Energy Benefits of Urban Platooning with Self-Driving Vehicles

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Abstract**—**The primary focus of this paper is the generation of energy-optimal speed trajectories for heterogeneous electric vehicle platoons in urban driving conditions. Optimal speed trajectories are generated for individual vehicles and for an entire platoon under the assumption that they can be executed without errors, as would be the case for self-driving vehicles. It is then shown that the optimization for the "average vehicle in the platoon" generates similar transportation energy savings to optimizing speed trajectories for each vehicle individually. The introduced approach only requires the lead vehicle to run the optimization software while the remaining vehicles are only required to have adaptive cruise control capability. The achieved energy savings are typically between 30% and 50% for stop-to-stop segments in cities. The prime motivation of urban platooning comes from the fact that urban platoons efficiently utilize the available space and the minimization of transportation energy in cities is important for many reasons, i.e., for environmental, power, and range considerations.

Keywords**—**Electric vehicles, energy efficiency, optimization, platooning, self-driving vehicles, urban traffic.

I. Introduction

WITH the confluence of self-driving cars and a smart transportation infrastructure, the opportunity of embedding algorithms into vehicles to optimize their operations is an obvious choice. One goal of such an algorithm could be minimizing the transportation energy utilized by a vehicle. Also, in [1], it is shown that by adding a sufficient portion of autonomous vehicles executing these embedded algorithms, the effect of stop-and-go waves in highways can be minimized, at least in dense traffic, benefiting not only the optimized but also the surrounding vehicles.

This paper explores vehicle-embedded algorithms that minimize energy usage by electric vehicles (EVs) in urban platoons from stop-to-stop segments. While the approach taken can theoretically be applied to any type of vehicle, this paper is limited to electric drive systems. The proposed concept analyzes the expended battery energy for a heterogeneous mix of vehicles driving through a typical urban scenario, i.e., from stop-to-stop. To do so, the vehicles in the mix, the distance to be covered, and the desired average speed between two stops are taken into account. The proposed optimization then generates an optimal speed-versus-time trajectory that satisfies the given constraints and will minimize the transportation energy for the platoon of electric vehicles. In order to perform this optimization, the lead vehicle needs to be aware of all vehicles in the platoon. The optimization algorithm uses these parameters and drive segment information to generate the energy-optimal speed profiles that will be executed by the platoon.

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The concept of urban platooning analyzed in this paper is important for three main reasons. First, a speed profile that is realizable for all vehicles in the platoon which also minimizes the overall transportation energy can be generated. Second, vehicles that are not equipped with the transportation energy optimization algorithm or are not fully autonomous but are only equipped with adaptive cruise control are capable of joining the platoon and, therefore, obtaining energy savings. Finally, in dedicated lanes of traffic such as high-occupancy vehicle (HOV) lanes or bus lanes, platoons are capable of providing efficient space usage.

A number of studies have shown that heavy-duty vehicle (HDV) platooning can generate savings in fuel consumption. The improvement obtained in each study can vary depending on the testing procedure chosen. In [2], the improvement obtained varied from 3.8-7.7%, while improvements between 7-16% were observed in [3]. Results shown in the literature also show savings for both, leading vehicle (4-5%) and following vehicles (10-14%) [4]. Platoon of heavy-duty hybrid vehicles have also been studied, where an additional 11% of improvement could be achieved in comparison to platoons of vehicles equipped with regular internal combustion engines (ICEs) [5].

Platoons of electric vehicles have been studied as well. However, in general, these studies tend to focus more on the communication technologies utilized between vehicles [6] and systems to control the execution of these platoons [7]. A different approach to vehicle platoons is analyzed in [8], which studies a wireless power transmission system to charge electric vehicle batteries at low speeds without stopping the vehicle while the EVs move in a platoon formation.

