A functional combination of platooning and traffic-adaptive intersection control

Kai Timon Busse
Faculty of Technology, Policy and Management
Technische Universiteit Delft
Mekelweg 2, 2628 CD Delft
The Netherlands
Email: timonbusse@googlemail.com

***Abstract*—Congestion and emissions have lately been termed as one of the major challenges for the urban traffic network through various governmental bodies. In this work, a potential solution to this, namely a functional combination between platooning and traffic-adaptive intersection control is first developed and then evaluated. The evaluation is concerned with the expected congestion and emission savings on a 6-km-long provincial road over a period of 60 minutes. For the purpose of evaluation a VISSIM simulation is employed, calibrated and executed. The simulation results show that the proposed combination of platooning and JUNO, a traffic-adaptive intersection controller, allows for emission savings of 7.85 g/km and an increase in average velocity of 1.04 km/h when compared to conventional cars and model-predictive control.**

I. INTRODUCTION

Pursuing the goal of minimizing urban congestion and emissions, research projects have lately shifted their focus to developing so-called smart traffic solutions. Smart traffic solutions seek to represent an alternative to costly and lengthy road expansions. This paper proposes and evaluates one such smart-traffic solution, namely a functional combination of traffic-adaptive intersection control and platooning.

In order to guide the reader through the development of this solution, the Section at hand starts off by introducing the two concomitant technologies - platooning and intersection control - individually. In this context, the intersection control section focuses on illustrating the functionality of JUNO, a controller algorithm that although being associated with the traffic-adaptive controller domain, features certain ameliorations that are useful for a combination with platooning. Based on these explanations, Section II elaborates on their functional combination and the development of a platooning controller, which enables cooperative intersection-platoon functionality. For the purpose of evaluating this technical design, a case study of the N260, Tilburg is employed and simulated in Section III. This simulation distinguishes four scenarios, whereas each scenario features a different technological setup. Section IV, subsequently presents the congestion and emission savings for a) the N260 base case scenario with conventional traffic-adaptive control, b) the platooning scenario, c) the JUNO scenario and d) the scenario with the proposed functional combination of both technologies. Section V provides a conclusion, as well as some recommendations for future work.

1) Traffic-adaptive intersection control: It is generally agreed that the current status of intersection controllers leaves plenty of space for improvements. It lies within their nature of facilitating opposing traffic flows that they represent a crucial piece in every urban traffic optimization attempt. Across various literature it is agreed upon that they represent one of the biggest bottlenecks of the common road network (see e.g. Rouphail et al., 1992; Fouladvand et al., 2004; Van Katwijk, 2008), subsequently contributing to the mentioned congestion and emission problems. One approach on tackling these shortcomings are so-called traffic-adaptive intersection controllers. In contrast to the currently dominant fixed-time or traffic-actuated controllers, they employ a complex traffic model in order to evaluate the surrounding traffic situation. Based on this model, a decision-tree is established, which lays the basis for a decision-making process. This process eventually proposes a signal plan, which optimizes a certain objective. Most often, this objective is either to minimize congestion or emissions.

JUNO (Van Katwijk, 2008) is one of these traffic-adaptive intersection controllers and the algorithm of choice, which is analyzed and utilized in this paper. As mentioned however, it brings along certain ameliorations over conventional traffic-adaptive controllers. That is, JUNO does not only fall into the domain of traffic-adaptive controllers but also into the sub-domain of green light optimized speed advice (GLOSA) controllers, which itself builds upon the idea of vehicle-infrastructure cooperation. As the name says, GLOSA controllers provide approaching vehicles with speed advice such as that these vehicles can adapt their trajectories according to the green light schedule of the controller. It makes use of a V2I-channel, mutually retrieving data from approaching vehicles and sending information back. Especially the latter capability, is relevant for JUNOs functionality. That is, as any other look-ahead traffic-adaptive controller JUNO executes an optimization process of a given decision tree. A byproduct of that optimization process is the calculated value of a so-called estimated time of departure t_{ed}. This estimated time of departure represents the time, which the controller-internal traffic model predicted until a certain vehicle is able to cross the stopping line. This value is calculated for every approaching vehicle. What distinguishes JUNO from competitive traffic-adaptive controllers is that the algorithm makes use of this t_{ed}-parameter. The estimated time of departure can be communicated with approaching vehicles and hence serves as a basis for an emission- and congestion-optimizing approach towards an intersection entry. Effectively, this allows to amplify the positive effects of traffic-adaptive control on traffic flows and further harvest its benefits.

