Quantifying the impact of connected and autonomous vehicles on traffic efficiency and safety in mixed traffic

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Abstract— **Connected and Autonomous Vehicles (CAVs) are expected to bring major transformations to transport efficiency and safety. Studies show a range of possible impacts, from worse efficiency of CAVs at low penetration rates, to significant improvements in both efficiency and safety at high penetration rates and loads. However, these studies tend to explore efficiency and safety separately, focus on one type of a road network, and include only cars rather than other vehicle types. This paper presents a comprehensive study on impact of CAVs on both efficiency and safety, in three types of networks (urban, national, motorway), simulating different penetration rates of vehicles with multiple levels of automation, using historical traffic data captured on Irish roads. Our study confirms existing results that near-maximum efficiency improvements are observed at relatively low penetration rates, but reveals further insights that the exact penetration ranges between 20% and 40% depending on the network type and traffic conditions. Safety results show a 30% increase of conflicts at lower penetration rates, but 50-80% reduction at higher ones, with consistent improvement for increased penetration. We further show that congestion has a higher impact on conflicts than penetration rates, highlighting the importance of unified evaluation of efficiency and safety.**

I. INTRODUCTION

Wider deployment of Connected and Autonomous Vehicles (CAVs) is expected to bring significant changes to traffic and transportation, ranging from different vehicle ownership and business models (*e.g.*, car-sharing), changes in urban design, travel patterns, traffic congestion and road safety. First real-world tests involving several CAVs confirm the benefits of automated cars on traffic flow [1]. However, evaluation of their full impact on congestion, as well as traffic safety, is currently possible only in carefully designed simulations, aiming to predict the characteristics of large-scale deployment scenarios. Due to the number as well as complexity of factors that will affect future deployments, existing studies generally focus on a subset of the complete picture; for example, only a single type of automation level is evaluated, the impact is evaluated only on one type of a road network, safety and flow are evaluated separately, or simplified assumptions about the demand patterns are made.

To address these shortcomings, in this paper we present a comprehensive microscopic simulation study of CAV impact, performed in SUMO[1], as follows. We evaluate the impact of CAVs in three different settings which represent three main road network types in Ireland: an urban network (consisting of 435 signalized intersections), a 17.1km stretch of national road, and a 7km 4-lane motorway including two major interchanges with junctions to national roads. Further, we evaluate different levels of automation, different rates of penetration and different vehicle types, by including level 2 and level 4 cars and heavy goods vehicles (HGVs), with penetration rates of level 2 vehicles in 0–50% range, and level 4 in 0–20% range. As a result, overall rates of CAV penetration have been evaluated for 2.5%, 7%, 20%, 40%, and 70%. Motivated by previous studies suggesting improvement at 20-30% penetration rate when mixed with Human-driven vehicles (HDVs), we included fine-grained increases at lower penetration rates to investigate short term deployment scenarios and possible drawbacks of early technology adoption. We generate traffic loads based on traffic flow data recorded in Ireland between 2012 and 2019, and for each scenario extract three most critical traffic load types: freeflow, saturated, and congested. Most importantly, we use the same scenarios to investigate the impact of CAVs on efficiency and safety jointly, enabling us to evaluate the impact of efficiency on safety as well (for a range of automation levels, road networks, penetration levels, and traffic loads). We also make our road network models in SUMO, cleaned datasets and full set of results publicly available[2] to serve as basis for potential further investigations by the community.

II. RELATED WORK

As CAV deployment is still at an early stage, research studies utilize microscopic traffic simulation and indicators [9], [10] to evaluate the impact of CAV technologies. A recent extensive survey of CAV simulation [11] highlights that effects of CAVs on traffic flow characteristics and traffic safety have both been investigated in multiple studies, but separately. The authors highlight that less attention is given to broader impacts of CAVs, that could be evaluated by combining metrics (*e.g.* traffic congestion has been shown to have an impact on road safety [12]). The study also highlights that only a few simulations include HGVs and no existing study models multiple levels of automation at the same time. Studies that do model more heterogeneous flows with different types of vehicles [7] or different in-vehicle technologies [5] are more representative of a realistic

