A Cooperative Platooning Controller for Connected Vehicles

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Abstract: One of the key priorities of technologies is performance. In the area of transportation, performance is typically intertwined with increased mobility and reduced costs. Congestion alleviation which is a persistent challenge faced by many cities is a priority. The use of infrastructure is inherently inefficient, resulting in higher vehicle fuel consumption and pollution. This in turn burdens commuters and businesses. Therefore, solving this issue is of prime significance because of the potential benefit. Many technologies have been and are being developed. These include adaptive traffic signals and various dynamic traffic control strategies. This paper introduces a platooning controller that keeps relatively small time gaps between consecutive vehicles to increase mobility, and eventually reduce travel costs. This controller also accounts for complex dynamic and kinematic restrictions controlling vehicle motion. The controller is tested in a virtual environment on highways in downtown Los Angeles. A drop-in travel time, delay, fuel consumption was observed across the area for connected automated vehicles (CAVs) and non-connected vehicles, at various market penetration rates (MPRs). Reductions of up to 5%, 9.4%, and 8.17% in travel time, delay, and fuel consumption, respectively are observed. These observations are observed for all vehicles platooned and non-platooned.

1 INTRODUCTION

A dynamic phenomenon that requires sophisticated modelling is roadway traffic. Nevertheless, different properties can be observed directly. These properties include (1) the density of the traffic stream (k): the number of vehicles per unit length per road or lane; and (2) the space-mean velocity (u): the density weighted average velocity of the traffic stream. Congestion is intertwined with high density and slow space-mean speeds. Through designing technologies that direct traffic and use the infrastructure as efficiently as possible, researchers are attempting to reduce traffic congestion. Wireless networking advancements, ground breaking driver assistance systems (Bevly et al., 2017) have made ideas developed on paper become a reality. Platooning is one of these ideas. Platooning is basically a group of cars traveling at the same speed and keeping limited space in between and is usually referred to as cooperative adaptive cruise control (CACC). This basic idea has the potential to boost transportation. Its perceived benefits are efficient mobility, lower fuel consumption, reduction in CO_2 emissions, and increased highway capacity. Particular attention was and is still being allocated to the development of platoons. The work of Deng and Ma (Deng & Ma, 2014) utilized Pontryagin's maximum principle (PMP) to develop a platooning algorithm for trucks. They claim up to 30% reduction in fuel consumption on the deceleration regime and up to 3.5% in the acceleration regime.

Al Alam et al. (Alam, Gattami, & Johansson, 2010) were inconclusive with respect to fuel consumption reduction for platooned large vehicles equipped with a commercial adaptive cruise control (ACC). However, they reported a maximum energy saving ranging from 4.7 to 7.7% with maximum savings corresponding to a time gap of 1 s. They acknowledged that a short time gap results in maximum drag reduction, yet it comes with

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challenges (i.e., feedback and communication delays) which in turn threaten the safety as well as the comfort of passengers.

Carl et al. (Bergenhem, Shladover, Coelingh, Englund, and Tsugawa, 2012) reported various platooning projects, namely, safe road trains for the environment (SARTRE) (an European platooning project), partial automation for truck platooning (PATH) (a California traffic automation program), grand cooperative driving challenge (GCDC) (cooperative driving initiative), and SCANIA platooning and energy ITS. They emphasized the importance of connectivity V2X which involves vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication, as well as vehicular and non-vehicular sensors in allowing platooning to address the issues of synchronization and vehicle longitudinal and lateral stability. Increased safety and reduced emissions were reported by Davila et al. (Davila & Nombela, 2012) in the SARTRE project. Virtual testing showed that better engineered vehicle aerodynamics results in less energy consumption. Platooning automation is expected to enhance safety since 95% of accidents are primarily caused by humans (Brown, 2005).