Van Katwijk and Gabriel (2015) provide a comprehensive explanation of how this emission-optimizing intersection approach is calculated and how it is communicated with the driver in form of a speed advice. Consequently, no further explanation is provided here. What is relevant for this paper however, is JUNOs main drawback. Namely, this is that human drivers usually exhibit rather high levels of inaccuracy in implementing this speed advice. Although still leading to improved congestion and emission values, this infers less savings than theoretically possible. The next section explains how autonomous vehicles and especially platoons can help to overcome these human-typical shortcomings. Firstly however, the concept of platooning is introduced.

A. *Platooning*

In an era in which computers are pushing their way into the transport sector and governments are striving towards eco-friendlier traffic solutions, platooning has gained its spot among the most promising approaches on enabling this shift. Logically, this concept has lately moved into the innovation spotlight of multiple GMOs, although being constrained to highway application until now. Companies like Scania (Scania, 2017), Volvo (Volvo, 2017) or MAN (MAN, 2017) are gradually working their way towards a realization of highway platooning.

More specifically, through the on-going integration of driver assistance systems, cars are gaining autonomy and driverless vehicles are on the edge of becoming reality. With the continuous improvement and integration of sensing technologies, both passenger vehicles and trucks will soon be able to observe their environment self-reliantly. Enabled through innovative vehicle-to-vehicle communication, the inaccuracies and shortcomings of a human driver (such as reaction time, negligence or fatigue) can thus be resolved. Braking or steering motions can be triggered simultaneously throughout the platoon and sensed information is shared among the vehicles.

In this sense, platooning describes the driverless formation of two or more vehicles in a very short range to each other enabled through this gained capabilities (Chen and Wang, 2005). Within the European Truck Platooning Challenge this is defined as follows: "Platooning comprises a number of cars equipped with state-of-the-art driving support systems, one closely following the other. This forms a platoon with the cars driven by smart technology, and mutually communicating." (Eckhardt, 2015, p. 16). "These linked vehicles then proceed to travel along the [...] road system acting as one unit" (Kavathekar and Chen, 2011, p. 2). Eventually, through the synthesis between sensing and communication technologies vehicles are capable of driving in an array with significantly lower vehicle clearances than conventionally possible, what brings along a set of benefits with the most prominent of those being the reduced drag resistance for following vehicles. Yet, this is not the only possible application of the gained driving capabilities. In the following Section it is shown how these capabilities can be employed to form a functional combination with JUNO.

II. A FUNCTIONAL COMBINATION BETWEEN PLATOONING AND INTERSECTION CONTROL

It was previously explained how the two concepts - platooning and JUNO - both have their potential benefits for congestion and emissions in a traffic network. Now what further needs to be understood is that both these technologies represent generally proven concepts. Although neither of them has shown long-term real-world functionality yet, plenty of research exists, demonstrating their general workability (for a status quo summary of platooning see e.g. Kavathekar and Chen, 2011 or Bergenhem et al., 2012; for a JUNO workability proof see e.g. Van Katwijk and Gabriel, 2015). The underlying message that is conveyed through literature centering around these technologies is, that sooner or later both will make their way into the common traffic network. Hence, within this work they are assumed as functional and accepted as a given. The research at hand does not desire to develop or modify any of them further, but just to alter their functionality as such to enable a combination between them. Hereby, one major design objective for their combination is to minimize the necessary modifications in either of the systems.