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[1]https://sumo.dlr.de/

[2]https://github.com/maxime-gueriau/ITSC2020_CAV_impact.git

TABLE I

SUMMARY OF EXISTING STUDIES ON IMPACT OF CAVS ON TRAFFIC EFFICIENCY AND SAFETY

Reference	Levels of automation	Type of vehicles	Penetration rates (%)	Network type	Network scale	Traffic level(s)	Impact on traffic	Impact on safety
Makridis *et al.* [2]	Level 2 (C-ACC)	Cars	0,25,50,75,100	Highway (ring road)	119 km	1h real data +/- 20%	Fuel consumption, speeds	✗
Guériau *et al.* [3]	Level 2 (C-ACC)	Cars	0,20,40,60,80,100	Highway	10 km	Saturated (2000 veh/h/lane)	Flow, speeds, density	✗
Stanek *et al.* [4]	Level 4 CAV	Cars	0,10,30,50,70,90,100	2 freeway sections	20 miles, 10 miles	AM peak period (calibrated)	Network delay, speeds	✗
Talebpour and Mahmassani [5]	CV, AV level 4	Cars	0,10,25,50,75,90 (mix of HDV, CV and AV)	One-lane highway	infinite length	Platoons with 100, 80, 60, 40, and 20 vehicles	Flow, density	✗
Ye and Yamamoto [6]	Level 2 (C-ACC)	Cars	0,25,50,75,100	2-lane road	10 km	50 veh/km/lane, 100 veh/km/lane	✗	TTC
Morando *et al.* [7]	Level 4 (2 models)	Cars, HGVs (95/5%)	0,25,50,75,100	Signalised intersection, roundabout	1 km	1 h (8-9am)	✗	Conflicts from TTC and PET
Xie *et al.* [8]	Levels 1,2,3,4	Cars	0,20,40,60,80,100	Freeway, CBD, Campus	30×30km, unknown, unknown	3 uniform fixed loads	Travel times	Conflicts from TTC
This paper	Level 2 (C-ACC), Level 4	Cars, HGVs (%real data)	0,2.5,7,20,40,70 (mix of level 2 and 4)	Motorway, National, Urban	7km, 5.3km, 3×3 km	Free flow, saturated, congested	Congestion Index, Travel rate, Total Time Spent	Conflicts from TTC and PET

flow and show reduced CAVs impacts than those making simplifying assumptions.

First field tests with 21 CAVs on a one-lane ring-road [1] show the positive impact that CAVs can have on improving traffic flow, increasing throughput by 14% and reducing fuel consumption by 20–40%. However, when simulation-based studies investigate CAV impact from a long-term perspective, potential improvement seems to be bounded. For instance, [4] shows a 20% average speed improvement at around 60% penetration rate upwards in mixed traffic situations on freeways. Existing simulation studies forecast the adoption of a single type of automation technology at a time, mainly a Cooperative-Adaptive Cruise Control (C-ACC) style of automated control [10], [2], [3] or Road-Side Unit based speed and lane advisory system [3]. Existing work also points out that capturing heterogeneity of behaviours, for instance using a variability of models parameters [3], [10] or different models [4], [2] contributes to more realistic simulations and therefore more accurate impact assessment. The recent work from Xie *et al.* [8] stands out from other related work as it investigates the impact of multiple levels of automated driving in multiple networks. However, this study uses a fixed percentage of one level of automation with an equal share of HDVs and other levels (for instance, 20% level 2 with 5% of HDV, 5% of level 3, etc.). While this ensures heterogeneity in traffic flow, this setting is hard to position within the expected timeline of successive CAV deployments.

A smaller number of studies addresses CAV impact on road safety. The study presented in [7] shows that a reduction in the number of potential conflicts of around 20–60% is expected at 50–100% penetration rate of level 4 automated driving technologies. Presented results also show a slight increase of observed conflicts by around 10% for low penetration rates (25%). The work presented in [8] showed a gradual increase in the number of conflicts when more level 2 automated vehicles are introduced in the simulated network, while level 3 shows no impact and level 4 results in a decrease. A similar study focusing on CAV level 2 [6] showed a gradual reduction of speed variability and a decrease of low time-to-collision values during the introduction of a vehicles equipped with C-ACC.

The summary of these studies on traffic and safety impact is captured in Table I. By reviewing related work we have identified that findings presented in existing studies can be affected by the choice of setups and models. The lack of realistic scenarios seems to be the most limiting factor, and heterogeneity of traffic flow is often restricted to HDVs vs. one level of automation. The work presented in our paper goes a step further, by proposing scenarios that account for mixed levels of automation (level 2 and 4), several types of vehicles (cars and HGVs), different road networks and traffic demand patterns. This paper also investigates the introduction of CAV technologies under different adoption rates and evaluates their potential impact both on traffic and road safety simultaneously. Traffic demand (flow and vehicles types) has been calibrated from real data and adoption scenarios allow to estimate short- to long-term CAV adoption scenarios.

