

A Collision Mitigation Strategy for Intelligent Vehicles to Compensate for Human Factors Affecting Manually Driven Vehicles

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Abstract—Human factors include human errors and human weaknesses such as long reaction time, limited visibility, limited jerk sustainability, etc. Such human factors account for a large portion of vehicular accidents involving manually driven vehicles (MDVs). Future Intelligent Vehicles (IVs) are expected to have higher perception ranges, faster reactions and coordinated mobility capability. At early market penetration, IVs will share road with MDVs and will adjust its driving dynamics according to the dynamics of other neighboring vehicles.

In such a scenario, we investigate how IVs can compensate for human factors impacting MDVs and accordingly improve traffic safety in mixed traffic conditions. We model a centralized Model Predictive Control (MPC) based controller and integrate constraints derived from human factors. We show that IVs may not only reduce collisions, but also increase traffic density without negatively impacting traffic safety. We finally assess the impact of a gradual penetration of IVs in a mixed vehicle scenario.

I. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) are being developed to support human drivers in their driving duties. Warning-based ADAS alert human drivers about imminent threats or advanced navigations through GUI (visual), auditory or haptic feedback [1]. Control-based ADAS provide control functions for lane keeping, lane change, automated vehicle parking, or adaptive cruise control (ACC). Vehicles equipped with ACC functionalities can ensure front end collision avoidance. It yet may not be able to avoid rear end collisions with following (manually driven) vehicles [2] without cooperation and coordinations. Vehicles equipped with ACC and Vehicle-to-Everything (V2X)¹ communication technologies, which cooperate and coordinate by sharing vehicle state and control information, are known as Cooperative ACC (CACC) vehicles. Both ACC and CACC vehicles are considered as Intelligent Vehicles (IVs).

In a traffic consisting of CACC vehicles only, coordinated control strategies are necessary to harmonize flows or avoid collision [3] (e.g. Fig. 1). Examples of coordinated control strategies for multi vehicle braking, roundabout clearance, lane merging, etc. can be found in the survey [4] assuming perfect knowledge of parameters under ideal circumstances. Under less than ideal circumstances (delayed or missed detection), coordinated control strategies face emergency-like situations to

avoid collisions. In such situation, the objective changes from coordinated control for *maneuvering* to coordinated control for *braking* [5].

The presence of manually driven vehicles (MDVs) without V2X capabilities brings additional challenges to cooperative control strategies. Compared to IVs, human drivers in MDVs are subject to human factors, such as long reaction times, limited anticipation or visibility, over-speeding and unexpected driving maneuvers. These human factors have a negative impact on safety and can result in collisions. At early IV market penetration, IVs and MDVs will coexist, which will lead to uncertainties in the control strategies. Accordingly, IVs and MDVs will adjust their maneuvers based on one another and create an *indirect interaction* between them. To maneuver safely in mixed traffic scenarios, CACC vehicles might need to parameterize and model MDV's behavior [6] or perform intent estimation [7]. CACC vehicles are also expected to impact MDVs by mitigating the impact of human factors on traffic safety.

In this paper, we purposely evaluate this aspect. Considering perception response time as human factor, we investigate how CACC vehicles mitigate its propagation on a string of MDV vehicles in a coordinated braking scenario. We model a centralized controller according to a Model Predictive Control (MPC) method and include human factor constraints. We gradually mix CACC vehicles with MDV and evaluate the capabilities of our proposed MPC controller to avoid collisions. We also evaluate how the recommended safety distance between MDVs may be occupied by CACC vehicles without creating accidents. Reduced inter-distance is known to increase traffic flow in pure CACC scenarios. We aim at demonstrating to also be the case in mixed scenarios, thanks to CACC vehicles compensating for human factors affecting MDVs. Moreover, the proposed technique is non-intrusive and does not actually require installation of additional hardware in MDVs.

The rest of this paper is organized as follows: In Section II, we provide background on centralized control systems. In Section III, we model a mixed traffic scenario and formulate our MPC based control strategy. In Section IV, we evaluate its performance to compensate for human factors. Section V finally draw conclusions and shed light on future work.

¹V2X technologies refer either to DSRC/ITS-G5 or to the future C-V2X.

