2018 European Control Conference (ECC)
June 12-15, 2018. Limassol, Cyprus

Energy and Time-Optimal Connected Autonomous Vehicle Interaction: Cruising and Overtaking*

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Abstract— **This paper considers the energy optimality aspect of Connected Autonomous Vehicle (CAV) interactions. The aim is to study optimal velocity profiles from the perspective of balance between cost of energy and cost of opportunity in an overtaking scenario. The objective is to find optimal velocity profiles, balancing both costs. In the proposed analysis a vehicle encounters another agent cruising at lower speed, and while the agents can platoon, the problem is set up to study an overtaking maneuver. Two scenarios are considered. A cooperative one where both agents are subject to a control input, and a reference, noncooperative one, where the overtakee ignores the overtaken. Results gives ideas for development of the decision-making framework for optimal CAV operation, and present the scale of improvement in the area of traffic energy efficiency which the connectivity will enable. In this approach traffic agents will cruise at various velocities, adding complexity, but can offer average energy savings of 21.4% while performing an overtaking maneuver.**

I. INTRODUCTION

Today's paradigm of road vehicle operation is far from optimal: individual human drivers compete for position, lack understanding of vehicle physics, are subjected to fatigue, perception and cognition biases. As a result, the velocity profiles are variable, saturated with deceleration and acceleration events and high peak velocities. All of these maneuvers, apart from being risky, contribute to increased energy consumption and unnecessary pollution [1].

The literature review suggests that the future paradigm of road transport appears to head in a clearly defined direction: the emergence of driverless and automated traffic [2]. The feasibility of autonomous cooperative control in the period of transition is increasing with most recent research [3]. Such automated vehicles, however, will require high computational power and machine-based situational awareness, which may be supplied not only by the onboard sensors, but also by means of cooperative perception [4] mediated by vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) wireless communication systems [5]. Research on these technologies is advancing quickly and the emergence of these capabilities creates an opportunity for an optimization framework facilitating a high-level vehicle control strategy selection for CAV, which would provide a decentralized optimal control solution in scenarios as platooning, overtaking and low density intersections.

*This project is co-sponsored by the EPSRC (epsrc.ac.uk) and Arrival Ltd. (arrival.com).

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This paper analyses the problem of Connected Autonomous Vehicle (CAV) interaction from its energy-time optimality perspective in a scenario where it interacts with a slower agent ahead. In such event, vehicles can platoon, or perform an overtaking maneuver. The objective of the optimization problem is to find optimal velocity profiles during an overtaking scenario. The resources managed are energy consumed by vehicles and time understood as the user's value of time as an opportunity cost [6]. These costs, for both vehicles, together with a proximity penalty function, add up to form the overall cost function. Velocity profiles for each vehicle, that minimize the cost are then found.

The information exchange between agents is required to perform such maneuver. Since the inter-vehicle connectivity technology is rapidly developing [7], we can safely assume the information exchange to be complete and perfect [8]. This technology will eliminate uncertainty and can further enhance the smoothness of vehicle operation by enabling cooperation. It also provides capability for negotiation, which allows for fine-tuning of local optimality by means of strategy selection bargaining [9]. An example of game theoretic approach to negotiation of inter-device resource allocation is studied in [10] shows method's applicability.

Studies on autonomous overtaking were already published in the previous decade, focusing mainly, however, on the theoretical background to guide further development and harmonization of the lateral and longitudinal controls or the technical requirements to handle it [11] [12]. More specialized studies on the control challenges associated with the overtaking propose division of the maneuver into three phases to apply adaptive control algorithm [13], or application of spacecraft rendezvous algorithms to approach the problem [14]. Authors in [15] study the feasibility of autonomous overtaking performed by Model Predictive Control (MPC), taking the safety and comfort as an objective. The cost function is defined to penalize deviation from the reference velocity and trajectory and to consider the distance to the oncoming vehicle. However, the formulated method assumes no cooperativity and does not track energy consumption but rather focuses on the feasibility of the MPC application to the optimal control problem of comfort and safety.