In contrast to the aforementioned work, the platoons analyzed in this paper are constituted of small, personal vehicles. In addition, instead of optimizing the energy consumption for long segments (highway operation), we focus on the urban and suburban scenarios, where stops due to traffic lights and stop signs are inevitable.

The numerical optimization of speed profiles between stops for vehicles equipped with internal combustion engines has already been studied based on extensive on-road and dynamometer testing of a number of vehicles [9]. Guidelines for how a driver should operate the vehicle were then created; however, in some cases, these guidelines differed significantly, even for similar vehicles. Energy-optimal speed trajectories for large vehicles were also considered in [10]. However, the analysis was based on vehicles equipped with ICEs where their efficiency and its dependency on speed and torque were not

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taken into account.

From the results obtained in this paper, it is noticeable how either, utilizing the speed profile generated for an average vehicle in the platoon or each vehicle executing its own optimal speed trajectory produce significant savings in transportation energy. However, by utilizing the average vehicle model, all vehicles in the platoon are capable of executing the optimal trajectory, i.e., the possibility of a vehicle not being able to execute its optimal trajectory due to the presence of another (slower) vehicle in front of it is eliminated.

The energy optimization for urban scenarios usually focuses on generating savings and reduction of emissions by reducing speed variations and idling times. This is frequently done by calculating speeds for which the probability of green lights when approaching signalized intersections based on traffic light controller information is maximized [11], [12]. In some cases, multiple available no-stop speed profiles are analyzed in order to choose the one that utilizes the minimum amount of energy [13].

This paper is structured as follows: in Section II, the model for power flow and energy of a single electric vehicle and for a platoon of EVs is introduced. Section III starts by describing a speed-optimization scheme used to minimize the transportation energy of a vehicle. It then provides simulations for different scenarios of the single vehicle case followed by simulations for a platoon of vehicles where the impact caused by the size and average speed of the platoon as well as the length of the optimized segment are analyzed. Section IV provides conclusions and future research topics.

II. The Model

A. Single Vehicle Analysis

In order to calculate the energy used to execute a speed trajectory by a platoon of vehicles, one needs to be able to calculate the energy usage of each individual vehicle. The individual energy of a vehicle can be calculated by considering all power-absorbing components, i.e., air drag, rolling resistance, variations in kinetic energy, and hill climbing. Based on models presented in [14], the sum of all power-absorbing components provides us with the power at the wheel of single vehicle P_w, as shown in (1). The analysis presented in this paper assumes a flat surface, i.e., no hill climbing. To calculate the power at the wheel, one needs to know the vehicle and environmental parameters, such as mass m, frontal drag coefficient C_d, cross-sectional area A, rolling resistance coefficient f_r, air density ρ, and gravitational acceleration g. The vehicle mass includes the driveline inertia, which appears as a constant additional mass, i.e., a single gear transmission is assumed [15]. The velocity of the vehicle is denoted by $v(t)$ and its acceleration by $\dot{v}(t)$.

$$P_w(t) = mv(t)\dot{v}(t) + {}^1\!/_2 C_d A\rho v(t)^3 + mgf_r v(t) \quad (1)$$

Based on (1), it is possible to obtain a discretized equation for the energy at the wheel of the vehicle $E_{w,n}$ as shown in (2).

$$E_{w,n} = \frac{m}{2}\left(v_{n+1}^2 - v_n^2\right) + \frac{1}{2}C_d A\rho v_n^3 \Delta t + mgf_r v_n \Delta t \quad (2)$$

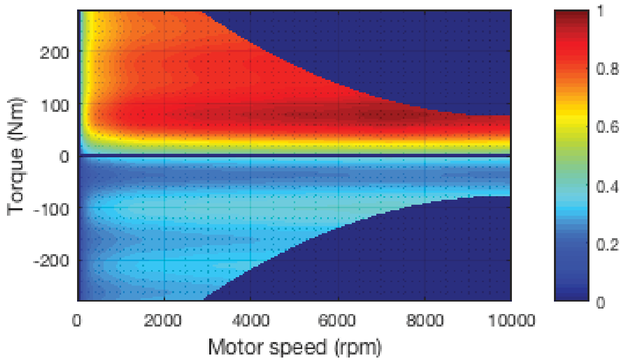

Fig. 1 Typical characterization of efficiencies.

where n is the index of a discretized time segment. The acceleration of the vehicle is approximated by the difference in kinetic energy at each segment.