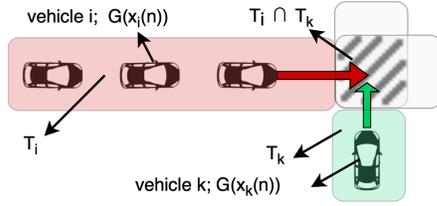


Fig. 1. Scenario description - intersection collision avoidance

II. INTRODUCTION TO CENTRALIZED CONTROL SYSTEMS

Consider a Model Predictive Control (MPC)-based controller receiving status information (position and velocity) of each of the n_v vehicles at each instant. Based on a set of given constraints, the MPC controller calculates a set of control inputs u minimizing a target cost function while respecting the constraints. The first control input is applied by each vehicle and then the process is repeated in the next iteration. Accordingly, optimal control inputs for all vehicles over a finite time horizon² N are calculated using the following model:

MPC Control Input

Considering the *state* variable x_i of vehicle i ($i \in 1 \dots n_v$) as a *position-speed* tuple:

$$x_i = [p_i \ v_i]^T \quad (1)$$

the control system in a continuous time domain can be represented as:

$$\begin{aligned} \dot{x}_i(t) &= f_i(x_i(t), u_i(t)) \\ \dot{x}_i(t) &= Ax_i(t) + Bu_i(t) \end{aligned} \quad (2)$$

where $u(t)$ is the control input, and assuming a linear control system. In discrete form, (2) may be expressed as (see [3]):

$$x_i(n+1) = Ax_i(n) + Bu_i(n) \quad (3)$$

where n is any sampling instant ($n \in 1 \dots N$). Assuming basic kinematic relationships (e.g. $\dot{p}_i = v_i$, $\dot{v}_i = u_i$, $\dot{u}_i = j_i$), *exact* discretization of (2) leads to:

$$A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} (\Delta t)^2/2 \\ \Delta t \end{bmatrix} \quad (4)$$

where Δt is the time between two consecutive samples n and $n+1$; j denotes jerks.

MPC Constraints

The control system given by (3) is subject to the following constraints:

- **Initial and final state constraints**

Initial state and the final state vectors are represented as $x_i(0)$ and $x_i(N)$.

- **Path constraints**

If T_i corresponds to the set of spatial coordinates on a predefined *path* and $G(x_i)$ corresponds to the spatial coordinates (area) that vehicle occupies when the state is

x_i at instant n , the constraint, which ensures that each vehicle stays on the initially decided path is given as:

$$G(x_i(n)) \subset T_i \quad (5a)$$

where an intersection can be defined as an area where two paths intersect:

$$T_i \cap T_k \quad \forall i, k \in 1 \dots n_v, \quad i \neq k \quad (5b)$$

- **Vehicle and passenger constraints**

In real life scenarios, there are limitations related to admissible values of jerks, acceleration, velocities modeled as follows:

$$\begin{bmatrix} p_i^{min} \\ v_i^{min} \end{bmatrix} \leq x_i(n) \leq \begin{bmatrix} p_i^{max} \\ v_i^{max} \end{bmatrix} \quad (6a)$$

$$u_i^{min} \leq u_i(n) \leq u_i^{max} \quad (6b)$$

$$j_i^{min} \leq j_i(n) \leq j_i^{max} \quad (6c)$$

where $(\cdot)^{min}$, $(\cdot)^{max}$ corresponds to minimum and maximum value of that parameter for vehicle i . Please note that negative acceleration signifies braking and u_i^{max} and u_i^{min} stand for maximum acceleration and maximum braking limits.

- **Safety constraints**

Condition 1: Two vehicles cannot occupy the same space, neither completely nor partially at any time instant.

Condition 2: Distance between vehicles cannot be reduced to zero, at any time instant. These conditions can be expressed as:

$$G(x_i(n)) \cap G(x_k(n)) = \emptyset \quad \forall i, k \in 1 \dots n_v, \quad \forall i \neq k \quad (7a)$$

$$d_{i,k}(n) > 0 \quad \forall i \in 2 \dots n_v, \quad k = i - 1 \quad (7b)$$

where $d_{i,k}$ denotes the distance between vehicles i and k .