III. METHODOLOGY AND CAV MODELLING

In this section we detail the parameters used to model vehicles and the selection of metrics we use to measure traffic flows and road safety.

A. Automation levels, vehicles modelling, and parameters

In this study, we model level 2 and 4 of automation. Level 2 refers to Advanced Driver Assistance Systems which control the vehicle but requires the driver supervision at all time and level 4 refers to fully automated driving. The choice not to model level 3 automation (conditional automation) is motivated by studies highlighting the potential adverse effect of keeping human in the loop while deploying CAVs [13], [14], which might lead to a bad acceptability of these systems and thus should encourage the adoption of level 4+ automated systems straight from level 2 instead.

Our study relies on microscopic traffic modelling in which the motion of vehicles is a result of the combination of a longitudinal and a lateral model. Longitudinal behaviour (*i.e.* the vehicle acceleration) relies on *car-following model* that can be fine-tuned to reproduce a variability of driving styles or vehicles capabilities (*e.g.* cars and HGVs). Lateral behaviour is computed using a *lane-changing model*, that usually features decisions based on surrounding lanes perception. Again, parameters allow fine-tuning of this behaviour. While these type of models have been shown suitable for reproducing traffic behaviour and flow instabilities [15], literature does not converge on the use of a specific model per vehicle type. In our study, human-driven vehicles (HDVs) use default car-following model of SUMO, which represents level 0 of automation. CAVs level 2 are assumed to be connected through Vehicle-to-Vehicle (V2V) communication and their acceleration relies on an implementation of C-ACC [16]. Finally, we use the Intelligent Driver Model (IDM) for CAVs level 4 as it better mimics the behaviour of an automated system and is more conservative since designed to be collision-free [15].

TABLE II

CAR-FOLLOWING MODELS AND PARAMETERS VALUES

Parameters	**HDV (car)**	**HDV (HGV)**	**CAV level 2 (car)**	**CAV level 2 (HGV)**	**CAV level 4 (car)**	**CAV level 4 (HGV)**
Car-following model	Krauss [17]		C-ACC [16]		IDM [15]	
Speed deviation (%)	0.1	0.1	0.05	0.05	0.05	0.05
Time headway (s)	1.2	1.5	0.8	0.8	0.6	0.6
Min gap (m)	2.5	2.5	1.5	1.5	1	1
Max accel. (m/s^2)	2.5	2.5	1.5	1.5	1	1
Deceleration (m/s^2)	7.5	4	7.5	4	7.5	4
Max decel. (m/s^2)	9	7	9	7	9	7
Imperfection	0.5	0.5	0.05	0.05	0.05	0.05
Lane-changing model	SUMO lane-change model [18]					
Cooperation	0.5	0.5	0.5	0.5	1	1
Anticipation	0.5	0.5	0.5	0.5	1	1

Car-following models and parameters values used in this study are presented in Table II. The choice of parameters was motivated by recent related work: while most of vehicles characteristics (different behaviours of cars and HGVs) rely on SUMO default settings [17], headway and minimum gap values have been modified to match the related work [8], [10]. A driver imperfection factor (between 0 and 1, with 0 denoting perfect driving) has been applied for HDVs. We also assume that CAVs would not have a perfect perception and thus we adjusted this factor to 0.05. Lane-change behaviour also varies depending on the level of automation. For level 2, we assume that driver intervention is required to trigger overtaking manoeuvres and that routing behaviour does not take advantage of V2V communication. Thus, HDVs (level 0 of automation) and CAVs level 2 exhibit similar lane-change behaviour based on the default SUMO lane-change model [18]. For CAVs level 4, we assume that V2V and Infrastructure to Vehicle (I2V) communication combined with higher penetration rate of sensing and localization technologies would contribute to informing vehicles of the network traffic state, which allows CAVs to exhibit more anticipation in their routing strategy, resulting in earlier strategic lane-changes when joining/exiting main sections. In addition, we assume that CAVs level 4 would benefit from their extensive perception to operate more cooperative lane-changes and facilitate slots for surrounding vehicles when possible.

