2X applications.

A. Vehicle speed and road gradient

Figure 2 illustrates the EC in kWh/km of our reference vehicle driving at different constant speeds. The three sets of curves shown in the figure correspond to a road gradient of -5%, 0% and +5%, respectively. Each set consists of four curves representing different auxiliary consumer power demand setups. Note that the knees observed in the curves result from gear shifts in the energy model and that a negative EC corresponds to recuperation.

Focusing on the set of curves without road gradient for now, we observe that without auxiliary consumers, EC increases steadily with velocity. With auxiliary consumers, however, we observe a U-shaped curve which has its lowest point near 30 to 50 km/h, depending on the auxiliary consumer configuration. The higher the power demand from auxiliary consumers, the more distinct the U-shape of the curve. This effect can be

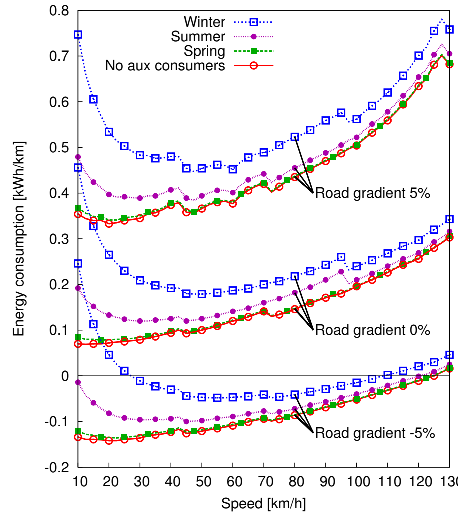


Fig. 2. Energy consumption at constant velocity

explained by considering the travel time of the vehicle at the respective speed. A slower vehicle requires more time to cover the same distance, thus the total amount of power drained per kilometer by auxiliary consumers is inversely proportional to the vehicle's speed. The resulting EC is therefore the sum of two functions with inverse slopes, i.e., a U-shape.

The other two sets of curves illustrate that the road gradient results in a shift of the curves in y-direction. In addition, the slope of the curves becomes steeper with increasing road gradient and vice versa. Similarly, the U-shape becomes more or less distinct, depending on the gradient of the road.

B. Acceleration and deceleration

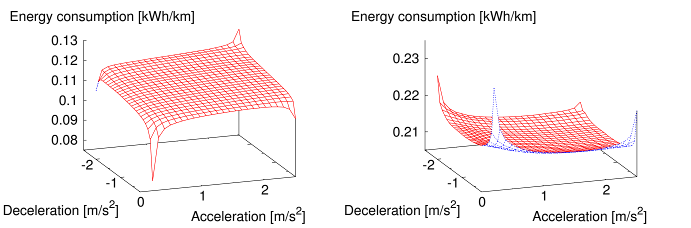
Figure 3 illustrates the impact of acceleration and deceleration on the EC of our reference vehicle in a scenario consisting of a 1 km long road on which the vehicle stops from 50 km/h at 500 m and reaccelerates to 50 km/h. We have simulated acceleration and deceleration values from 0.2 m/s^2 to 2.5 m/s^2. Figure 3a shows that, if there is a low power demand from auxiliary consumers, accelerating and decelerating slowly results in the lowest EC. However, when the power demand from auxiliary consumers is high as in Figure 3b, the longer travel time for slow acceleration and deceleration results in a high overall EC. Therefore, it is more energy efficient to decelerate and accelerate quickly.

V. Traffic Light to Vehicle Communication

In TLVC, a traffic light broadcasts its scheduling information periodically over the wireless medium. A vehicle equipped with the corresponding receiver technology can then calculate its optimized trajectory based on the traffic light's green phases and offer speed advice to the driver.

A. Simulation setup

The considered scenario consists of a single vehicle approaching a single traffic light at 50 km/h on a 900 m long road. The traffic light is positioned at 650 m and has a red phase of



(a) *Spring* (b) *Winter*

Fig. 3. Average EC for different acceleration and deceleration values when stopping from 50 km/h on a 1 km long road

57 s, followed by a yellow phase of 3 s and a green phase of 30 s. We assume that the driver has a visual range of 100 m, an acceleration and deceleration preference of 1 m/s^2 and exactly follows the speed advice given by TLVC if available.