MPC Cost function

Rapid acceleration or deceleration is shown [8] to be stressful to the vehicles occupants. The goal is therefore to maximize comfort whilst ensuring collision avoidance. Accordingly, we take the 2-norm on the control inputs to penalize large deviations as follows:

$$J = \sum_{i=1}^{n_v} \sum_{n=1}^N \|u_i(n) - u_i(n-1)\|_2 \quad (8)$$

MPC centralized CACC control model

We can incorporate the various constraints and the cost function given by (8) into an optimization model as:

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{n_v} \sum_{n=1}^N \|u_i(n) - u_i(n-1)\|_2 \\ \text{subject to} \quad & (1), (3), (4), (5), (6), (7) \end{aligned} \quad (9)$$

Equation (9) returns a set of control inputs (acceleration values) for a CACC only traffic scenario. If collisions are

²Setting the correct value of such time horizon is important as it influences the computational time.

inevitable, (9) will not return any control input. Solving such a scenario is out of scope of this paper.

To highlight human factors affecting MDV and the benefit of CACC vehicles in a mixed traffic scenario, we modify the MPC formulation in (9) to include state parameters and constraints describing human factors impacting manually driven vehicles.

III. COORDINATED BRAKING IN MIXED TRAFFIC

A. System Modeling

Based on the level of automation and communication/sensing capabilities, we categorize vehicles as *active* participants (APs) or *passive* participants (PPs). APs support dedicated V2X communications and coordinated control capabilities (e.g.: CACC). Other vehicles, which are manually driven and subject to human factors are PPs. In this paper we consider a mixed traffic scenario consisting of PPs (MDV) and APs (CACC). We consider a scenario with multiple vehicles braking on a single lane (1D) as shown in Fig. 2.

Modeling PPs

Two major human factors affecting PPs are the reaction time and the limited visibility. We model the PP's reaction time as the driver's *perception reaction time* (PRT) (t_{prt}) [9], and assume PP's visibility to be limited to the front vehicle only. Moreover, we define $t_{prt,i}=[t_{i,i-1}, t_{i,1}]$ as the pair of PRT of a PP i compared to the vehicle in front and the first vehicle respectively. It means that a PP i would react $t_{i,i-1}$ seconds after vehicle $i-1$ and $t_{i,1}$ seconds after vehicle 1. And $t_{i,1}=t_{i,i-1}+t_{i-1,i-2}+\dots+t_{2,1}$ if all 2, 3... i front vehicles are PPs (e.g Fig. 2). Thus the reaction time of a PP is proportional to the number of other PPs immediately ahead. Assuming each PP i brakes at maximum capacity after its PRT and comes to a halt in t_i^s seconds, the braking profile of manually driven vehicles can be defined by:

$$u_i(n) = \begin{cases} 0 & 0 \leq n \leq c \cdot t_{i,1} \\ u_i^{min} & c \cdot t_{i,1} < n \leq c \cdot T_i^s \\ 0 & n > c \cdot T_i^s \end{cases} \quad \forall i \in Z^c \quad (10)$$

where $T_i^s = t_{i,1} + t_i^s$. Values in seconds are multiplied with constant $c = 10$ and converted to instances (1 second = 10 instances). Let Z be the set of all APs, $1 \leq size\{Z\} \leq n_v$. Thus Z^c is the complement set of Z , which signifies that $i \notin Z \forall i \in n_v$. If $size\{Z\}$ is zero, means no APs, only PPs. Equation (10) is used to generate state parameters (location and velocity) of manually driven vehicles for simulations. But in real life scenarios, state parameters for PPs would be regularly updated at the centralized controller by the use of detectors placed by the side of the roads, or extracted by CACC vehicles' camera's and lidar scanners, and transmitted via V2X communications.

We assume that APs are warned at the same instant of a potential collision and immediately react on control inputs from the centralized entity. APs implicitly warn PPs of their braking through braking lights. Accordingly, the reaction time

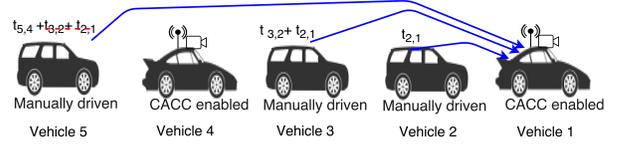


Fig. 2. braking delays derived from finite reaction time of MDVs.

of a PP i behind an AP will be much shorter than a PP k behind another PP (i.e.: $t_{i,1} < t_{k,1}$), as indicated in Fig. 2.