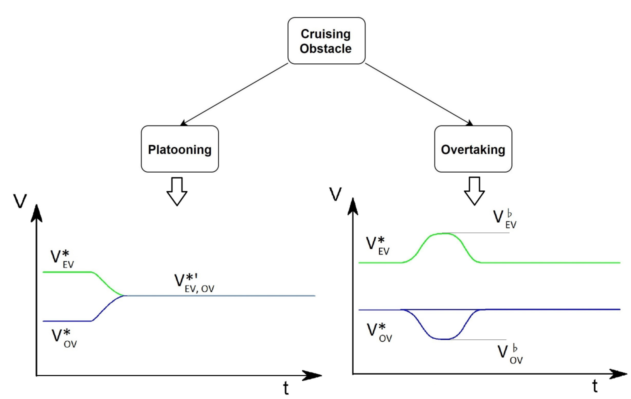
Literature review lacks thorough analyses on the energy management in scenarios which autonomous vehicles may encounter. Since it also does not offer any guidance on energy optimality of overtaking maneuver, this paper's objective is to provide a novel study of the resource optimality of such maneuver. As advances in automation will soon enable on-board optimization of vehicle operation strategies. The largest contributors to the energy inefficiency are velocity transients and aerodynamic drag. The former can be minimized by elimination of necessity for braking and acceleration events. The latter, considering that kinetic energy and drag are proportional to the square of velocity, can be addressed by careful selection of optimal velocity.

II. The CAV Operation Framework

The conceptualized framework developed here, taking the overtaking case as an example, is geared to balance resource utilization, that is both energy and user's time, in accordance with user-specified objective, while handling traffic interruptions by means of cooperation between CAVs, attempting to minimise variations in velocity, in similar manner to the paper on fluent coordination of intersections [16]. The framework is expected to solve multi-objective problem of energy- and time-optimality while cruising or managing e.g. a slower vehicle ahead, according to the decision tree presented in Fig. 1. The decision objective is to minimize cost, given that platooning causes delay cost and the overtaking maneuver costs energy, but mitigates the delay. Further work will consider an intersection, possibly offering a more general alternative to the Cooperative Adaptative Cruise Control (CAAC) system [17]. Here we intend to find optimal cruising velocities V^* and self-enforced consensus on velocity profiles for vehicles. That is negotiation of the platooning velocity V'^*, or agreement on cooperative maneuver's velocities $V^{*\flat}$ and the need for side payments. At this stage of development, safety and drivetrain models are simplified.

This framework also carries a capability to empower future users of CAVs to adjust their operating strategy based on one's immediate demand, providing an added value not only of advanced energy optimization, but also as a sense of system's agility, beyond that of a public transport system [18]. The users would be able to define their cost of time delay, thereby influencing the cost function's profile. This concept's potential consequences, in particular on complexity of high density traffic interaction between vehicles with varying cost function weights, have not yet been subject of any research. Another important consequence of this paradigm is that members of traffic would cruise at varying velocities, in similar fashion to today's traffic, as opposed to arbitrarily defined value as it is assumed in most studies on efficiency of platooning nowadays [19].

Fig. 1: A the decision tree for a scenario where a slower vehicle ahead is encountered. A decision whether to overtake or platoon is negotiated and optimal velocity profiles are selected from energy optimality point of view.



III. Problem Formulation

A cooperative overtaking scenario is being considered. Two vehicles are given: the Ego Vehicle (EV), and the Obstacle Vehicle (OV) which is ahead of the EV and prevents it from maintaining its optimal cruise velocity. Vehicles are modelled in single, longitudinal dimension, in time domain. Modelling of lateral dynamics, as well as user's comfort and safety associated with oncoming vehicles or road topology are neglected as the investigation of energy optimality is the objective of this work.

The study is set up as a single optimization problem, where the objective is to minimize the total cost function J, which depends on the control input vector u, corresponding to the car's throttle position, controlling the propulsive force of each vehicle. The optimal trajectory of the decision variable u for both EV and OV, is optimized such that

$$\operatorname{argmin} J = u := \begin{bmatrix} u_{EV,1} & \dots & u_{EV,N} \\ u_{OV,1} & \dots & u_{OV,N} \end{bmatrix} \tag{1}$$

where N is the number of timesteps.