The energy at the battery $E_{b,n}$ for forward motion and regenerative braking, i.e., reverse power flow, is then given by (3):

$$\Delta E_{b,n} = \begin{cases} \eta_{frw}(T,\omega)^{-1} E_{w,n} & \text{for } E_{w,n} \geq 0 \\ \eta_{reg}(T,\omega) \quad E_{w,n} & \text{for } E_{w,n} < 0 \end{cases} \quad (3)$$

where $\eta_{frw}(T,\omega)$ and $\eta_{reg}(T,\omega)$ are the efficiency of the vehicle for forward power flow and reverse power flow, respectively. T is the torque of the motor, and ω is its rotational speed. The efficiency values correspond to the complete powertrain, including the mechanical drivetrain and battery efficiencies which have very little variations under different power levels. Fig. 1 shows a typical characterization of efficiency. Note that at T and ω equal to zero the efficiencies are also equal to zero.

Therefore, by adding all discretized energy segments, the total energy drained from the battery E is given by (4), where N is the final discrete time-segment, i.e., when the vehicle reaches a stop.

$$E = \sum_{n=1}^{N} \Delta E_{b,n} \quad (4)$$

B. Platoon Analysis

Having the model for the energy utilized by a single vehicle, the total energy utilized by the platoon is then given by the summation of every vehicle in the mix. Assuming a group of M vehicles with energy consumption E_m, $m = \{1, ..., M\}$, the total energy of the platoon E_p is given by (5):

$$E_p = \sum_{m=1}^{M} E_m \quad (5)$$

With the aforementioned assumption, the energy of the platoon can be expressed as shown in (6).

$$E_p = \sum_{m=1}^{M}\left(\sum_{n=1}^{N}\alpha_m\left(v_{n+1}^2 - v_n^2\right) + \beta_m v_n^3 \Delta t + \gamma_m v_n \Delta t\right) \quad (6)$$

where:

$$\alpha_m = \frac{m_m}{2} \quad (7)$$

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$$\beta_m = \frac{1}{2} C_{d,m} A_m \rho \tag{8}$$

$$\gamma_m = m_m g f_{r,m} \tag{9}$$

Assuming all vehicles in the platoon move at the same speed at all times, we have:

$$\begin{aligned} E_p = \sum_{n=1}^{N} \Big(\sum_{m=1}^{M} \alpha_m \Big) \Big(v_{n+1}^2 - v_n^2 \Big) + \Big(\sum_{m=1}^{M} \beta_m \Big) v_n^3 \Delta t \\ + \Big(\sum_{m=1}^{M} \gamma_m \Big) v_n \Delta t \end{aligned} \tag{10}$$

Substituting the inner summations with constants (A, B, and C), the total energy can be expressed as the energy of a vehicle with its parameters equivalent to the summation of the parameters of all individual vehicles.

$$E_p = \sum_{n=1}^{N} A \Big(v_{n+1}^2 - v_n^2 \Big) + B v_n^3 \Delta t + C v_n \Delta t \tag{11}$$

Dividing E_p by M provides the energy consumption for an "average vehicle in the platoon", i.e.,

$$E_{avg} = \frac{E_p}{M} = \sum_{n=1}^{N} \frac{A}{M} \Big(v_{n+1}^2 - v_n^2 \Big) + \frac{B}{M} v_n^3 \Delta t + \frac{C}{M} v_n \Delta t \tag{12}$$

In (12), the expressions A/M, B/M, C/M correspond to the average platoon vehicle coefficients related to mass, airdrag and rolling resistance.