Other nationally funded projects targeting platooning technologies were also unveiled. Within the framework of the Japanese national intelligent transportation system (ITS) project, Tsugawa et al. (Tsugawa, Kato, & Aoki, 2011) created a system that could assist vehicles to platoon automatically. They showed that experiments on three fully autonomous trucks operating at a speed of 80 km/h and a distance gap of 10m (i.e., time gap of 0.45 s) results in 14% fuel savings and hence a decrease in CO2 emissions.

In another study, a series of platooning tests on large vehicles were performed. Michael et al. (Lammert, Duran, Diez, Burton, & Nicholson, 2014) tried different vehicle mass, speeds as well as distance gaps in search for the optimum configuration resulting in the highest energy consumption reduction. This combination turned out to be a cruising velocity of 88 km/h (55 mph) and a 9.1 m (30 ft) gap distance for a fuel saving of 6.4%. This percentage is significant given the modest initial investment. The unintended effects of platooning on trucks, were highlighted by Ellis et al. (Ellis and Gargoloff, 2015). They stressed the significant aerodynamic drag reduction. However, if the gap-distance is low (i.e., 5m), the air flow through the engine is greatly decreased, resulting in the continuous fan activation which in turn reduced potential fuel economy. Different platooning configurations for large vehicles on highways were tested by Vegendla et al. (Vegendla, Sofu, Saha, Kumar, & Hwang, 2015). Using computational fluid dynamics, up to 23% reduction in fuel consumption can be achieved by trucks traveling in a platoon. Yet, two trucks traveling side by side on highways consume 11% more.

Beside the technologies developed for heavy duty vehicles similar technologies were and are being developed for passenger cars. For instance, Stanger and Del Re (Stanger and del Re, 2013) developed a linear predictive control model that directly optimizes the fuel consumption of the vehicles inside the platoon. A simplified car-following model was adopted, and a quadratic approximation of the fuel consumption was chosen, they claim a 20% reduction in fuel. Other elaborate models were also proposed. For example, using a non-linear vehicle model, Schmied et al. (Schmied et al, 2015) have developed a non-linear model predictive control (NMPC) logic that takes into account various non-linear constraints. It is important to mention here that the nonlinear nature of the model presents a computational burden preventing its real-time implementation. Nevertheless, the controller was tested using a hardware-in-the-loop (HIL) configuration and the authors claimed 13% reduction in fuel consumption as well as 24% reduction in NO_x emissions. With the benefits provided by the platoon, it is important to note some of the disadvantages it has. These drawbacks are partly related to the extreme case. Specifically, long platoons and platoons that are near an entrance ramp do cause merging failures and congestion, where the incoming vehicles find no proper gap to merge (Wang, Maarseveen, Happee, Tool, and Arem, 2019).

The present effort delivers a platooning logic principally inspired by a change of variables. It extends the literature in the following aspects: (1) it considers platoons of arbitrary lengths; (2) the platoons are formed and broken in a dynamic fashion; (3) realistic vehicle dynamics are considered in the plattoning and (4) the algorithm is tested on a large-scale virtual implementation. In order to simplify the analysis, and primarily due to the lack of an aerodynamic drag coefficient function that determines the subject force on the trailing vehicle when the two considered vehicles are of significantly different sizes (i.e., a truck and a car), this paper addresses platoons composed only of passenger vehicles. Buses and trucks are not considered. The same algorithm will operate with all types of vehicles, given that the correct dynamic behaviour information associated with the considered vehicle is available. In the following section, we detail the dynamic forces a vehicle can be subject to as well as the dynamic and kinematic constraints. Details of the controller and the simulation setup are presented in the same section. In the third section, results are presented and finally concluding remarks and future work are presented.

2 METHODOLOGY AND FORMULATION

In this section, the vehicle dynamic model, associated constraints, the proposed platooning controller as well as the test settings are presented.