Further work will consider negotiation algorithm with perfect and complete information, yielding a deterministic solution for all agents Hence cooperativity is assumed to be enforced, and the globally optimal solution might be suboptimal for the agents. The solutions lacking local optimality will be then addressed by the concept of side-payment transactions between agents [20] [21]. In the problem as formulated here, enforcement is realized as summation of cost functions J_i of each respective vehicle in the set $i \in I = 1, 2$. It is defined as a balance of cost C_E of energy $E(t)$ consumed and cost of opportunity C_T, which defines the value of time T user or product spends on the service

$$J_{i,n} = C_E E_{i,n} - C_{T,i} T_n \tag{2}$$

where $n \in \{0...N\}$. Then, if the cost functions are associated to vehicles $EV \to 1$ and $OV \to 2$, the total cost function J can be defined in discrete time as

$$J = \sum_{n=t_0}^{T} \Big(J_{EV,n} + J_{OV,n} + J_{p,n} \Big) t_{step} \tag{3}$$

where t_{step} is the timestep, such that $N = T/t_{step}$, and J_p is the penalty function defining the interaction between vehicles by introducing a cost boundary penalising proximity, which can defined as

$$J_{p,n} = \begin{cases} -\Delta x^2, & \text{if} - X < \Delta x < X \\ -X^2, & \text{otherwise} \end{cases} \tag{4}$$

where Δx is the distance between vehicles and X is the maximum distance, when the penalty function adds cost for proximity. The function attains its maximum of $J_p = 0$, when $\Delta x = 0$, and is minimal at $J_p = -X^2$ whenever agents are more than X meters apart. Note that while the J_p assumes negative value when $x > |X|$, the solution is not sensitive to it. The proximity penalty is added when $X < 10$ meters.

Vehicles are modelled as quasi-static mass points. Each is defined by: mass m_i, maximum force on wheels $F_{Wmax,i}$, aerodynamic drag coefficient $C_{d,i}$, aerodynamic reference area A_i and rolling resistance coefficient $\mu_{roll,i}$. The control of the agents is exercised by the input $u_{i,n}$, which adjust the force on wheels $F_{W,i}$, thereby mimicking the throttle as

$$F_{W,i,n} = u_{i,n} F_{Wmax,i,n}. \tag{5}$$

The force applied to wheels $F_{W,i,n}$, which is assumed to represent torque of the motor and relates to balance of forces is defined as

$$F_{net,i,n} = F_{W,i,n} - F_{roll,i,n} - F_{drag,i,n} \tag{6}$$

where the force of rolling resistance is defined as

$$F_{roll,i,n} = v_{i,n} \mu_{roll} \tag{7}$$

and the aerodynamic drag force as

$$F_{drag,i,n} = \frac{1}{2} A_i \rho_{air} C_{i,d} v_{i,n}^2. \tag{8}$$

The above equation defines the change of velocity

$$a_{i,n} = \frac{F_{net,i,n}}{m_i}. \tag{9}$$

Vehicles' state is defined by its acceleration above $a_{i,n}$, velocity $v_{i,n}$ and longitudinal distance $x_{i,n}$

$$v_{i,n+1} = v_{i,n} + a_{i,n} t_{step} \tag{10}$$

$$x_{i,n+1} = x_{i,n} + v_{i,n} t_{step}. \tag{11}$$

The motive power of each vehicle $W_{i,n}$ is calculated from the change of distance and force applied

$$P_{i,n} = \eta_{i,M} \eta_{i,PE} \eta_{i,B} v_{i,n} F_{W,i,n} t_{step} \tag{12}$$

where $\eta_{i,M}$, $\eta_{i,PE}$, $\eta_{i,B}$ are drivetrain efficiencies: respectively of motor, power electronics and battery. The values are assigned to efficiency variables. Here we have chosen $\eta_M = 0.96, \eta_P E = 0.95, \eta_B = 0.90$. Both drivetrains are assumed to be purely electric, as it is the simplest drivetrain enabling active energy recovery. To model this phenomenon, throttle position can assume values in range from U_{min}, which is negative, to U_{max} so the control input is constrained to

$$U_{min} < u_{i,n} < U_{max}. \tag{13}$$

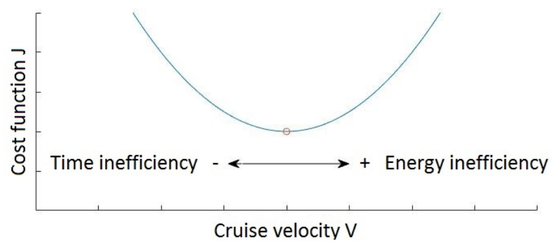
Friction breaking is neglected here, as any use of breaks is wasteful from the energy efficiency perspective, and hence, since the safety is neglected, optimal solutions would never use it. It will be introduced in future, together with battery charge and health models.