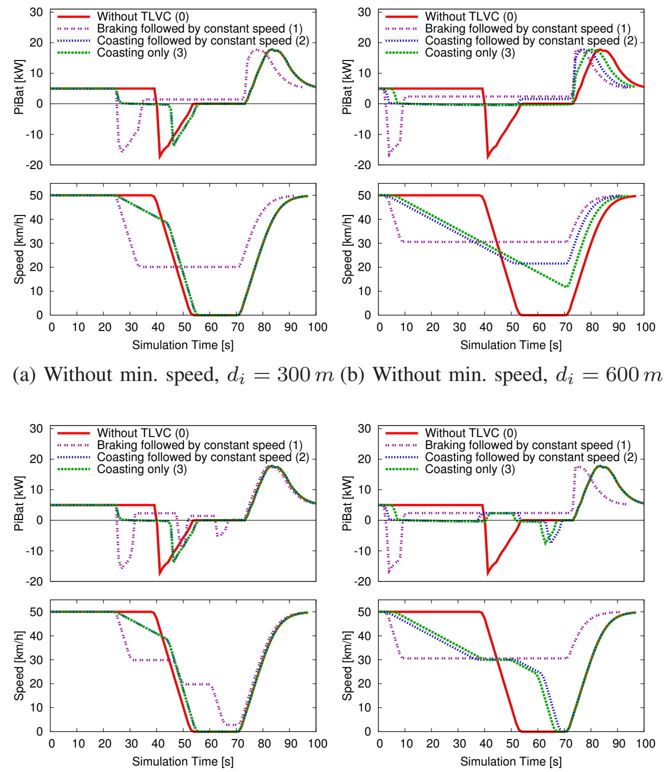
We evaluate the impact of three TLVC strategies as described below, three auxiliary consumer setups as listed in Table I and two different information distances d_i (cf. Section III). In addition, we analyze how a minimum speed requirement impacts the potential savings. Such a requirement may be necessary to ensure the acceptance by other drivers. If applied, the minimum speed in our setup amounts to 30 km/h up to 100 m from the traffic light, 20 km/h between 100 m and 20 m and 0 km/h between 20 m and 0 m.

B. TLVC strategies

Figure 4 illustrates a number of potential speed adaptations based on TLVC information in one and the same traffic situation. The left and right column of plots correspond to an information distance of 300 m and 600 m, respectively, while the upper and lower row reflect speed adaptations without and with minimum speed. Each plot shows the vehicle's speed and EC (excluding auxiliary consumers) with respect to simulation time for the driver without TLVC (red line, in the following denoted as *strategy 0*) and the following TLVC strategies:

1) *Braking followed by constant speed* (purple line): The driver brakes moderately (-1 m/s^2) to a constant speed at which he can pass the traffic light during its green phase. This strategy aims at maximizing the vehicle's speed at the traffic light.
2) *Coasting followed by constant speed* (blue line): The driver takes his foot off the gas pedal (modeled as constant deceleration with -0.165 m/s^2) until a constant speed is reached at which he can pass at a green light[1].
3) *Coasting only* (green line): The driver takes his foot off the gas pedal at a suitable distance so that he reaches the traffic light at the moment it turns green. The objective of this strategy is to maximize coasting time, i.e., the time during which the engine does not consume energy.

[1]Since BEV do not have an engine brake, they have a significantly lower deceleration when taking the foot off the gas pedal than ICE vehicles. While the exact deceleration value for coasting is speed dependent, -0.165 m/s^2 is a reasonable approximation in our setup.