III. Simulations

A. Optimization Problem

In order to minimize the transportation energy between two consecutive stops, one needs to accelerate and decelerate the vehicle utilizing the most efficient operating points of the drivetrain. An optimization problem can be formulated in order to find a speed profile that minimizes the energy consumption of a vehicle.

The aforementioned optimization problem can be set as shown in (13).

$$\begin{aligned} &\min_{v_n} \sum_{n=1}^{N} \Delta E_{b,n} \\ &s.t. \sum_{n=1}^{N} \frac{v_n}{N} = v_{avg} \\ &\quad 0 \le v_n \le v_{max} \\ &\quad d_{max} \le \frac{v_{n+1} - v_n}{\Delta t} \le a_{max} \ \forall \ n \in \{1, ..., N-1\} \\ &\quad d_{max} \le \frac{-v_n}{\Delta t} \le a_{max} \qquad if \ n = N \end{aligned} \tag{13}$$

where v_{avg} is the desired average speed, v_{max} is the maximum allowed speed, d_{max} is the maximum allowable deceleration, and a_{max} is the maximum allowable acceleration.

The optimization problem can then be solved by a nonlinear programming (NLP) algorithm, as the one used in MATLAB's *fmincon*.

B. Speed Profiles

In most cases, vehicle platoons are analyzed for large vehicles moving at high speeds [2]- [4]. In contrast, the mix of vehicles utilized in the simulations shown in this paper consist of five types of small, personal EVs. The parameters of each one are listed in Table I. The parameter sets are based on the vehicles Tesla Model S, Nissan Leaf, Honda Fit, Fiat 500e, and BMW i3. For each vehicle, a scaled version of the efficiency map shown in Fig. 1 was used as its efficiency characterizations.

Fig. 2 shows a typical speed profile (blue) and the generated optimal speed profile (orange) for a vehicle type 4 in a short segment (500m). It also shows the vehicle's energy consumption for such segment as well as its efficiency for each scenario. For the purpose of this paper, typical speed trajectories were generated by scaling and averaging stop-to-stop segments from the FTP 75 urban cycle [16]. Segments with significant speed variations were not considered since speed variations are a known cause of unnecessary energy usage [11]. This approximation of typical speed profiles maintains the initial acceleration close to typical acceleration values in urban scenarios, e.g., around $1.35 m/s^2$ when the final velocity is $10 m/s$ [17].

In contrast to short optimized segments, for longer traveled distances, there are multiple periods of coasting. The vehicle accelerates and coasts repeatedly before the final slowdown, i.e., when the vehicle reaches a complete stop. This behavior can be seen in the simulation shown in Fig. 3 which corresponds to a 1000-meter segment executed by the same vehicle type 4.

C. Urban Platoon

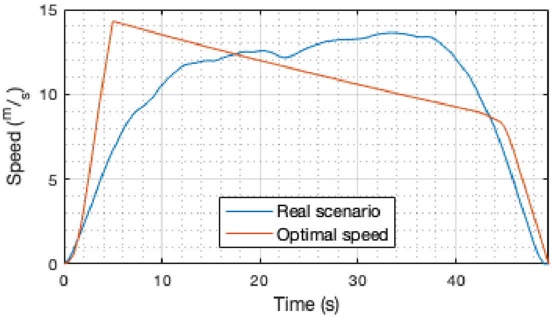
Building upon the concept of energy-optimal speed profiles for a single vehicle shown in Section III-B, multiple simulations were performed where the number and types of vehicles in the platoon, segment length, and average speed were varied to study the viability of an urban platoon. The obtained results are shown below.