B. Traffic flow indicators

Observing the effects of a growing proportion of CAVs is not straight-forward in large-scale networks since congestion can happen locally and global traffic behaviour results from the interaction of numerous entities. Consequently, we evaluate the impact of CAV at a link level, allowing us to better capture congestion levels and their spreading over the network. Our evaluation relies on the computation of traffic indicators, aggregated for each link. We use three different indicators, as follows: The Congestion Index (CI) [19] gives an estimate of the level of congestion for a section, and can range from 0 (free flow) to 1 (all vehicles are stopped). To observe vehicle speeds, we use the Travel Rate (TR) [20] that gives the rate of motion in minutes per kilometre (min/km), showing an estimation of travel time based on the observed average speed for the studied section. We evaluate the efficiency of traffic through recording the Total Time Spent (TTS) [9] that consists of adding up of all of the individual vehicle travel times on the studied section.

C. CAV safety indicators

To evaluate the impact of CAVs on road safety, we calculate an estimate of the risk of collision between vehicles in the simulation. We record surrogate microscopic traffic safety indicators (also called Surrogate Traffic Measures [21]) which describe metrics computed between two close vehicles. Following a similar methodology as in [7], we identify conflicts between vehicles and we classify them by type of vehicles involved (HDV–HDV, HDV–CAV, CAV–HDV and CAV–CAV conflicts). We selected specific indicators to be representative of the type of conflicts mainly observed on each type of road network. Thus, for both national and motorway scenario, we have selected the widely-used Time-to-collision (TTC) [10] indicator, that is suited for capturing car-following types of conflicts (*i.e.*, potential rear-end collision). For the urban network, we selected the Post-Encroachment

Time (PET) [9], that is more appropriate for intersecting conflicts [10] (*e.g.*, potential transversal collision), which is motivated by the high number of (signalised or not) intersections in Dublin. A conflict is detected when the value of an indicator is below a pre-defined threshold [7], and this methodology has been shown to result in similar locations on simulated and real networks [22]. Similarly to [7] and to account for the different capabilities of CAVs *vs.* HDVs, we selected these thresholds as follows: for national and motorway 1.5s TTC for HDV–* and 0.75s TTC for CAV–* conflicts, and in the urban network 0.75s PET for all types of conflicts (as they mostly occur within junctions).

IV. Evaluation Scenarios

In this section we present the scenarios in which we evaluate CAV effects, detailing the evaluated CAV penetration rates, road networks, and traffic demand levels.

CAV deployment scenarios: Table III presents the deployments scenarios that were simulated to investigate the gradual introduction of CAVs on the road networks.

TABLE III
Vehicle shares in evaluated CAV adoption scenarios

Scenario	HDV	CAV level 2	CAV level 4	All CAV
A	100%	0%	0%	0%
B	97.5%	2.5%	0%	2.5%
C	93%	5%	2%	7%
D	80%	15%	5%	20%
E	60%	30%	10%	40%
F	30%	50%	20%	70%

Scenario A has no CAVs, *i.e.* it simulates 100% HDV traffic, and allows us to observe the current baseline traffic behaviour. Other scenarios have been designed to first account for low penetration rates (short-term deployment) up to medium and large scale deployments that would generate highly mixed traffic (for instance, scenario E consists of 60% HDVs and 40% CAVs level 2 and level 4).

Road networks: CAV impact on safety and traffic is evaluated in multiple networks that were selected to obtain a wide range of driving situations and are representative of types of networks CAVs will encounter. We modelled three settings that represent three main network types in Ireland: (i) urban network, covering 5km×3.5km of the Dublin city centre area consisting of 435 signalized intersections, (ii) national road, a 3-lane/two-way road (N7) of 17.1km length with 11 on- and off-ramps each way, and (iii) a 7km 4-lane motorway stretch (M50) including two major interchanges with junctions to national roads (N7 and N9).