One could observe that the individual costs J_i are essentially a balance between cost of energy used for cruising, E and the cost of user's time elapsed, T. Hence, one could hypothesize that, considering the variability of energy cost C_E and situational change of opportunity cost C_T as well as roll and aerodynamic drag, there exists an optimal cruise velocity V^* such that

$$\forall\Big((C_E E), (C_T T), (C_{i,drag} A_i), \mu_{roll}\Big) \rightarrow \exists V_i^*. \tag{14}$$

Then, Fig. 2 shows an indicative plot of cost function J for given set of vehicle parameters as a function of velocity.

Fig. 2: Visualisation of cost function J in relation to cruise velocity. Optimization of cruising speed, which balances the cost of energy and user's opportunity cost offers space for fuel consumption and emissions minimization.



IV. SIMULATION STUDY

The optimization problem is solved using MATLAB's *fmincon* function, which is based on the Sequential Quadratic Programming (SQP) method [22], to iterate the solution until optimality is attained.

Four cases with varying vehicle parameters are provided. Their numerical values listed in Table I and are selected to mimic possible future autonomous vehicles while probing result sensitivity to main differentiating factors, that is propulsive force F_W, mass m, cost of time C_T and aerodynamic drag coefficient C_d. Note that values are biased, so the OV always cruises at lower optimal cruise velocity $V_{EV}^* > V_{OV}^*$, so it can serve as an obstacle for the faster EV behind. F_W values correspond to motor power of $P_m = 15$ kilowatts for case 1 and $P_m = 6$ kilowatts for the remaining cases. In each case, two simulations are performed: a cooperative and, for comparison, noncooperative one. While the former features the original optimization problem as defined in (1), in the latter excludes the u_{OV} vector, which is held constant such that velocity is maintained at V_{OV}^*, and assumes the form

TABLE I: Numerical values for all vehicle parameters.

Param. \ Veh.	EV1	OV1	EV 2	OV 2	EV3	OV3	EV4	OV4
$C_T[\$/h]$	130	100	130	100	100		100	
$F_w[kN]$	5		2		2		2	
$m[kg]$	1000		1000		1000		1200	
C_d	0.3	0.4	0.3	0.4	0.25	0.4	0.25	0.4
μ_{roll}	0.005		0.005		0.005		0.005	
$A[m^2]$	2		2		2		2	
$\rho_{air}[kg/m^3]$	1.18		1.18		1.18		1.18	

$$\text{argmin}\, J = [u_{EV,1} ... u_{EV,N}]. \tag{15}$$

As mentioned in Section II, manageable resources are assumed to be energy E and user's time T, and are being assigned weighting factors. They energy weighting factor is defined based on statistics [23] and settled at $C_E = 0.157 \quad [\$/kWh]$. In the foreseen framework the cost of user's time will be defined by the user. In this case it has been for both agents arbitrarily chosen to be $C_T = 100 \quad [\$/h]$.

Since the problem is computed in time domain, to compute the J_{EV} and J_{OV}, which are dependent on T, the equations defining the cost of time are converted to the distance domain form, it assumes that the meaning of a forward movement cost is C_{dist}. It is calculated from C_T and reference velocity, which is assumed to be $V_R = 25$ meters per second, i.e.

$$C_{dist} = C_T / V_R. \tag{16}$$

Then the equation defining individual cost function assumes the form

$$J(i,n) = (C_E W_{i,n} - C_{dist} v_{i,n}) t_{step}. \tag{17}$$

Selection of the function shaping J_p has been analysed for sensitivity to the shape and size of the penalty cost. It has been concluded that there is little correlation between velocity profiles and aforementioned parameters. Thus, the proposed quadratic penalty cost function $J_{n,p}$ does not influence the characteristics of the solution. However, the peak velocity difference depends on the value of penalty function's peak.