Equation (10) ensures PPs come to a halt, whereas to ensure that all APs also reach zero terminal velocity before the intersection, we modify the final state parameter as follows:

$$v_i(N) = 0 \quad \forall i \in Z \quad (11)$$

B. Proposed Mixed Traffic Centralized Control Model

Computing control inputs for APs whilst considering specific braking profile for PPs (10) signifies a mixed vehicle scenario. Ensuring zero terminal velocity (11) signifies a braking scenario. Equation (7b) further ensures collision avoidance considering human factors. Restricting jerks within certain bounds (6c) ensures smooth braking for APs³. As it is a 1D scenario, the initial and final position information directly define the path T thus (5a) and (5b) can be ignored. The cost function is chosen to maximize comfort (8). At each instant the centralized controller computes control inputs for APs considering all vehicles (APs and PPs) in the traffic by solving the following:

$$\text{minimize } \sum_{i=1}^{n_v} \sum_{n=1}^N \|u_i(n) - u_i(n-1)\|_2 \quad (12)$$

subject to

$$x_i(n+1) = A_i x_i(n) + B_i u_i(n)$$

$$\dot{p}_i = v_i; \quad \dot{v}_i = u_i; \quad \dot{u}_i = j_i$$

$$A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} (\Delta t)^2/2 \\ \Delta t \end{bmatrix}$$

$$\begin{bmatrix} p_i^{min} \\ v_i^{min} \end{bmatrix} \leq x_i(n) \leq \begin{bmatrix} p_i^{max} \\ v_i^{max} \end{bmatrix}$$

$$u_i^{min} \leq u_i(n) \leq u_i^{max}$$

$$j_i^{min} \leq j_i(n) \leq j_i^{max} \quad \forall i \in Z$$

$$d_{i,k}(n) > 0 \quad \forall i \in 2 \dots n_v, \quad k = i - 1$$

$$u_i(n) = \begin{cases} 0 & 0 \leq n < c \cdot t_{i,1} \\ u_i^{min} & c \cdot t_{i,1} < n \leq c \cdot T_i^s \\ 0 & n > c \cdot T_i^s \end{cases} \quad \forall i \in Z^c$$

$$v_i(N) = 0 \quad \forall i \in Z$$

Without loss of generality, it is assumed that a centralized entity has full knowledge (at instant $n = 0$) of the state parameters and vehicular constraints of all PPs and APs. The centralized entity is further able to solve the convex

³PPs' control inputs cannot be controlled and thus jerks are not considered for PPs

optimization problem represented by (12). We solve it using CVX [10] on MATLAB⁴. The proposed model calculates control inputs for APs taking into account APs and the human factors from PPs. APs will implement control inputs derived from (12), whereas PPs will implement the braking model described by (10).

IV. PERFORMANCE ANALYSIS

A. Simulation set I

For this simulation set, we consider a scenario of five vehicles⁵. The first vehicle is an AP. The ego vehicle X (the subject vehicle) is located in the slot $slot_{ego}$ and the rest are PPs. We use the following notation: [PP X PP PP AP], the right most vehicle is closest to the intersection, and vehicles are located at $[p_5 p_4 p_3 p_2 p_1]$ with velocities $[v_5 v_4 v_3 v_2 v_1]$. Three potential scenarios are considered as function of the role of the ego vehicle:

Scenario 1: The ego vehicle X is absent, $slot_{ego}$ is empty. Only four vehicles are present in this scenario.

Scenario 2: The ego vehicle X is a PP.

Scenario 3: The ego vehicle X is an AP.

Figure 3 depicts these three scenarios, where $slot_{ego}$ is location p_4 .

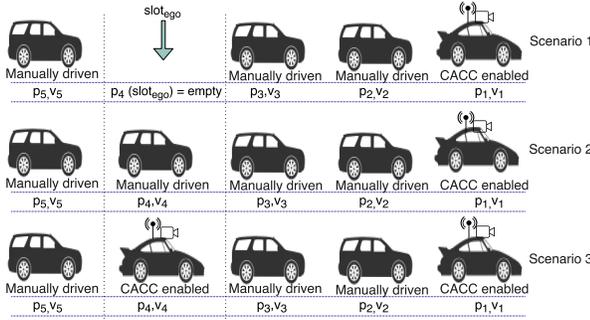


Fig. 3. 3 scenarios being simulated:- 1. ego vehicle is absent 2. ego vehicle is a PP 3. ego vehicle is an AP.