In order to analyze the energy savings generated by an urban platoon, the concept of a dedicated lane of traffic where EVs can execute their optimal speed trajectories is assumed. This approach may take advantage of existing HOV lanes or bus lanes. The concept of an urban platoon for optimized EVs is important due to the difference in characteristics between each vehicle as well as its efficient usage of space of such dedicated lanes. Due to the difference in vehicle parameters, it is likely that the optimal speed trajectory for a type of vehicle may not be the optimal trajectory, or even be infeasible, for another vehicle.

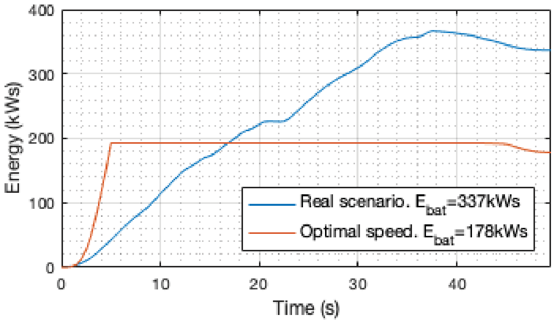
To analyze the energy savings of a heterogeneous mix of platoon vehicles, a random group of uniformly distributed EVs of the types shown in Table I is assumed. The total energy consumed by the mix of vehicles is calculated for the cases where each vehicle is executing a typical speed trajectory, each vehicle is executing an optimal trajectory based on its own characteristics, and a scenario where the vehicles execute a trajectory optimized for an average vehicle in the platoon. As

TABLE I
VEHICLE PARAMETER SETS UTILIZED IN SIMULATIONS

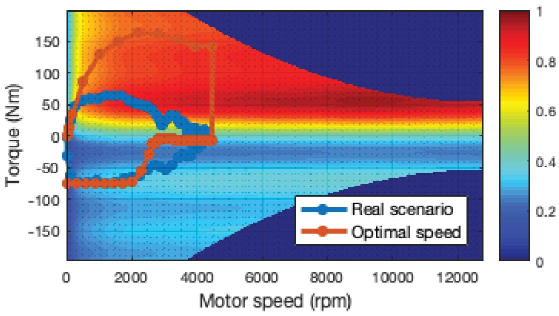
Vehicle	**Mass** (kg)	**Frontal area** (m^2)	**Drag coefficient**	**Max. acceleration** (m/s^2)	**Max. deceleration** (m/s^2)
Vehicle type 1	2,018	2.8	0.24	8	2.5
Vehicle type 2	1,525	2.27	0.29	4.6	2
Vehicle type 3	1,475	2	0.28	2	1.5
Vehicle type 4	1,351	2.25	0.311	4.8	2
Vehicle type 5	1,390	2.38	0.3	5	2



(a)



(b)



(c)

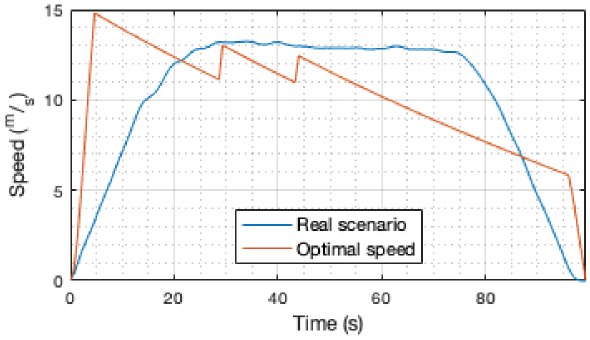
Fig. 2 (a) Typical and optimal speed trajectories, (b) corresponding cumulative energy consumption, and (c) efficiencies over a 500-meter segment.

shown in Section II-B, the average vehicle in the platoon has average rolling resistance, air drag coefficient, cross-sectional area, and mass. It is important to note that the values for maximum acceleration and deceleration obey (14) and (15)