The regenerative breaking is capped at 60% of peak propulsive force $F_{w,min} = -0.6 F_{w,max}$, so the optimization routine is constrained only at upper U_{max} and lower bounds U_{min} for the control input, i.e.

$$\begin{aligned} U_{max} &= \quad 1 \\ U_{min} &= -0.6. \end{aligned} \tag{18}$$

The simulation is initiated with a initial conditions such that the OV is 100 meters ahead of the EV, that is $\Delta x = -100$, and run for $T = 60$ seconds with timestep $t_{step} = 0.1$ seconds, as this value provides resolution close to that of real time control systems. Before initiation of the data recording, the simulation runs for several seconds at negative time to ensure convergence of the algorithm. Same is done at the end of the run, to prevent the optimization routine from excessive energy recovery while approaching completion of the time horizon, which is defined respectively for cooperative and noncooperative cases as $T_{C,end} = 100$ seconds and $T_{NC,end} = 150$ seconds. The objective of the extended time horizon is to force the overtaking manoeuvre by providing horizon on which a time delay would occur, to disincentivise the decision to platoon, as it is not a subject of this study.

A. Simulation Results

This section presents the results of the eight simulations: four cases, each with two scenarios. Firstly, the plots of vehicles' control input, that is the throttle traces, are presented in Fig. 3. The result of the reference simulations is presented in Fig. 3a and the respective plot for the cooperative cases is presented in Fig. 3b. The input is maximized when approaching the OV and energy recovery begins immediately upon passing. The main difference is the behavior of the OV. In noncooperative case it is constant, while in the cooperative case the OV's input a mirror of the EV's input. Its input attains minimum when EV is at its maximum and in reverse. Vehicles tend to minimize time spent in within the bounds of the proximity penalty zone by maximizing their velocity difference. After the maneuver, energy is recovered to return to the optimal cruise velocity, as shown in plots of vehicle velocity. The profiles vary for all cases depending on mass and power, but agents with smaller C_d are likely to begin the maneuver earlier, as they require less energy for the same gain in velocity.

Velocity profiles for both cases are presented in Fig. 4. The noncooperative case in Fig. 4a and the cooperative case in Fig. 4b. The former features higher velocity peak and take more time to perform the meneuver. Variability of optimal cruise velocity, depending on cost of time C_T and drag coefficient C_d, is noticeable. In both cases there is a sharp change in the acceleration the when penalty function J_p attains maximum, i.e. when vehicles are alongside. The sensitivity of this behavior to comfort and more complex powertrain model should be studied, in particular to the battery state of health (SOH) and combustion engine's emissions, both of which can promote coasting. Tab. II lists the velocities measured before, during and after the maneuver. Cruise velocities beforehand (V_b^*) and afterwards (V_a^*) differ. The economic reasoning behind an overtake is to overcome an obstacle, which prevents maintenance of optimal velocity. While platooning causes a time delay cost, the overtaking maneuver costs energy, with the benefit of continuing cruising at optimal velocity afterwards. And since the proposed cases are simulated with a finite horizon, the reason for increased velocity ahead V_a^* is to speed up the occurrence of overtake, so the time while cruising at the optimal velocity V^* can be maximized. Hence, the distance which agents will travel together, defines the quantity of saving an overtake provides.

TABLE II: Cruising and peak velocities.

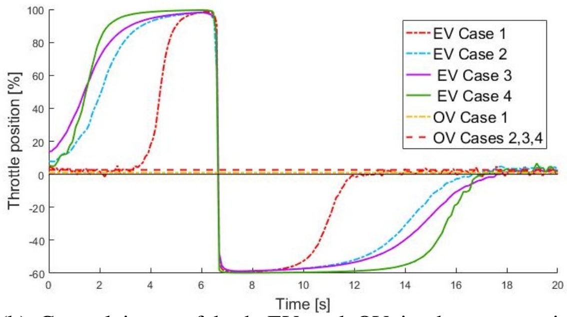
all $[m/s]$	EV1	OV1	EV2	OV2	EV3	OV3	EV4	OV4
Cooperative								
V_b^*	14.94	9.41	14.65	9.89	14.73	9.38	14.55	10.53
V_{peak}	21.64	0	20.2	2.72	20.81	1.79	19.55	3.6
V_a^*	13.93	10.56	13.95	10.52	13.34	10.53	13.37	10.56
Noncoop								
V_b^*	16.45	10.53	15.45	10.53	14.07	10.53	14.98	10.53
V_{peak}	27.11	10.53	23.6	10.53	23.61	10.53	22.96	10.53
V_a^*	13.96	10.53	13.96	10.32	13.38	10.53	13.37	10.53