(a) Without min. speed, $d_i = 300\,m$ (b) Without min. speed, $d_i = 600\,m$

(c) With min. speed, $d_i = 300\,m$ (d) With min. speed, $d_i = 600\,m$

Fig. 4. One exemplary traffic situation: Vehicle speed and corresponding EC for different TLVC strategies and parameter settings

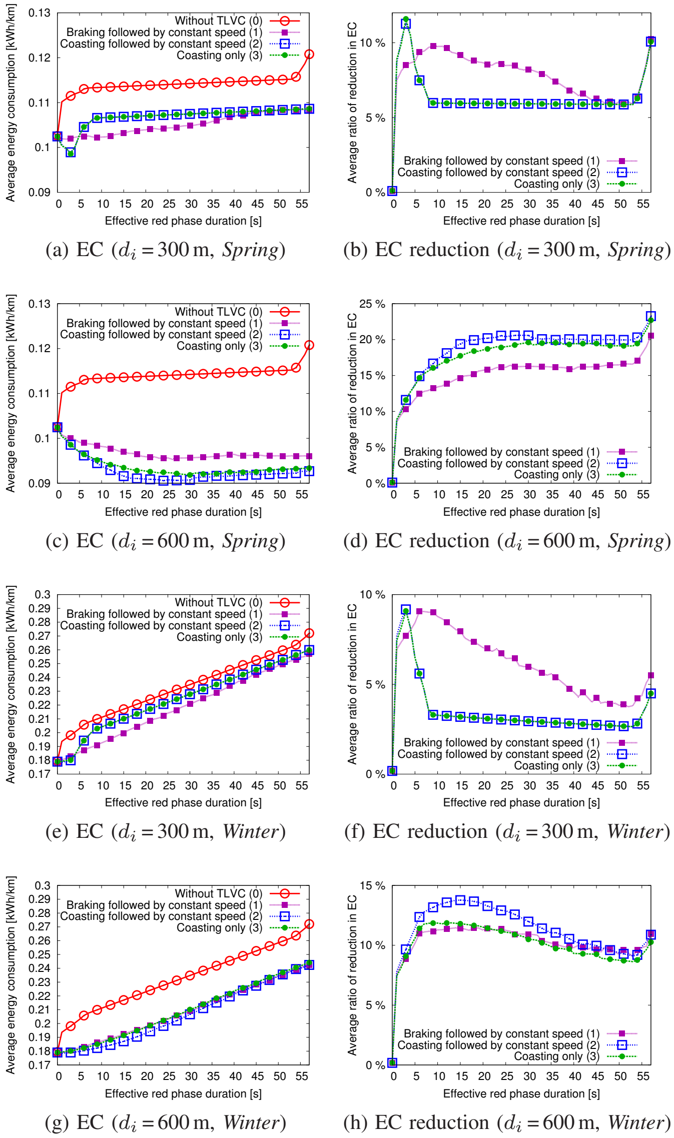
Note that the curves for strategy 0 are identical in all four plots, since the traffic situation, i.e., the combination of initial vehicle speed and traffic light cycle offset, is the same. Furthermore we observe that for $d_i = 300\,m$, strategies 2 and 3 result in the same trajectory. In general, these strategies require larger information distances to differ significantly.

C. Results without minimum speed

To account for the situation dependency of the outcome of the different strategies, we have simulated the scenario with multiple traffic light cycle offsets. In the following, we quantify the impact the red phase has on the approaching vehicle by means of the *effective red phase duration* t_{red}, i.e., the duration the traffic light would remain red if the vehicle passed it without reducing its speed at all. Note that the average values shown are deterministic.