Simulation parameters

We evaluate the performance of our proposed control model given by (12) by solving it for input values sampled from the input space $(u^{min}, t_{prt}, d_{i,k}, v_i(0), slot_{ego})$. u^{min} is sampled from a normal distribution $\mathcal{N}(-0.6g, (0.1g)^2)$ [11] and capped at $-0.4g$ and $-0.8g$, and t_{prt} is sampled from a normal distribution $\mathcal{N}(1.33, (0.27)^2)$ [9] and capped at 0.8s and 1.8s. The initial velocity of vehicles $v_i(0)$ is chosen between $v_p \pm 2.5\%$, where $v_p = 96kmph$ to model a high speed scenario. $slot_{ego}$ denotes the position of ego vehicle, randomly chosen to be either position 3 (p_3) or 4 (p_4).

To reflect a *high collision probability* scenario, a high initial velocity, small inter vehicular distances and a small distance

⁴Strict inequalities have been avoided wherever possible by adding a small offset and converting them into a non-strict ones.

⁵Our methodology may be extended to an arbitrary large set of vehicles. We limited it to five for computational purpose only.

to potential-collision are configured. We set the initial location of the lead vehicle $p_1(0) = 95.9m$, which is the distance by which at least one DSRC/ITS-G5 safety message may be received with 99.5% probability, derived from [12]⁶. The time headway between vehicles $d_{i,k}$ is chosen between 0.2s (≈ 5 m) and recommended time headway 1.8s [13].

TABLE I
GENERAL VALUES

Symbol	Parameter description	Value
g	gravitational constant	$9.88 m/s^2$
l_v	length of any vehicle	$4 m$
Δt	sampling time	$0.1 s$
N	Sampling horizon	140 instances (14 s)

The location of the potential collision is the intersection, assumed to be the origin (0 in 1D space), and vehicles are moving towards the origin. $p_i^{min} > 0$ ensures vehicles do enter the intersection. $v_i^{min} = 0$ implies vehicles cannot go in reverse direction. Simulations performed in this paper do not require p^{max} and v^{max} . $u^{max} = 0$ guarantees a pure deceleration scenario, and j_i^{min} and j_i^{max} values are capped to -0.25 and $0.25 m/s^3$ respectively. We do not assume any restrictions on the jerk for PPs. Other general parameters used in the simulations can be found in Table I.

For consistent evaluation results, we perform 100 runs for each of the three simulation scenarios, with different values for each vehicle being generated from the above distributions in the input space $(u^{min}, t_{prt}, d_{i,k}, v_i(0), slot_{ego})$ for each run. We can observe that out of 100 runs, if the location of the ego vehicle is left empty (scenario 1), 21 accidents were avoided, whereas if the ego vehicle is present and is a PP (scenario 2) only 1 accident was avoided. This is a straightforward observation from the fact that larger inter vehicular distances reduce the chances of collisions. If $slot_{ego}$ contains an automated vehicle, then the number of collisions avoided increases to 25. This is an 19.04% improvement compared to scenario 1 (4 additional collisions avoided).

For a more detailed investigation, we choose one simulation run out of the 100, where our proposed model effectively avoids collisions in scenario 3, and collisions take place in scenarios 2 and 1. Parameters corresponding to this particular simulation run can be found in Table II. The initial distance between vehicles is $[d_{2,1} \dots d_{5,4}]$ is $[5 \ 25 \ 10 \ 5]$ m.

In scenario 1, as there are multiple consecutive manually driven vehicles, the reaction delay keeps accumulating downstream, and thus vehicles downstream and the first vehicle do not start braking at the same time. This is illustrated on Fig. 4, which shows vehicle 2 starting to brake after vehicle 1 (AP), vehicle 3 does after vehicle 2, so on... Due to this cumulative reaction time, despite the adaptive control from the AP (see Fig. 4), manually driven vehicles collide as shown in Fig. 5.

Scenario 2 has more vehicles in the same space, thus if collisions could not be avoided in scenario 1, collisions cannot

⁶We leave a more detailed investigation of such detection range to future work.