Traffic loads: The effect of CAV introduction was also studied for 3 different levels of traffic demand. Demand patterns and volumes have been generated from real data: we averaged several months of data excluding holidays and weekends to create a typical workday traffic. For the motorway and national networks, traffic demand was generated from loop sensors data from the open dataset made available by Transport Infrastructure Ireland[3] that covers the Irish motorways and national roads and includes 5 minute aggregated traffic flows per lane and direction for several years up to 2019. For the urban network, we use Dublin SCATS dataset[4]. SCATS is an adaptive traffic light control system deployed in Dublin, and the dataset consists of vehicle counts every 6 minutes at 480 locations in the city center. Locations of SCATS sensors used in our simulation are shown in Figure 1 (note that a single dot represents multiple sensors, as each junction has a sensor per lane per approach per direction). Similarly to motorway and urban scenarios, we used data from several months (January to April 2012) and averaged workdays to create a typical traffic pattern.

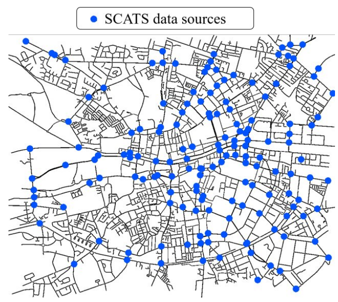

Fig. 1. Location of SCATS sensors used to generate traffic demand in the urban network model

Following the analysis of data, for each network, we selected a time of the day to represent each of three sets of traffic conditions: free flow situation (generally early morning), a saturated traffic situation (traffic level is high and congestion starts to appear) and a congested traffic state (reflecting the highest traffic demand situation observed in the simulation and data). Specific hours and number of vehicles for these conditions have been listed in Table IV.

TABLE IV
Traffic demand periods (vehicles number) for each network

Network	Free flow	Saturated	Congested
Urban	4-5am (3,179)	8-9am (27,167)	5-6pm (27,702)
National	4-5am (1,236)	5-6pm (12,191)	7-8am (12,769)
Motorway	1-2pm (20,822)	3-4pm (23,508)	7-8am (25,316)

For reproducibility and to allow other research to compare to our work or expand it, we make all scenarios presented in this paper publicly available[5].

V. Results and Analysis

In this section we present the impact of CAVs on traffic flow and safety, as observed in individual scenarios, followed by the overall joint analysis of the findings. For each scenario, due to space restrictions, we show only one time

[3] `https://www.nratrafficdata.ie/`
[4] `https://data.gov.ie/dataset/traffic-volumes`
[5] `https://github.com/maxime-gueriau/ITSC2020_CAV_impact.git`

period (generally highly congested one, as CAV effects are the most observable there), but we make the full sets of results available online[5]. Similarly, for traffic flow indicators, we only show Travel Rate results, which are representative of the overall patterns, and make the full results for Congestion Index and Total Time Spent available online[5].

A. Impact on traffic flow

Motorway scenario (M50): The motorway network model focuses on the busiest road in Ireland, where very high level of congestion can be observed during the morning peak hour (7-8am). Figure 2 depicts vehicles speeds aggregated per section and presented as Travel Rates in min/km for each deployment scenario.

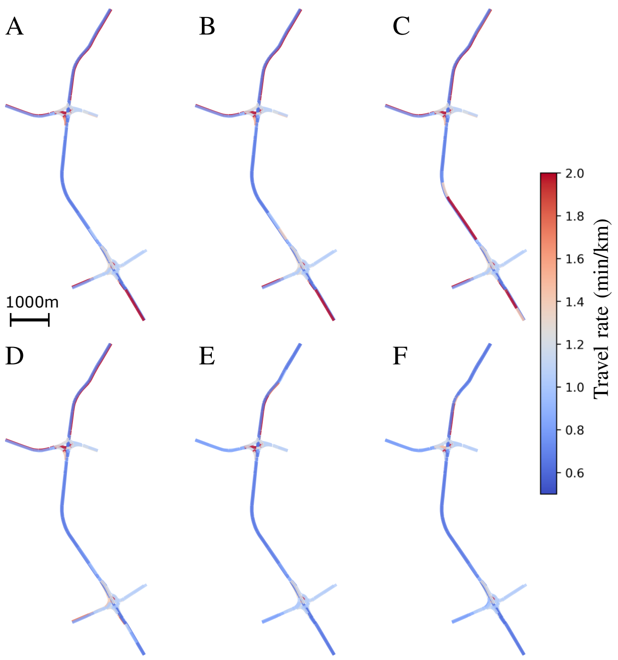

Fig. 2. Impact of CAV depoyment scenarios on traffic (Travel Rate in min/km) in the motorway case study for the morning peak hour (7-8am)