2.1 Vehicle Dynamic Model and Constraints

Vehicles on the road are subject to various external forces and constraints. These include, dynamic forces, such as tractive and resistive forces, velocity, and acceleration constraints (H. Rakha, Pasumarthy, P., and Adjerid, S., 2009). The tractive force is defined in Equation (1), the resistive force is the sum of the aero dynamic resistance R_a (Equation (2)), rolling resistance R_r (Equation (3)) and grade resistance R_g (Equation (4)). Therefore, the upper bound for the acceleration is given by Equation (5) (Hesham Rakha & Ahn, 2004; H. Rakha, Lucic, Demarchi, Setti, & Aerde, 2001). The variables introduced in Equations (1)-(7) are summarized in Table 2.

$$F = \min\left(\frac{3600\eta_d P}{v}, m_{ta} g\mu\right) \tag{1}$$

$$R_a = \frac{\rho C_d C_h\, C_f\, A_f v^2}{2} \tag{2}$$

$$R_r = mgC_{r0}(C_{r1}v + C_{r2}) \tag{3}$$

$$R_g = mgG \tag{4}$$

$$a_{max}(t) = \frac{F(t) - R_a(t) - R_r(t) - R_g(t)}{m} \tag{5}$$

The airflow subject to the current vehicle might be altered due to the presence of another vehicle in front. We introduce the drag corrective factor C_f to capture the impact of platooning on the vehicle drag coefficient (Equation (6)) (Hussein and Rakha, 2020).

$$C_f = \begin{cases} a\, G^b + c & if\ G \le G_0 \\ 1 & otherwise \end{cases} \tag{6}$$

where, G is the gap in meters and a, b, and c are calibrated constants. The critical gap value, G_0 depends on the type of the vehicle. Table 1 presents the different parameters that can be used in the model depending on the position of the vehicle in the platoon. For further details about this model the reader is referred to the work in (Hussein and Rakha, 2020).

Table 1: Values of the parameters for Equation (6), for various vehicle positions in the platoon, based on (HUSSEIN & RAKHA, 2020).

Vehicle position	Parameters			
	a	b	c	$G_0\ (m)$
Lead	-0.89	-1.67	1.02	-
Middle	-0.90	-0.51	1.14	39.62
Trail	0.60	0.12	1.14	79.75

The maximum deceleration a vehicle can experience is given by Equation (7)

$$a_{min} = -(G + 1)g\ \mu\ b_e \tag{7}$$

Table 2: Description of the various variables.

Variable	Description
η_d	driveline efficiency (unitless)
m_{ta}	mass of the vehicle on the tractive axle (kg)
P	vehicle power (kW)
g	gravitational acceleration (m/s^2)
μ	coefficient of road adhesion or the coefficient of friction (unitless)
ρ	air density at sea level (kg/m^3)
C_d	vehicle drag coefficient (unitless)
C_h	altitude correction factor (unitless)
C_f	Drag a correction factor (unitless)
A_f	vehicle frontal area (m^2)
C_{r0}	rolling resistance constant that varies as a function of the pavement type and condition (unitless)
C_{r1}	second rolling resistance constant (h/km)
C_{r2}	third rolling resistance constant (unitless)
m	total vehicle mass (kg)
G	roadway grade (unitless)
b_e	braking efficiency

where a_{min} and a_{max} are the absolute bounds for the acceleration of the vehicle. However, when there are other vehicles on the road collision avoidance is of utmost importance. Therefore, another constraint on the acceleration is introduced. This constraint has the exclusive role of decelerating the vehicle to a velocity that of the vehicle ahead of it while at the same time keeping adequate spacing. To avoid collision, the minimum deceleration is given by Equation (8).