TABLE II
SIMULATION PARAMETER VALUES CORRESPONDING TO A PARTICULAR
RUN IN SIMULATION SET I

Vehicle	1	2	3	4	5
$p_i(0)$ [m]	95.90	104.90	133.90	147.90	156.90
$v_i(0)$ [m/s]	v_p	v_p	$0.98v_p$	$1.01v_p$	v_p
u_i^{min} [m/s ²]	$-0.55g$	$-0.63g$	$-0.68g$	$-0.6g$	$-0.65g$
t_{prt} [s]	–	1.3	1.2	1.4	1.3

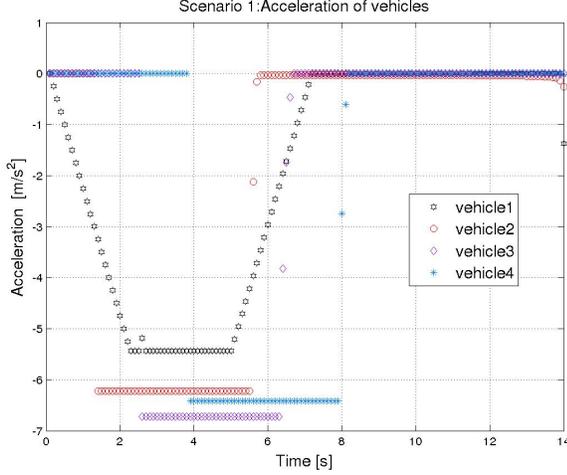


Fig. 4. Scenario 1 - adaptive deceleration of a single AP does not helping in avoiding accidents.

be avoided in scenario 2, which is indeed the case (not shown due to the lack of space).

Scenario 3 has the same density of vehicles as scenario 2, but an AP occupies p_4 instead of a PP or an empty space. We observe that the vehicle 5 in position p_5 avoids collisions unlike in scenarios 2 and 1. The corresponding locations and decelerations are depicted on Fig. 7 and Fig. 6 respectively. This collision avoidance may be explained as follows: (i) the time taken by a PP behind an AP (vehicle 5 behind vehicle 4) to start braking in scenario 3 is lower compared to the one in scenario 1 and 2 (which has a PP behind another PP); (ii) Note that the MPC based model assigns APs control inputs (braking profile) based on the braking of other PPs and APs, to avoid front and rear end collisions. A secondary observation is that the penetration of APs (CACC vehicles) in PP traffic can actually increase traffic density without impacting safety.

B. Simulation set II

To study the impact of a bigger penetration of APs, we consider different number of APs (0,1,2...5) and PPs (5,4,3...0) such that the total number of vehicles n_v is constant. The locations of APs and PPs are random. 100 simulation runs of each of the six combinations are conducted with different values for parameters sampled from the input space (u^{min} , t_{prt} , $d_{i,k}$, $v_i(0)$). The corresponding results are summarized in Table III. Results show that a bigger percentage of APs brings more flexibility to the system to accommodate PPs and compensate for human factors impacting PPs.

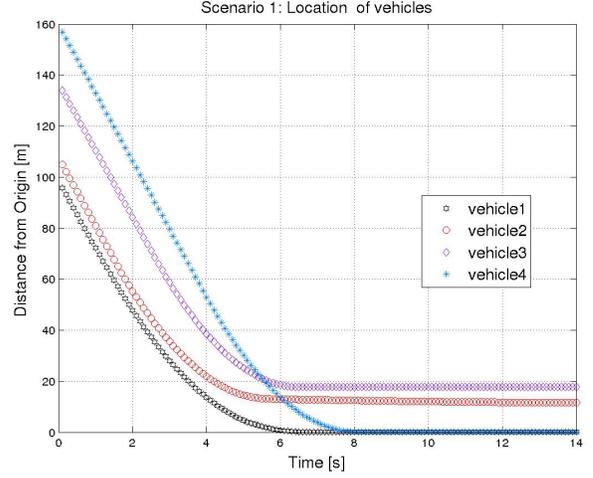


Fig. 5. Scenario 1 - Illustration of collision despite $slot_{ego}$ being left empty (collisions observed by intersecting lines).