In the baseline scenario A, congestion reaches its maximum level in a vast part of the network, mostly around the north junction but also before the south junction for northbound traffic, due to high level of vehicles entering and leaving the network. The observed effect of CAV deployment is gradual, but at small penetration rates (2.5% and 7%, *i.e.* scenarios B and C) they worsen traffic conditions. This is particularly visible for southbound traffic accumulating to exit the south junction in scenario C. Higher percentages of CAVs (20% and higher, scenarios D to F) show a drastic improvement of traffic flow compared to scenarios A, B, and C, achieving a smoother traffic with more homogeneous speeds and therefore lower travel rates. The effect at the north junction is visible from 40% of CAVs (scenario E) while the south junction is cleared from congestion earlier, starting from scenario D (20%). These results confirm the expected positive long-term impact of CAVs, but also show worsening in the early deployment stages (B and C).

National road network (N7): The national road network model is characterized by high speeds and traffic volumes. As we can observe from Figure 3, several exit and entry points cause instabilities and are source of traffic congestion (this is clearly visible from scenario A).

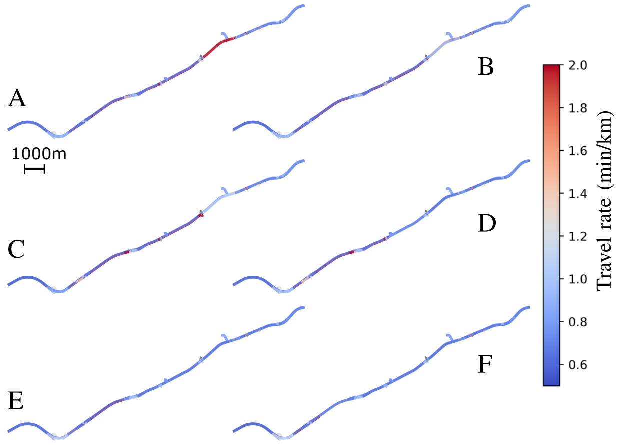

Fig. 3. Impact of CAV deployment scenarios on traffic (Travel Rate in min/km) in the national road case study for the morning peak hour (7-8am)

The effects of CAVs in these scenarios is gradual and follows a simple trend: more CAVs results in less congestion and lower travel rates (resulting from higher speeds). This impact is however not linear; improvements are quite significant up to scenario D (20% of CAVs), and then slow down (40% and up, scenarios E and F). However, even in scenario F. congestion is not fully smoothed out, which suggests that the benefits of CAVs on traffic might be bounded by the network capacity.

Dublin city centre: During the saturated period (evening peak hour, 5-6pm) the impact of CAVs is clearly visible on the urban network, as shown in Figure 4. Scenario A shows that high traffic volumes travel through Dublin on a typical workday. The introduction of level 2 and then level 4 CAVs impacts traffic following two main trends. Firstly, low penetration rates of CAVs create more congestion (scenarios B and C) resulting in higher average travel rates. This effect is reversed by the gradual deployment of level 4 technologies, and a positive impact on traffic flow can be observed from 20% of CAVs (scenarios D to F). The improvement appears to be bounded in the centre of the network at higher penetration rates, but north-east travel rates further decrease.

B. Impact on road safety

Motorway scenario (M50): Figure 5 shows the detected conflicts in the motorway network. We observe that the conflicts are located close to interchanges, *i.e.* where high variability of speeds can be observed, usually caused by congestion propagating from exit or entry ramps and backward up to the main sections. Late lane changes have also been observed to cause more conflicts in our scenarios, which tend to be smoothed out by the increased anticipation we can expect from highly automated vehicles. Our study suggests