B. Energy and Time Analysis

This section presents the results of the analysed cases from the time and energy management perspective. Table III shows the time delay and energy consumption data for both scenarios. Note that a negative value means time saved. The data are visualized in Fig. 5.Because the cruise velocity

Fig. 3: Throttle traces. Phases of plots are aligned.

(a) Control input of both EV and OV of the reference, noncooperative case. The EV's throttle trace is much wider, adding too much higher peak velocity. After the maneuver, the energy is recovered while returning to optimal cruise velocity.



(b) Control input of both EV and OV in the cooperative case. The maneuvre sequence is shorter, and thus takes less space. The OV's begins the menuvre earlier than the EV.

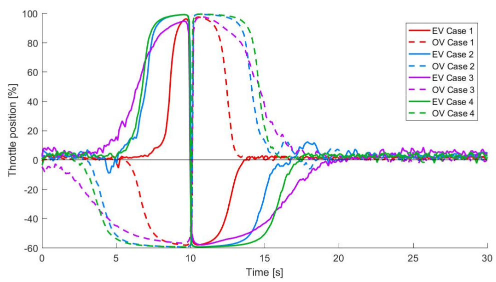
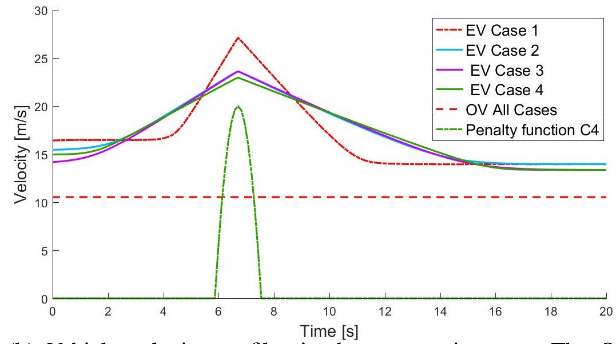
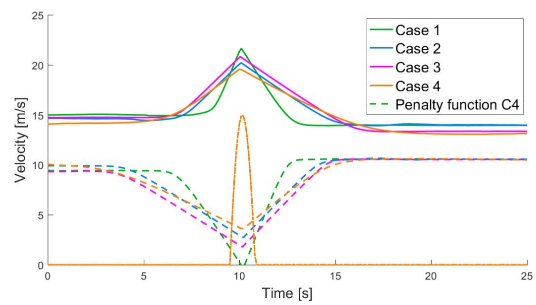


Fig. 4: Velocity profiles. Peaks are synchronized.

(a) Velocity profiles in the noncooperative case. The OV neglects the EV's behavior, and larger peak velocity is required. Velocty maximizes, when in range of the proximity penalty function.



(b) Vehicle velocity profiles in the cooperative case. The OV decelerates to almost 5 meters per second. Note the difference in cruise velocity beforehand and after the maneuver.



before and after the overtaking sequence differs, there is an imbalance of kinetic energy difference ΔE_k which needs to be accounted for according to

$$\Delta E_k = \frac{1}{2} m (V_b^{*2} - V_a^{*2}). \tag{19}$$

The energy data in the table are accounted for the kinetic energy difference in relation to the optimal cruise velocity V^*. A cooperatively performed maneuver offers little time gains as opposed to the noncooperative maneuver, which saves on average 6.4 seconds of EV's time at the cost of excessive energy consumption. Cooperativity yields, for the provided cases, averaged, global energy saving of 21.4%. There is little sensitivity of OV's energy consumption between the scenarios, thus benefit of the cooperativity is EV's energy saving, at the expense of the OV's delay cost. Therefore, a form of externalization of costs is necessary for its practical purposes. A concept of financial exchange between traffic agents has already been introduced in [20] and shall be considered when developing a bargaining algorithm, which may utilize Game Theory in order to obtain a self-enforced cooperation framework [24], in which negotiations of high-level control decisions could be provided with self-enforcement mechanism in form of a payment exchange system. Table IV presents summarised global energy savings for individual cases, and the scale of delay to agents, what may aid gauging the nature of the of negotiation and payments required to enforce cooperativity.