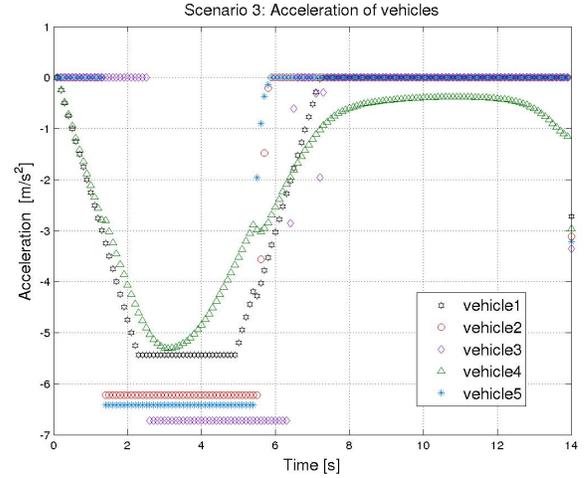


Fig. 6. Scenario 3 - Adaptive braking of two APs (vehicles 1 and 4) in a five vehicle braking scenario helps avoid collisions despite an extra vehicle.

Although scenario 2 from the simulation set I and 40% AP penetration in simulation set II have the same number of APs (2), but the number of collisions avoided are 25 and 11 respectively. This is due to the fact that the position of APs relative to PPs influences the collision avoidance statistics in mixed vehicle scenario. Evenly spread APs between PPs are more efficient in helping collisions compared to them being grouped.

V. CONCLUSIONS

In this work, we investigated how future Intelligent Vehicles (IV) supporting Cooperative Adaptive Cruise Control (CACC) can compensate for human factors affecting manually driven vehicles (MDVs). We formulated a mixed vehicle coordinated traffic scenario and presented a Model Predictive Control (MPC) based controller integrating constraints derived from human factors affecting MDVs. We showed that a gradual

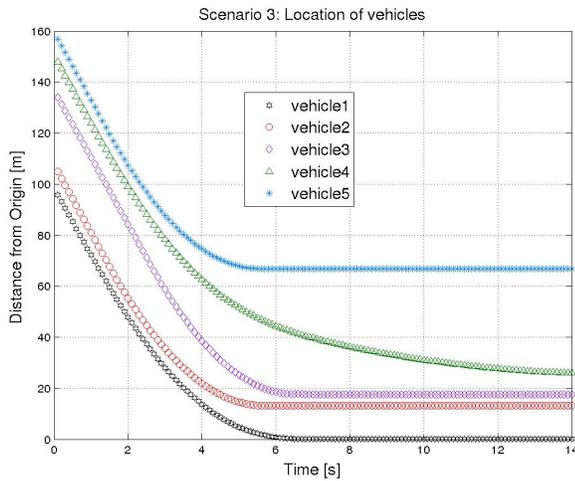


Fig. 7. Scenario 3 - Location of vehicles over time showing no impact, despite an extra vehicle.

TABLE III
SIMULATION SET II RESULTS

Percentage penetration of APs	0	20	40	60	80	100
Collisions Avoided	0	1	11	35	57	61

penetration of CACC vehicles not only reduces collisions induced by human factors, but also increases the traffic density at no impact on traffic safety. Major reasons behind this are the ability of CACC vehicles to: (i) react immediately and synchronously; (ii) adjust controls to avoid collisions at both ends; (iii) intercept the shockwaves created by the propagation of the perception response time through anticipative actions

This study only considered the impact of human factors consisting of perception reaction times of MDVs. It is expected that human drivers feel uncomfortable driving beside IVs. MDV could show unpredictable or antipathetic reactions whereas IVs could try to mimic MDV's driving behavior. In future work, we plan to extend our MPC model by first incorporating other human factors and second accounting for these reactions. We will also extend the scale of our study to evaluate the impact of IVs on a larger scale and in more complex scenarios.

Our study also showed that solving the optimization model and generate control inputs took a few seconds on a 4 core processor at 3.10GHz and 16 GB ram. This delay is a critical limiting factor for real time implementations. In future work, we will develop a decentralized version of our strategy. Addi-

tionally, we will study the impact of imperfect communications and localization, as well as control implementation delays.

ACKNOWLEDGEMENTS

Authors would like to thank Dr. Lara Codeca for her contribution towards this work. Raj Hareesh Patel is a recipient of a PhD Grant from the Graduate School of the University Pierre Marie Curie (UPMC), Paris. EURECOM acknowledges the support of its industrial members, namely, BMW Group, IABG, Monaco Telecom, Orange, SAP, ST Microelectronics and Symantec.

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