$$a_{collision} = \frac{b^2_{kinematics}}{(b_{desired} + g\ Gr\ )} \tag{8}$$

where, $b_{desired}$ is the desired deceleration level,

$$b_{kinematics=} \frac{\left(v_n^2 - v_{n-1}^2 + \sqrt{(v_n^2 - v_{n-1}^2)^2}\right)}{4\left(x_{n-1} - x_n - s_j\right)} \tag{9}$$

where, v_n is the velocity of the current vehicle, v_{n-1} is the velocity of the vehicle ahead of it, x_n is the position of the current vehicle, x_{n-1} is the position of the vehicle ahead, and s_j is the spacing at jam conditions. $b_{kinematics}$ is the deceleration level needed for the following vehicle to reduce its speed to that of the vehicle in front with the stopping distance being equal to the distance gap separating them. Therefore, the acceleration of any given vehicle needs to satisfy the following conditions.

$$\begin{cases} a_n(t) \leq a_{max}(t) & if\ a_n > 0 \\ a_{min}(t) \leq a_n(t) \leq a_{collision}(t) & if\ a_n \leq 0 \end{cases} \tag{10}$$

The RPA car-following model (Hesham Rakha, Pasumarthy, & Adjerid, 2009) accounts for the constraints on the acceleration in the perspective of velocity. The velocity of the vehicle following another one needs to satisfy the condition presented in Equation (11), (Bichiou & Rakha, 2019).

$$v_n(t+\Delta t) = min \begin{cases} v_n(t) + a_{max}(t)\,\Delta t \\ \dfrac{-c_1 + c_3 u_f + s_n(t+\Delta t) - \sqrt{A}}{2\,c_3} \\ \sqrt{v_{n-1}(t+\Delta t)^2 + 2\,b_{desired}\left(s_n(t+\Delta t) - \dfrac{1}{k_j}\right)} \end{cases} \tag{11}$$

where,

$$c_1 = \frac{u_f}{k_j\,u_c^2}\left(2\,u_c - u_f\right),$$

$$c_2 = \frac{u_f}{k_j\,u_c^2}\left(u_c - u_f\right)^2,$$

$$c_3 = \frac{1}{q_c} - \frac{u_f}{k_j u_c^2},$$

$$s_n(t+\Delta t) = s_n(t) + [v_{n-1}(t) - v_n(t)]\Delta t + 0.5 a_{n-1}(t)\Delta t^2,$$

$$A = \left[c_1 + c_3 u_f - s_n(t+\Delta t)\right]^2 - \ 4\,c_3\left[s_n(t+\Delta t)\,u_f - c_1 u_f - c_2\right]$$

u_f is the free flow velocity, u_c is the velocity at capacity ($u_c \approx 0.85\,u_f$ based on empirical observations), k_j is the jam density, and q_c is the saturation flow rate. The car following model presented in Equation (11) is enforced at all times throughout the simulation.

2.2 Proposed Controller

In order to sustain a constant time gap between two consecutive vehicles, the introduction of a controller is necessary. The controller's objective is to maintain a constant/desired time gap ($h_{des} = 0.6\ s$) (Loulizi, Bichiou, & Rakha, 2019). This can be achieved by driving the error function –which transforms the desired time gap to a distance gap between two consecutive vehicles– defined in Equation (12) to zero. This can be accomplished by allowing consecutive and corrective acceleration or deceleration inputs to following vehicle. One of the simple ways of achieving this is presented in Equation (13).

$$e_n(t) = \left[x_{n-1}(t) - x_n(t) - s_j\right] - h_{des} \times v_n(t) \tag{12}$$

$$\frac{d}{dt}\left(e_n(t)\right) = -\lambda\, e_n(t) \tag{13}$$

where λ is a strictly positive real number. The solution to Equation(13) is given by

$$e_n(t) = \ e_n(0)\ exp[-\lambda\, t]$$

which guaranties that $e_n(t)$ converges to zero as time increases, provided λ is strictly positive. Substituting Equation (12) into(13) leads to

$$a_n = \frac{-\lambda\, e_n(t) + v_{n-1} - v_n}{h_{des}} \tag{14}$$

namely,

$$a_n(t) = \frac{1}{h_{des}}\left[-\lambda\left(x_{n-1}(t) - x_n(t) - s_j\right) + v_{n-1}(t) + (\lambda\, h_{des} - 1)v_n(t)\right] \tag{15}$$