Remembering that it is the overall goal to assess the congestion and emission impacts of such a combination, an evaluation basis has to be chosen. It is found that the traffic simulation software VISSIM offers all the necessary tools and possibilities here for. Through two APIs the VISSIM-internal driver and intersection behavior can be overwritten. Considering that the JUNO algorithm was developed using this software and that VISSIM offers all required sensor data to model platooning, it is henceforth determined the modeling basis of choice. The next section elaborates on the integration of a platooning model in VISSIM, before the combination between the two technologies is explained.

A. Platoon system modeling

In the second chapter of his master dissertation, Busse (2017) presents and motivates a set of main characteristics that are representative for platooning. Besides others, this comprises an intra-vehicle clearance of $d_{des}(t) \approx 10m$ at $90km/h$ and full lateral and longitudinal automation. This classifies the participating platooning vehicles as level-5 automated vehicles, according to the SAE vehicle autonomy framework (SAE, 2014), from which a conclusion can be drawn about the way how to model such vehicles. Namely, level-5 automation allots all driving tasks to the vehicle control system. The human driver is not contributing to the vehicle motions anymore. Hence, it is the vehicle control system, which has to be modeled as such that it conforms to the characteristics of Busse.

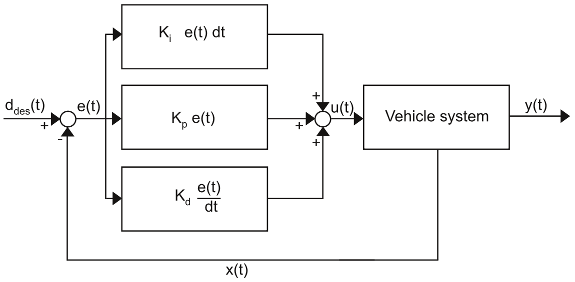

Fig. 1. Illustration of a vehicle controller system.

In order to do so, the vehicle control structure of the SARTE project (Robinson et al., 2010) is adopted. The SARTRE project is one of the leading platooning concepts and it features a controller scheme, where the combination of a set of decentralized longitudinal vehicle controllers conjointly enables platooning behavior. The idea behind this is to use a set of vehicle sensors in order to determine which actuator actions are necessary in order to reach or maintain a pre-defined safety gap $d_{des}(t)$ to the leading vehicle. If all vehicles adopt this behavior, eventually a platoon is established, which autonomously follows a platoon leader. As generically illustrated in Figure 1, a PID-controller strategy is employed to reach this goal. Sensor data $x(t)$ is used to calculate the controller error $e(t)$, which essentially is the difference between the desired safety gap $d_{des}(t)$ and the actual safety gap $d(t)$. Given this, a controller output can be calculated, which is aimed at minimizing the initial controller error. The output is calculated using the controller strategy

$$\begin{aligned} u_i(t) = &\frac{1}{h}(v_{i-1} - v_i))K_{d,i} + \frac{1}{h}e_i K_{p,i} \\ &+ \frac{1}{h}\int e_i(t)dtK_{ff,i} \end{aligned} \tag{1}$$

with $K_{ff,i} = 0,7$,$K_{p,i} = 1$ and $K_{d,i} = 0,8$. The output $u_i(t)$ takes the form of an acceleration value. Put in less mathematical terms: It is the vehicle control, which actuates the throttle of each platooning vehicle. It does so according to sensor data and with the goal of establishing the distance

$$d_{des}(t) = r + hv(t) \tag{2}$$

to its precursor. The mathematical details of this controller design, as well as its calibration and verification can be found in (Busse, 2017, Chapter 3). What is relevant for this paper is its functionality and its representativeness of platooning. In a lengthy validation process, the latter has proven to be sufficient for the purpose of evaluating congestion and emission impacts (see Busse, 2017, Chapter 7). The former is what is the basis for the following Section - the design of a functional combination with JUNO. This functional basis constitutes that the vehicle control system is capable of keeping a desired distance towards a precursor with a relatively low error function.