TABLE III: Time delay and energy balance results.

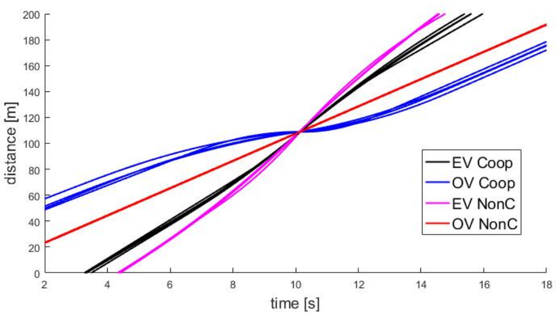
Case	Noncooperative		Cooperative		Saving
1	$\Delta T[s]$	Energy $[kJ]$	$\Delta T[s]$	Energy $[kJ]$	[%]
EV	-6.3	49.42	-3.64	38.02	16.5%
OV	0	18.82	3.29	18.64	
2					
EV	-6.05	54.78	-4.75	44.33	18.8%
OV	0	18.64	4.09	16.45	
3					
EV	-6.1	46.17	-4.91	33.03	23.5%
OV	0	20.07	5.54	17.62	
4					
EV	-7.32	37.84	-5.72	30.23	26.9%
OV	0	20.8	4.28	14.74	
Avg.	-6.44	47.05	-4.76	36.4	21.4%
	0	19.72	4.3	16.9	

TABLE IV: Global energy saving in comparison to time delay for all cooperative cases.

	C1	C2	C3	C4
Energy $[kJ]$	46.1	32.65	17.53	40.52
Delay$[s]$				
EV	-2.7	-1.3	-1.2	-1.6
OV	3.3	4.1	5.5	4.3

The vehicle model applied only considered the cost functions of time and energy. Further analysis requires the com-

Fig. 5: Relationship between distance and time for all cases. Curves are synchronized around the overtaking event to visualise delays. Note that the noncooperative variant offers global savings in time at the expense of energy.



putation time to be decreased, which will be addressed by the division of maneuver into phases and parametrisation of the control input to reduce complexity, but also consideration of safety and road topology constraints, and a more formal definition of an overtake, to enhance problem's feasibility to real scenarios and robustness. It could also require incorporation of combustion engine's pollution or electric vehicle battery degradation models to optimize not only user's time and energy, but also environmental sustainability and components degradation. Furthermore, in case of hybrid vehicles, cost function weights for each component could be introduced to optimize the drivetrain operation depending on its location. It would provide, for instance, a capability to penalize the use of combustion engine in urban area to favor electric operation, where air quality is an asset, or deter from electric motor operation while cruising in a rural area to reduce battery wear.

V. CONCLUSIONS

This paper considers the energy optimality aspect of Connected Autonomous Vehicle in an overtaking scenario. The concept behind is to study the feasibility of such simple but holistic approach to balancing cost of energy and cost of opportunity when shaping the velocity profiles of vehicles nearby. This results in agents cruising at variable velocities, which justifies why an overtake meneuver is selected as a case study. While the agents can choose to platoon, the cases are set up to perform an overtaking maneuver.

Two scenarios are considered: a noncooperative one, where the overtakee ignores the overtaken, and a cooperative one, where both agents optimize their velocity profiles. The objective was to study the feasibility of vehicle-to-vehicle-enabled cooperativity as a source of improvement. The results obtained show an average of 21.4% energy savings, at the inevitable expense of small time delays. It also suggests clues for the further development of the decision-making framework for CAV operation and presents the scale of improvement in traffic energy efficiency which the connectivity and cooperation will enable.

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