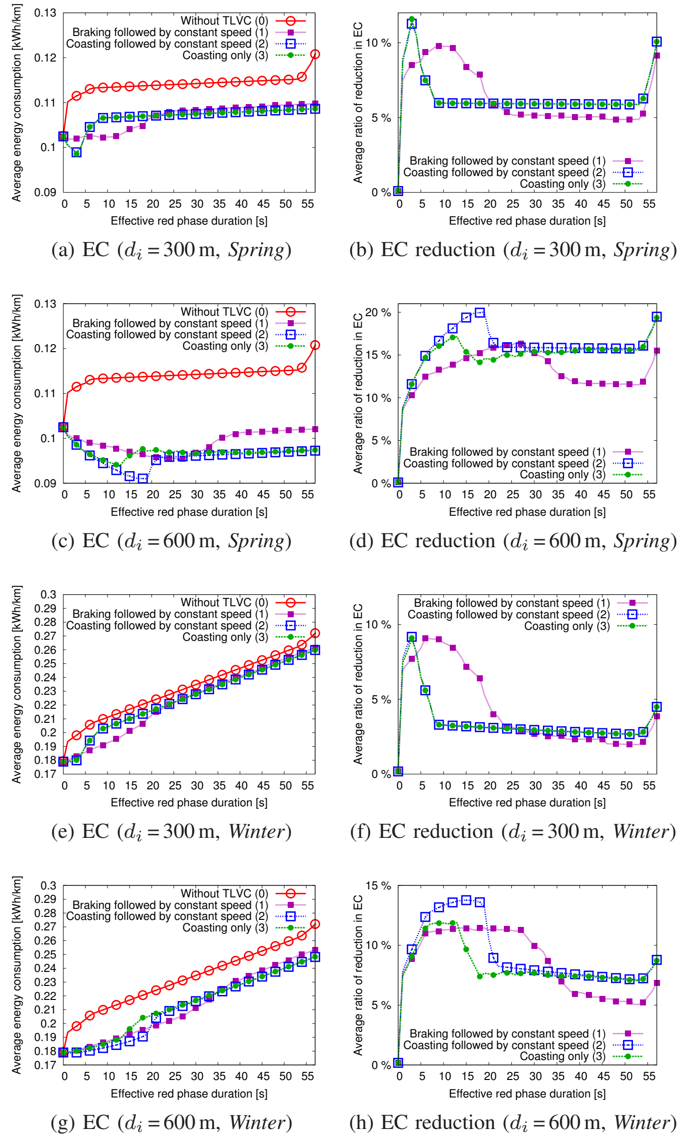
Figure 5 illustrates the average absolute EC (left column) and reduction in EC (compared to the base line without TLVC, right column) of our reference vehicle in the considered scenario with respect to t_{red}. The four rows of plots correspond to each of the combinations of $d_i = 300\,m$, $d_i = 600\,m$ and the auxiliary consumer configurations *Spring* and *Winter*. Each plot consists of multiple curves representing the different TLVC strategies. For example, the average results for the traffic situation in Figure 4 can be found at $t_{red} = 25\,s$.

We observe two "knees" in the EC curves of the uninformed driver (strategy 0). The first knee reflects that, for $t_{red} \geq 8\,s$,



(a) EC ($d_i = 300$ m, *Spring*) (b) EC reduction ($d_i = 300$ m, *Spring*)
(c) EC ($d_i = 600$ m, *Spring*) (d) EC reduction ($d_i = 600$ m, *Spring*)
(e) EC ($d_i = 300$ m, *Winter*) (f) EC reduction ($d_i = 300$ m, *Winter*)
(g) EC ($d_i = 600$ m, *Winter*) (h) EC reduction ($d_i = 600$ m, *Winter*)

Fig. 5. Average energy consumption (EC) *without* minimum speed



(a) EC ($d_i = 300$ m, *Spring*) (b) EC reduction ($d_i = 300$ m, *Spring*)
(c) EC ($d_i = 600$ m, *Spring*) (d) EC reduction ($d_i = 600$ m, *Spring*)
(e) EC ($d_i = 300$ m, *Winter*) (f) EC reduction ($d_i = 300$ m, *Winter*)
(g) EC ($d_i = 600$ m, *Winter*) (h) EC reduction ($d_i = 600$ m, *Winter*)

Fig. 6. Average energy consumption (EC) *with* minimum speed

the vehicle has to come to a full stop at the traffic light, requiring additional energy when reaccelerating. The second knee near $t_{red} = 55\,s$ reflects that a higher deceleration is required because the red light switch occurs beyond the default braking distance. This leads to less recuperation of energy and thus a higher overall EC. Between the two knees, we observe an incline of the curve which results from the add-up of the power demand by auxiliary consumers during standstill. Thus, the incline is steeper for configuration *Winter*.