B. Technical design

Besides conventional platooning, this capability can in a first instance be used to enable so-called single-link virtual platooning (see e.g. Medina and Nijmeijer, 2017). Single-link virtual platooning (SLVP) describes the ability of a car to maintain a constant longitudinal distance to a vehicle, which is not located on the same lane. Effectively, a vehicle from an adjacent lane is mirrored on the lane of the platooning vehicle. This is done by manipulating the vehicle controller through an artificially modified intra-vehicle distance $d(t) := d_{SLVP}(t)$. The sensor information $d(t)$ is overwritten. In the case of SLVP, this artificial distance is calculated based on the longitudinal position of the the precursor vehicle on the adjacent lane. If implemented correctly, this leads the platooning vehicle to detach from its direct precursor and align its longitudinal position according to the new target vehicle instead. By doing this, gaps for merge-in or merge-through through maneuvers can be created. Thus, it can not only facilitate merging maneuvers, but it lays the basis for a functional combination with JUNO.

That is, a principle similar to that of SLVP can be employed to enable a functional interaction with JUNO.

In order to shed more light on this, it first needs to be understood how the t_{ed}, which JUNO provides can be processed into an optimal intersection approach trajectory. Figure 2 illustrates the velocity curve of a human driver approaching a red light. As the vehicle with subordinated priority approaches the stop line, the driver is not aware of the time when the traffic light will turn green. No knowledge is available about the intersection controller-internal traffic model, neither when it plans to switch priorities. Naturally, the driver will therefore approach the intersection in such as manner, as he would approach a blockade (in VISSIM this blockade is modeled as a still-standing vehicle), consequently implying the black velocity curve. Given this curve, it is understood that upon t_{ed} the vehicle has to accelerate back to its initial velocity. This acceleration is associated with both unnecessary emissions and unnecessary congestion. The former is because, additional acceleration leads to additional energy consumption and the latter is because through the low arrival speed the vehicle requires more time to clear the intersection.

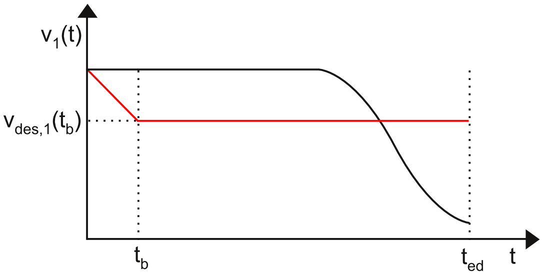

Fig. 2. Qualitative velocity curve during approach of a controlled intersection for a human driver and under virtual platooning. Velocity for the human driver is depicted in black, velocity for virtual platooning is depicted in red.

Having understood the shortcomings of this human velocity curve, it now becomes clear, why the alternative red curve has the potential to save on emissions and congestion. It depicts that trajectory which constitutes the highest possible speed upon arrival and is henceforth understood as the optimal intersection approach. Now in order to deploy this trajectory through the vehicle controller of a platoon leader, the trajectory has to a) be calculated and b) be processed as such that it can be used as a controller input $d(t)$.

What the black and the red velocity curve from Figure 2 have in common is that they cover the same distance $d_{int,i=1}$. At the time t_0 of receiving a t_{ed}-value, this distance can be calculated as:

$$d_{int,i=1}(t_0) = \int_{t_0}^{t_{ed}} v_1(t)dt. \tag{3}$$

Furthermore, the ideal trajectory can mathematically be described as

$$v_1(t) = \begin{cases} v_{des,1}(t) - a_{min} \cdot t & \text{for } t < t_b \\ v_{des,1}(t) & \text{for } t_b \leq t < t_{ed} \end{cases} \tag{4}$$

with $a_{min} < 0$ being the maximum deceleration of the vehicle at hand. Inserting this into (1), leads to

$$d_{int,i=1}(t) = \begin{cases} -\dfrac{1}{2}a_{min}(t_b - t)^2 & \\ \quad + v_{des,1}(t)(t_{ed} - t_b) & \text{for } t < t_b \\ v_{des,1}(t)(t_{ed} - t) & \text{for } t_b \leq t < t_{ed}. \end{cases} \tag{5}$$