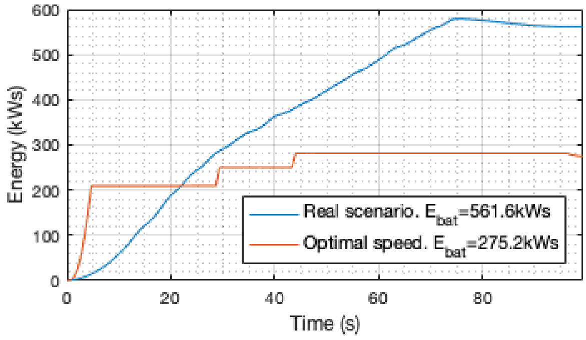
$$a_{max} = \min(a_{max,m}) \quad \forall\ m \in \{1, ..., M\} \tag{14}$$

$$d_{max} = \min(d_{max,m}) \quad \forall\ m \in \{1, ..., M\} \tag{15}$$

where M is the total number of vehicles in the platoon. In



(a)



(b)

Fig. 3 (a) Typical and optimal speed trajectories and (b) corresponding cumulative energy consumption over a 1000-meter segment.

order to generate the optimal speed trajectory for the average vehicle model, it is assumed that basic infrastructure and traffic flow information is available. In other words, the vehicles know the parameter set of each vehicle in the platoon as well as the distance to the next stop.

It is important to note that due to the difference in parameters between each vehicle in the platoon, vehicles would coast by decelerating at different rates. By optimizing the speed profile for the average vehicle in the platoon, during the coasting segment of the generated trajectory, some vehicles may be coasting, some may be braking and regenerating energy, while others may be applying small amounts of power to the wheels. However, the optimized trajectory is still capable of reducing the overall energy consumption.

Fig. 4 shows the total energy utilized by the platoon in a 500-meter segment (blue/left axis) and for a 1000-meter segment (orange/right axis) as a function of the number of vehicles in it. The assumption that all vehicles start executing the optimal speed profile at the same instant as well as that all vehicles are capable of perfectly following the optimal speed

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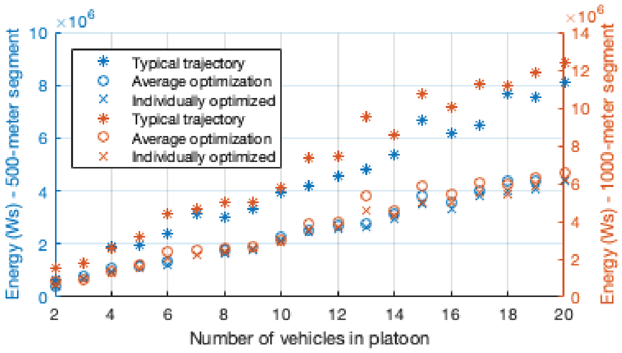

Fig. 4 Total energy spent by vehicles in a platoon for a 500m segment.

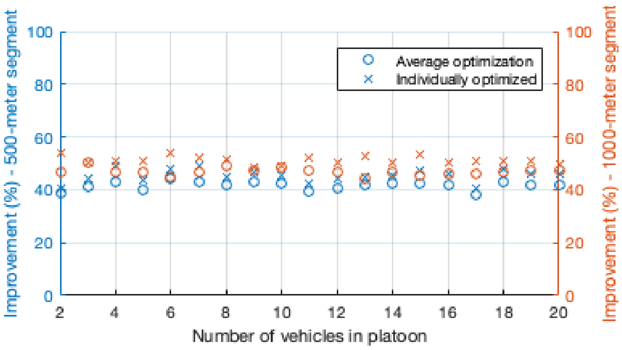

Fig. 5 Improvement in total energy spent by vehicles in a platoon for a 500m segment.