Equation (15) requires knowledge of the difference in position between two consecutive vehicles as well as their respective velocities, which can be achieved by having sensors on the vehicles or through V2V communication. The presented controller has one hyper-parameter (λ). The amount of data that needs to be transferred between the vehicles is minimum (i.e., the velocity and the position of the vehicle ahead). It is also possible to avoid this transfer of information by measuring the position and velocity of the vehicle ahead using radar. It is also important to note that the computed value for the acceleration $a_n(t)$ need to satisfy conditions presented in Equation (10).

2.3 Simulation Setup

In this paper we consider testing the proposed platooning controller on downtown Los Angeles, specifically, the highway stretches that traverse it from north to south and east to west. The total length selected for the platooning is approximately 123 km. The selected area is shown in Figure 1.

The network was modelled using the INTEGRATION software (H. A. Rakha & Van Aerde, 2020a, 2020b). The vehicle dynamic model, dynamic constraints, and car-following model presented in Section 2.1 are implemented in the software and are enforced all the time. The traffic demand was calibrated using loop detector data by computing the maximum likelihood static OD matrix using procedures described in (Van Aerde, Rakha, & Paramahamsan, 2003) and then adjusting the static OD matrix to compute the dynamic OD matrix using procedures described in (Yang and Rakha, 2019). A detailed description of the calibration effort can be found in (Du, Rakha, Elbery, and Klenk, 2018). This resulted in a total of approximately 144,000 trips over 1-hour simulation. The selected highways do have different lane counts. This count ranges from 3 lanes to 6 lanes. For the purpose of this study, we selected the two most left lanes as the lanes where we activate platooning. In addition, we assumed a single vehicle type, that is the 2018 Toyota Camry LE 2.5, one of the most popular models sold in the USA. Its characteristics are simulated in INTEGRATION software. The fleet of Toyotas are subdivided into two classes: class 1 and class 2. Class 1 are the Toyotas that do not form or join a platoon (non-CACC equipped vehicles). Class 2 are the Toyotas that do form and if possible, join other created platoons (CACC-equipped vehicles). The ratio of class 2 with respect to class 1 was selected to be the variable to discern the effects of various MPRs.

Figure 1: Downtown Los Angeles network, red represents freeway links for platooning.

Vehicle's fuel consumption is modelled using the VT-CPFM-1 model presented in Equation (16) (Ahn & Rakha, 2019), which is included in the INTEGRATION software.

$$FC = \alpha_0 + \alpha_1 P + \alpha_2 P^2 + \alpha_3 v \tag{16}$$

where, P is the vehicle's power and v is the vehicle's velocity. The vehicle's power is the product of the force experienced by the vehicle and its velocity.

$$P = F_e\, v \tag{17}$$

where,

$$\begin{aligned} F_e = mgG + \frac{mg\cos(\theta)\, CR_0 CR_2}{1000} + m\,a \\ + \frac{mg\cos(\theta)\, CR_0 CR_1}{1000}\, v \\ + \frac{1}{2}\rho\, C_d\, C_h\, A_f\, v^2 \end{aligned} \tag{18}$$

and a is the vehicle's acceleration, this model was validated in (Dion, Rakha, & Kang, 2004). The delay that can be experienced by vehicles is computed using Equation (19).

$$delay = \sum_t \frac{u_f - v}{u_f}\, \Delta t \tag{19}$$

where u_f is the free flow velocity on a given link.

3 RESULTS AND DISCUSSION

In order to account for varying traffic conditions from one day to another, simulations with various random seeds were performed. First, we wanted to determine the best platooning configuration to adopt. A series of simulations were performed using the configurations listed in Table 3.