Given, that the LV of the platoon has received a t_{ed}-value and a_{min} is known through the vehicle control, two unknown variables remain. These are $v_{des,1}(t)$ and t_b. Their relation can be described as:

$$v_{des,1}(t) = v_1(t_0) + a_{min} \cdot t_b. \tag{6}$$

Furthermore, the distance $d_{nt,i=1}(t)$ of (5) is known for $t = t_0$. At this point in time the desired distance to the intersection is equal to the current distance to the intersection ($d_{des,int,i=1}(t) = d_{int,i=1}(t)$), which itself represents available vehicle-internal sensor data. Inserting the values into the "for $t < t_b$"-case of formula (5) leads to:

$$d_{int,i=1}(t_0) = -\frac{1}{2}a_{min}(t_b - t_0)^2 + v_{des,1}(t)(t_{ed} - t_b) \tag{7}$$

Through inserting (7) into (5) and mathematic transformation, using the linear quadratic formula (Kalman et al., 1960) the following term for t_b is found:

$$t_b = t_{ed} + \frac{\sqrt{2a_{min}t_{ed}v_1(t_0) + a_{min}^2 t_{ed}^2 - 2a_{min}d_{int,i=1}(t_0)}}{a_{min}} \tag{8}$$

Eventually, this formula can be used to calculate and establish a desired driving behavior for the platoon leader. Until now, it has only been described how vehicles can use the controller strategy from formula (1) to follow their immediate precursor or a vehicle that is located on an adjacent lane. Now, finally an explanation can be provided on how the platoon leader itself determines a trajectory, which the other vehicles can follow. Namely, upon receipt of a t_{ed}-value though the V2I-channel between JUNO and the platoon leader, this leader can in a first instance employ formula (8) to calculate t_b. All necessary information in order to do so is either available through sensors or through the communication with JUNO. The gained knowledge can be used to manipulate the lead vehicle control system to follow above-mentioned optimal trajectory.

Similar to SLVP, a moving virtual vehicle is created, to which the LV will attempt to maintain $d_{des,i=1}(t)$.

Having understood the general functionality of the vehicle control system, the vehicle will internally calculate the error function $e_1(t)$ between the desired distance and the distance to the virtual vehicle $d_{virt,i=1}(t)$ and feed the result into the controller, which then calculates an acceleration accordingly. The leader adapts its motion according to this virtual vehicle, which implies that the trajectory of the virtual vehicle must lead the vehicle at hand to follow the path as described in (5). In that sense, the desired distance deviation calculated by the LV is:

$$e_1(t) = d_{virt,i=1}(t) - d_{des,i=1}(t). \tag{9}$$

The desired intra-vehicle distance $d_{des,i=1}(t)$ was fixed in (2), which is why $d_{virt,i=1}(t)$ needs to be adapted to lead the vehicle at hand on the desired path. Given that the lead trajectory is described as the desired intersection distance in (5), $e_{virt,i=1}(t)$ can be described as the difference of the actual intersection distance and the desired intersection distance:

$$e_{virt,i=1}(t) = d_{int,i=1}(t) - d_{des,int,i=1}(t). \tag{10}$$

Now, if the controller objective of the lead vehicle is reached, the LV will exactly follow the energy-optimal trajectory. Consequently, $d_{virt,i=1}(t)$ has to be described as:

$$d_{virt,i=1}(t) = d_{int,i=1}(t) - d_{des,int,i=1}(t) + d_{des,i=1}(t) \tag{11}$$

with

$$d_{des,int,i=1}(t) \begin{cases} -\frac{1}{2}a_{min}(t_b - t)^2 & \text{for } t < t_b \\ + v_{des,1}(t)(t_{ed} - t_b) & \\ v_{des,1}(t)(t_{ed} - t) & \text{for } t_b \geq t < t_{ed}. \end{cases} \tag{12}$$