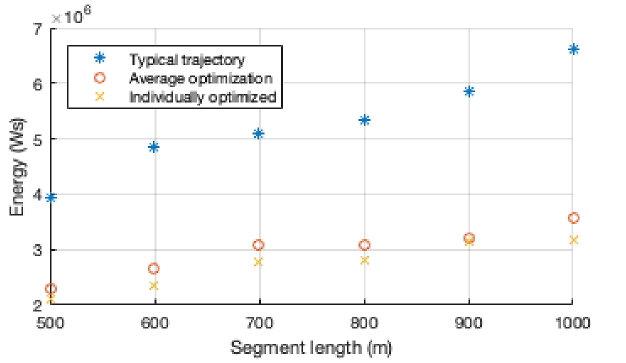

Fig. 6 Total energy spent by 10 randomly chosen vehicles in a platoon for different segment lengths with an average speed of 10 m/s.

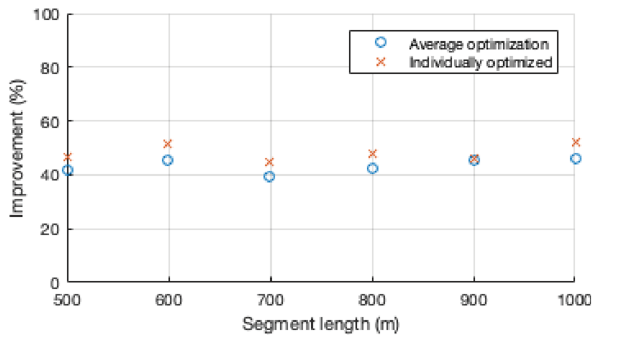

Fig. 7 Improvement in total energy spent by 10 randomly chosen vehicles in a platoon for different segment lengths with an average speed of 10 m/s.

trajectory is made. It is noticeable how either, utilizing the speed profile generated for an average vehicle in the platoon or each vehicle executing its own optimal speed trajectory produce significant savings in transportation energy.

Fig. 5 shows the percentage savings in energy transportation for both scenarios, i.e., utilizing the average model and each vehicle individually optimizing its speed trajectories. For the realizations shown in Fig. 4 and 5, the savings obtained while using the speed profile optimized for an average vehicle are, on average, 3.65% inferior to individually optimizing each vehicle for the 500-meter segment (blue/left axis). For the 1000-meter segment, the difference is equal to 4.36%. Since optimizing every vehicle individually would likely generate a non-realizable platoon due to different cruising speeds, it is clear that the concept of an urban platoon provides a great opportunity for reducing transportation energy in a scenario where stops are necessary.

The impact that the segment length has on transportation energy savings was also analyzed. Fig. 6 shows the energy consumption for a platoon of 10 randomly chosen vehicles with an average speed of 10 m/s for segments varying from 500 m to 1000 m. The respective savings obtained are shown in Fig. 7. It is clear that the savings produced by either, individually optimizing each vehicle or optimizing the speed profile for an average vehicle in the platoon maintain relatively constant savings, with little changes based on the segment length.

Similarly, Fig. 8 shows the energy cost for a platoon of 10 randomly chosen vehicles in a segment of 500 m with their average speed varying from 6 to 11 m/s. Fig. 9 shows the improvement obtained in each scenario. As in the results obtained in the previous case, the energy savings stayed relatively constant across the velocities tested with the average vehicle in the platoon and the individually optimized vehicles.

The impact of the reduction in air drag caused by the formation of a platoon is not analyzed in this paper. The work shown in [3] shows that these savings can exceed 15% for large vehicles at high speeds. The savings are expected to be much lower for small vehicles moving at lower speeds; however, the difference in air drag may reduce the gap in savings between the individually optimized vehicles and the average vehicle in the platoon that is shown in Fig. 5, 7 and 9.