In the right column of plots, we can see that increasing d_i from 300 m to 600 m increases the maximum savings by about 100% to 200% for $t_{red} \geq 8\,s$. We also observe that strategy 3 does not outperform the other options in any case of our setup. Generally, strategy 1 is preferable for $d_i = 300\,m$, while strategy 2 is better for $d_i = 600\,m$. In the first case, the benefit from avoiding standstill and thus accelerating less outweighs the benefit from not using energy while coasting and vice versa (cf. Figures 4a and 4b). An exception to this tendency occurs for $t_{red} \leq 3\,s$ in the case of $d_i = 300\,m$, where strategies 2 and 3 allow the driver to avoid braking at all and are therefore more energy efficient.

Figures 5e to 5h illustrate that in configuration *Winter*, the power drain by auxiliary consumers can become the dominating factor, resulting in a significantly higher absolute EC and less relative savings than in configuration *Spring* as well as decreasing savings with increasing t_{red}. Note, however, that the absolute reduction in EC is not changed.

D. Results with minimum speed

Figure 6 illustrates the average absolute EC (left column) and relative saving (right column) in the same configuration and layout as in Figure 5, but now with a distance-dependent minimum speed applied as described above. We generally observe a reduced saving potential for larger t_{red} than without minimum speed as well as a higher situation dependency of the preferable TLVC strategy. For $d_i = 300\,m$ and $t_{red} \geq 12\,s$, the minimum speed requirement prevents strategy 1 from keeping the vehicle at a constant speed (cf. Figure 4c). Since the vehicle has to reduce its speed more and more with increasing t_{red}, strategy 1 loses its advantage of a lower EC in the acceleration part and strategy 2 becomes more energy efficient, since it benefits from zero EC of the engine while coasting. For $d_i = 600\,m$ and $t_{red} \geq 18\,s$, the minimum speed requirement causes strategy 2 to reduce the vehicle's speed further than without minimum speed (cf. Figure 4d), resulting in a higher average EC. On the other hand, strategy 1 is not impacted by the minimum speed until $t_{red} = 28\,s$. Therefore, it outperforms strategy 2 for medium ranges of t_{red}, the exact values depending on the auxiliary consumer configuration.

VI. Discussion and conclusions

V2X communication, in particular TLVC, has been shown to have a significant potential for decreasing fuel consumption and emissions for ICE powered vehicles. BEV on the other hand feature special characteristics like energy recuperation and zero EC of the engine while coasting or standing still. Therefore the question arises whether BEV can benefit from TLVC in a similar way as ICE vehicles and if they require different optimized trajectories.

In this work, we have first evaluated how different factors related to driver behavior impact the EC of a reference BEV. Our results indicate that, while the road gradient has a significant impact, it does not change the general tendency that more speed equals higher EC. The power demand by auxiliary consumers, on the other hand, results in a U-shaped EC vs. speed curve. That is, it can be more energy efficient to drive faster when the auxiliary consumer power demand is high. Similarly, it can be more energy efficient to decelerate and accelerate quickly, even though more energy losses occur at the battery and less recuperation is possible than when the speed gradient is low.

Second, we have evaluated three different strategies for approaching a traffic light given TLVC information. Our results indicate that BEV can benefit from TLVC to a similar extent as ICE vehicles, up to 20% in our setup. While current implementations report a reliable communication range of about 300 m with IEEE 802.11p technology [9], BEV could significantly benefit from longer information distances. In our setup, doubling the information distance from 300 m to 600 m doubled to tripled the achievable savings. Related studies have found that the most efficient TLVC strategy for ICE vehicles is to decelerate quickly to a constant speed in order to maximize the speed when passing the traffic light. Our results confirm this general tendency for BEV for $d_i = 300\,m$. For $d_i = 600\,m$, however, it is more preferable to take the foot of the gas pedal instead of braking, since the engine does not consume energy while coasting. Next to the information distance and the traffic situation, the optimal TLVC strategy is further dependent on the auxiliary consumer power demand, the road gradient and whether or not a minimum speed is required. As laid out in this paper, these factors have a significant impact on the EC of BEV and taking them into account is likely to be beneficial for other V2X applications as well, e.g., for optimized navigation algorithms for BEV. In future work, we are going to investigate the impact of TLVC on BEV in a road network as well as the impact of other V2X applications on the EC of BEV.

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