Similar to SLVP, equation (11) can be used to overwrite the sensor-based distance $d_{i=1}(t)$ in conventional platooning. This manipulates the driving behavior of the platoon leader as such to follow the desired trajectory from Figure 2. This measure only takes action if the platoon leader receives a t_{ed} value through the V2I-channel. If done so, a virtual precursor is generated, which guides the platoon on the desired path. In this sense, JUNO is the hierarchically dominant system. Through sending its estimated time of departure, it triggers the platoon to adapts its trajectory according to the predictions of the intersection controller. As soon as $t > t_{ed}$, the vehicle falls back into its previous driving mode.

This newly imposed driving behavior allows for an effective implementation of the desired path without intervening in the underlying functionalities of either of the concomitant technologies. The technical design does therefore not only fulfill the design objective of a functional combination between platooning and JUNO, but also the earlier posed requirement, to minimize the necessary modification in either of the systems. Both, platooning and JUNO are accepted as a given. Each system maintains their general functionality and is solely expanded by a V2I communication channel and a module that establishes a desired intersection approach trajectory. This module is constituted through a software-based data process, which mainly relies on the generation of t_b (8) and $d_{des,int,i=1}(t)$ (12), whereas the former is a calculation input for the latter. The generated path can be incorporated in the already-existing vehicle control system of a level-5 automated vehicle (e.g. that proposed within the SARTRE project). This makes use of the already existing platooning functionality by overwriting the controller inputs when applicable. No additional equipment or modifications are necessary.

III. Case study: N260

The underlying idea of this case study is to evaluate the performance of the proposed technical design in a setting, which resembles real-world traffic conditions. For this reason, a simulation environment is chosen, which reproduces the road structure and traffic demands of the N260. The N260 is a provincial road in North Brabant, The Netherlands. The subject of simulation is a section of this road, which is part of the Tilburg Ring. Covering roughly 6200m in the North-South direction, the Section features three intersections, whose structural VISSIM models are illustrated in Figures 3 to 5. The maximum speed limit on the N260 is 80km/h, whereas the three distributor roads are restricted either to 50 or 30km/h. The N260 has two lanes in both directions over the full length of the considered section. The traffic demand of the 60-minute simulation represents that of an average day between 10:00:00 and 11:00:00 AM.

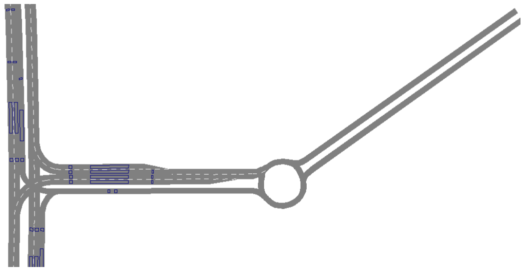

Fig. 3. Top-view of the VISSIM street model of the *Middeldijkdreef*-intersection.

The performance indicators of choice are the overall CO_2 emissions on the presented road network and the average travel time of all involved traffic participants, excluding pedestrians and bikes. For calculation of the former, the EnViver software is employed. EnViver utilizes an

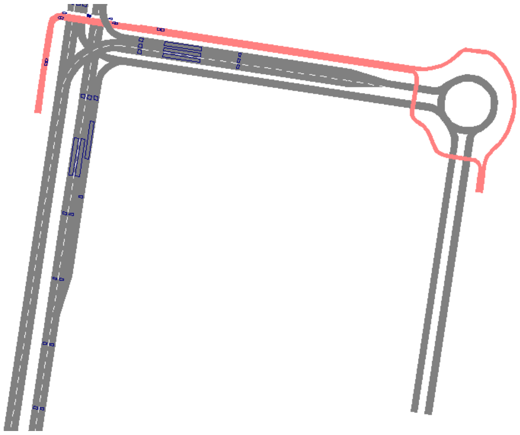

Fig. 4. Top-view of the VISSIM street model of the *Dalemdreef*-intersection.