IV. Conclusion

In this paper, we presented an optimization scheme to generate energy-optimal speed trajectories as well as an analysis of vehicle platoons in urban scenarios, i.e., platoons of vehicles executing such energy-optimal speed trajectories between two stops. It is shown that comparing the optimal speed trajectory generated for a single vehicle with typical speed trajectories seen in urban traffic, savings of more than 50% can be achieved. It is also shown that these savings can be carried over to platoons of EVs in dedicated lanes of traffic. The urban platoon can reach savings of almost 50% in typical urban and suburban stop-to-stop drive segments when compared to typically-seen speed profiles. This, in turn, corresponds to a range increase of almost 100%. The savings

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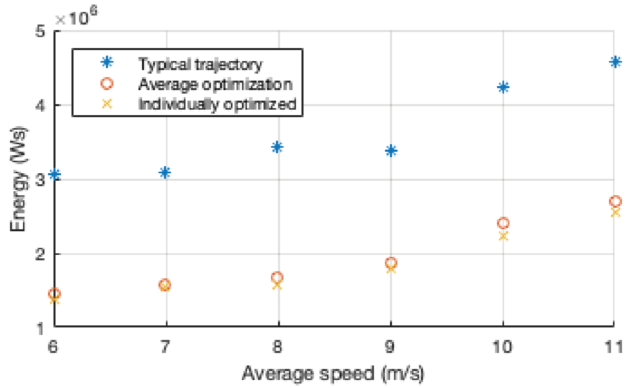

Fig. 8 Total energy spent by 10 randomly chosen vehicles in a platoon for different average speeds in a 500-meter segment.

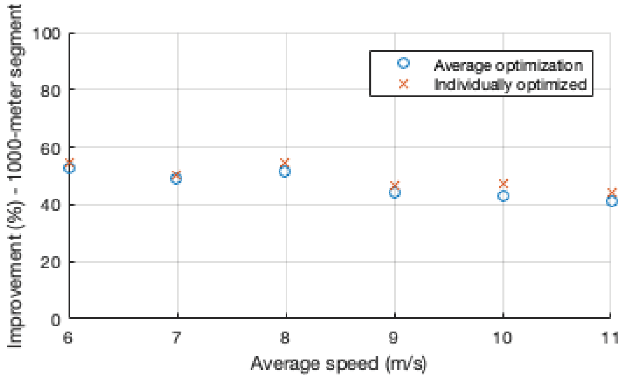

Fig. 9 Improvement in total energy spent by 10 randomly chosen vehicles in a platoon for different average speeds in a 500-meter segment.

are dependent on the vehicles that constitute the platoon, but consistent results were obtained for a number of randomly assigned mixes of vehicles in the platoon. Therefore, urban platoons for self-driving EVs can improve their range due to lower energy expenditure, reduce the demand from the grid caused through vehicle charging, and lower their operating cost. Consequently, an effect on emissions and thereby, global warming could be also achieved.

It is also shown that the urban platoons are capable of producing savings that are close to the ones seen by each vehicle optimizing its own speed profile, a difference of less than 5% for the realizations shown in this paper. Even though it is not analyzed in this paper, the reduction in air drag seen by vehicles caused by all vehicles moving in unison, i.e., performing the same trajectory, would certainly reduce the difference in savings between both cases. Of course, this requires short distances between vehicles, which is possible with connected vehicle approaches.

In order to realize the urban platoon, basic communication between vehicles is assumed. A vehicle that is generating an optimal speed profile for a platoon of vehicles needs to be aware of the parameter set of all vehicles present in the platoon. It is also necessary for the vehicles to have basic awareness about the road infrastructure; i.e., the vehicle needs to know the distance between two consecutive stops as well as the maximum speed allowed for such segment. This information could be easily retrieved from traffic applications that utilize geopositioning systems such as Google Maps or Waze.

The idea of an urban platoon presented in this paper can be implemented through different approaches. One such approach could be every vehicle exchanging its parameter set and each individual vehicle would then generate an optimal speed profile to be executed. A second and perhaps less computationally intensive strategy would be only the first vehicle in queue generating an optimal speed profile for the average vehicle in the platoon and all other vehicles follow its lead by using adaptive cruise control or another distance control scheme. The second approach would also allow more vehicles to join the platoon after it has already started where the only impact would be the average vehicle model not considering all vehicles in the mix.

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