Table 3: Tested platooning configurations.

Config.	Details
A	Platooning on all lanes of the highway
B	Platooning on all lanes of the highway – platoon size limited to 24 cars
C	Platooning on 1 lane
D	Platooning on 1 lane – platoon size limited to 24 cars
E	Platooning on 2 lanes – platoon size limited to 24 cars

Noting that in some configurations of Table 2 (B, D, and E) platooning is enforced on individual links in a disconnected manner from the links that follow. The average link length is 500 m, the speed limit (i.e., platooning speed) is 25 m/s, the selected time gap is $h_{des} = 0.6\, s$ (Loulizi et al., 2019), and a single vehicle occupies 21 m. Therefore, 500 m contains approximately 24 vehicles. Platoons are formed in a dynamic manner. Any vehicle attempting to join a platoon can increase its velocity by up to 7% beyond the speed limit (i.e., platooning speed) for a maximum duration of 6.5 s. If the vehicle is unable to join the platoon within this time frame, a new platoon is formed with this vehicle as a lead vehicle. These parameters are user-specified and thus can be varied.

The average results of five random seeds are presented in Table 4. It is clear from Table 4 that configuration E has the best performance. This corresponds to travel time, delay and fuel consumption reduction of 7.74%, 13.6% and 11.42% respectively. This configuration stipulates that platooning is enforced on the two leftmost lanes while limiting the size of the platoon. Therefore, in the subsequent simulations, we will only consider configuration E.

Table 4: Results for the configurations in Table 3.

	Travel Time (s)	Total Delay(s)	Fuel (l)	TT Change (%)	Delay Change (%)	Fuel Change (%)
Base	1032.6	561.7	0.89			
A	1056.0	566.2	0.74	2.27	0.80	-16.48
B	1085.7	587.2	0.84	5.15	4.54	-5.50
C	993.3	513.4	0.88	-3.81	-8.60	-1.19
D	1036.6	568.0	0.88	0.38	1.13	-0.72
E	952.6	485.3	0.79	-7.74	-13.60	-11.42

In order to further investigate the effectiveness of the platooning controller, we ran simulations with ten random seeds at different MPRs. An average of the results is presented in Table 5.

Table 5: Average performance metrics.

MPR (%)	Travel Time (s)	Total Delay (s)	Fuel (l)	TT Change (%)	Delay Change (%)	Fuel Change (%)
0	986.2	519.5	0.862			
1	1008	538.2	0.873	2.19	3.60	1.28
5	980	511.7	0.857	-0.67	-1.50	-0.59
10	990	524.8	0.863	0.36	1.02	0.17
15	1005	536.0	0.868	1.92	3.19	0.72
20	1001	530.6	0.863	1.50	2.14	0.18
30	948	481.7	0.831	-3.93	-7.27	-3.61
40	961	497.2	0.836	-2.52	-4.28	-3.02
50	979	513.9	0.840	-0.75	-1.07	-2.58
60	945	481.8	0.813	-4.21	-7.25	-5.63
70	954	488.8	0.811	-3.31	-5.91	-5.91
80	937	470.7	0.791	-5.02	-9.40	-8.17
90	968	497.9	0.801	-1.81	-4.16	-7.09
100	995	522.8	0.809	0.85	0.64	-6.15

Table 5 shows the average travel time, delay and fuel consumed for all vehicles in the network at various MPRs. We can clearly discern that up to an MPR of 20 % no significant advantage is provided by the CACC platooning. In fact, the performance metrics are about the same. Starting from an MPR of 30%, we observe a reduction up to 5% in travel time, a reduction up to 9.4% in delay, and a reduction between up to 8.17% in fuel consumption. It is important to mention here that the RPA car-following model and collision avoidance (Hesham Rakha et al., 2009) are enforced at all times between all the vehicles (platooned and non-platooned). This finding demonstrates that efficient movement of a subset of vehicles inside a large network leads to an improved mobility for the entire network. Figure 2,