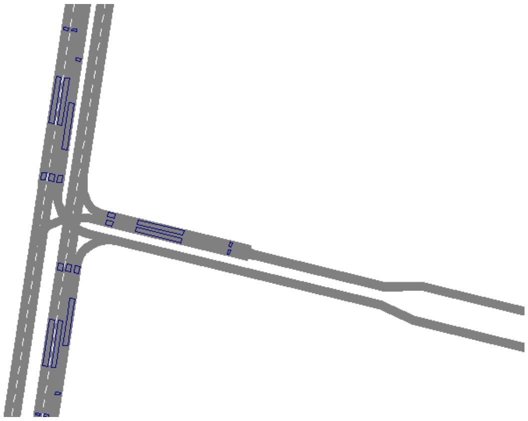

Fig. 5. Top-view of the VISSIM street model of the *Koolhovenlaan*-intersection.

aggregate emission model, which is based on 12.000 real-world emission tests on a variety of vehicles. In conjunct functionality with VISSIM it is capable of linking these emission values to the VISSIM-internally generated speed trajectories, which altogether allows for highly accurate emission evaluations.

IV. Simulation

As mentioned in the introduction section of this paper, four scenarios are employed and simulated for the N260 case study. As illustrated in Table I each of the scenarios features a different technological setup. In order to properly model the technological characteristics of platooning, V2I-, V2V- and sensor-information are processed by the vehicle control system with a delay of $\tau = 0.1$s. Furthermore, a maximum deceleration $a_{min} = -2m/s^2$ and a maximum platoon length of 5 vehicles are used.

It is solely within scenario 4, that the developed functional combination between platooning and JUNO is employed. The other scenarios serve as benchmarking simulations, which can be used to put the results of the fourth scenario in context. The simulation results that were collected over a 60 minutes simulation period are summarized in Table II.

TABLE I
Technological setups for the different simulation scenarios.

	Driving behavior	Intersection control
Scenario 1	Human drivers	Traffic-actuated
Scenario 2	Human drivers	JUNO
Scenario 3	Platooning	Traffic-actuated
Scenario 4	Platooning	JUNO

TABLE II
Technological setups for the different simulation scenarios.

	Performance measure	Calculated potential savings
Scenario 1	Average velocity	0
	Average emissions	0
Scenario 2	Average velocity	1.33 km/h
	Average emissions	6.08 g/km
Scenario 3	Average velocity	0.51 km/h
	Average emissions	7.84 g/km
Scenario 4	Average velocity	1.04 km/h
	Average emissions	7.85 g/km

V. Conclusions and recommendations

As it can be seen from Table II, no scenario strictly dominates any other. The only scenario that is dominated is the base case scenario, which however dominates in a (potential) calculation of necessary expenditures. Hence, it is upon the implementing entity to decide which technological setup is the best for the given situation.

Yet, it can be seen that both technologies hold potential contributions to the current traffic network. One of the main contributions is herewith that a functional combination between platooning and intersection control is possible. The fact that its contributions in terms of emission savings are limited is largely founded in the fact that the employed traffic model does not consider the reduced fuel consumption due to less drag resistance. A potential follow-up project could therefore additionally include this aspect and quantify the additional savings that can be made. Furthermore, additional travel time savings can be expected if a physically larger VISSIM environment is used. This is due to the fact that the formation of a platoon actually leads to additional emissions and longer travel times. If the travel distance is extended, hence the time horizon over which the benefits of platooning can be harvested is prolonged, an increased performance can be expected. This is concerned with both objective functions and should be considered in successive research.

However, it needs to be kept in mind that the work at hand targets a rather new research field, deeming its contributions disruptive and unproven. Hence, high attention should be paid when utilizing the model. It is suggested that further research needs to be conducted in order to validate the findings of this work. Furthermore, one must not forget that the overall purpose of the developed functional combination between platooning and intersection control was to determine the potential congestion and emission savings. In this sense, the technical design should not be used for any other purpose than quantifying these values.

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