Figure 3, and Figure 4 present a scatter plot of the reduction in travel time, delay and fuel consumption reported in Table 5. Even though various seeds were used for the simulation, the plots stress the reduction in the mentioned performance metrics. The slope of the decline of the fuel consumption is steeper than the other measures of effectiveness. This is essentially due to the significant reduction in the aerodynamic

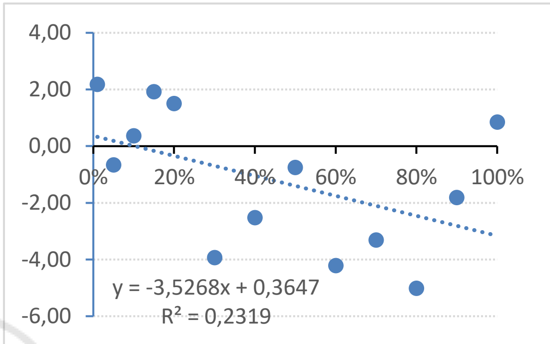

Figure 2: Scatter Plot of the Travel Time Reduction Percentage as a Function of the MPR.

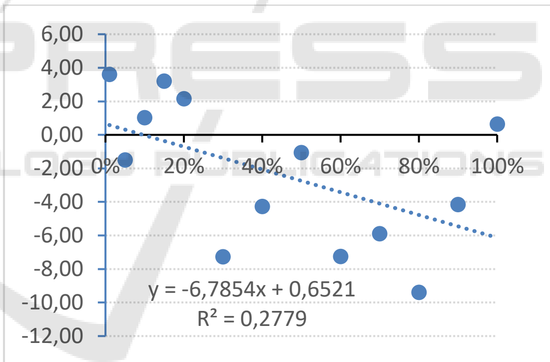

Figure 3: Scatter plot of the delay reduction percentage as a function of the MPR.

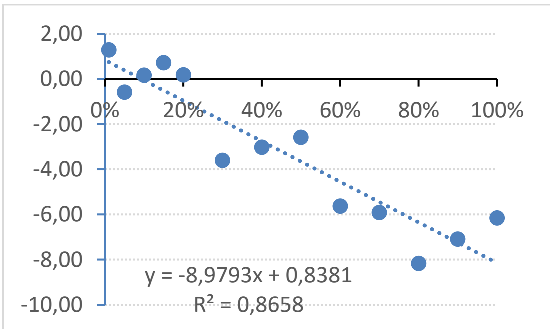

Figure 4: Scatter plot of the fuel consumption reduction percentage as a function of the MPR.

force to which the platooned vehicles are subjected and therefore the vehicle needs less energy to overcome that force. The slope for the reduction in travel time, delay, and fuel consumption are approximately -3.5%, -6.9%, and -9% respectively. The respective coefficients of determination (R^2) are 0.23, 0.28, and 0.87 which further stresses the steep reduction in fuel consumption due to platooning.

4 CONCLUSIONS

In this paper, an input minimal platooning controller is presented. This logic takes into account various dynamic and kinematic constraints that vehicles experience. These include acceleration, velocity, and collision avoidance constraints. This controller was later applied on the highways in downtown Los Angeles in the INTEGRATION software. The results suggest a clear trend towards a reduction in system-wide travel time, delay and notably fuel consumption. The average reduction in travel time for all the MPRs is up to 5%. The average reduction in delay as well as fuel consumption (and ultimately CO_2 emissions) are up to 9% and 8%, respectively. These results are for the fleet of all vehicles, platooned and non-platooned traveling through the downtown area. This leads us to deduce that controlling the trips of a subset of vehicles inside a large network does have the potential to benefit other road users in a positive manner. In the future work, we will be conducting a detailed investigation on the performance of this controller on a mixed platoon comprised of conventional, hybrid and electrical vehicles at various MPRs.

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