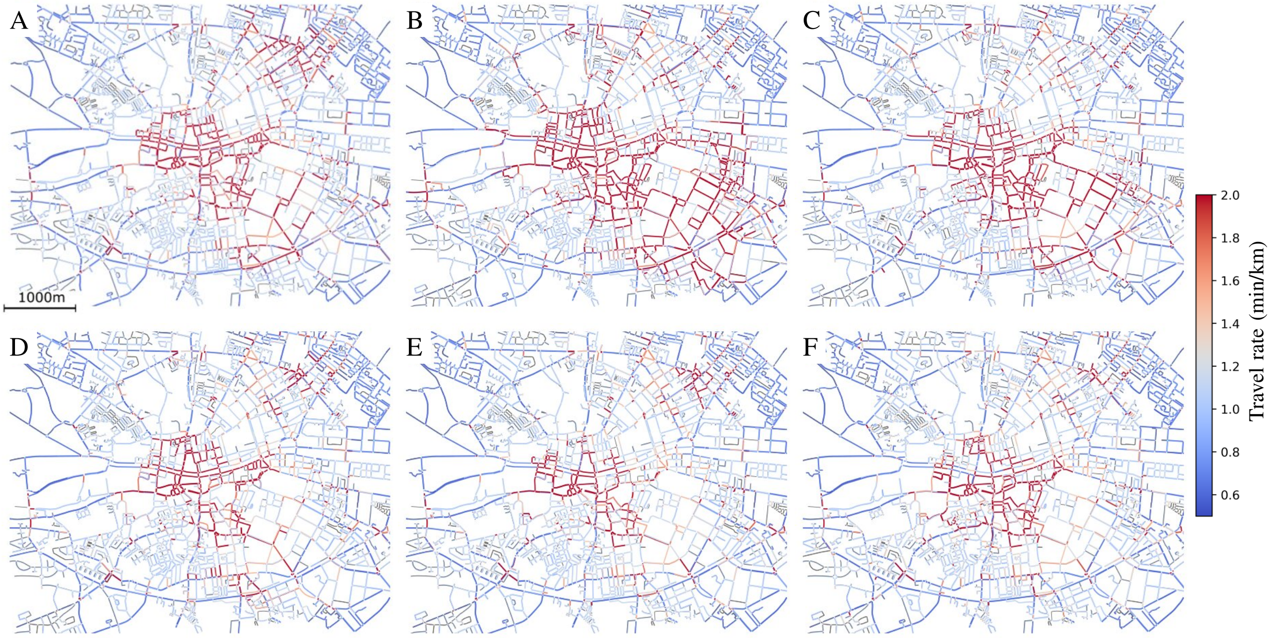

Fig. 4. Impact of CAV deployment scenarios on traffic (Travel Rate in min/km) in Dublin city centre for the afternoon peak hour (5-6pm)

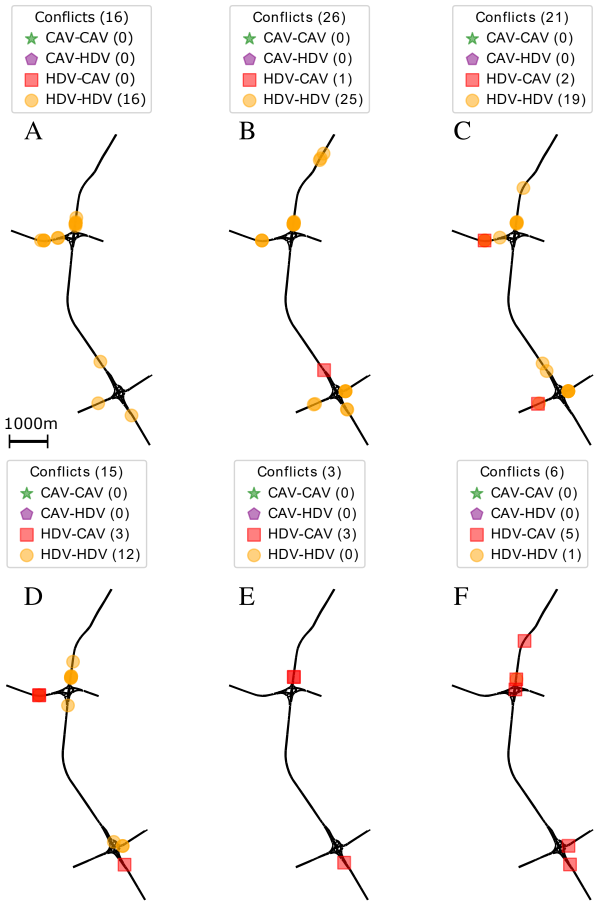

Fig. 5. Recorded conflicts in the motorway case study in the morning peak hour (7-8am)

that the introduction of level 2 automation will generate more conflicting situations (2.5% to 7% penetration rates, scenarios B and C). Further deployment of level 4 automation (20% and up, scenarios D to F) is shown to reduce the number of detected conflicts, confirming the positive impact of highly automated CAVs on safety. An interesting finding is that the initial increase in conflict numbers is mostly between non-automated vehicles (even though their relative numbers are reduced as the percentage of CAVs increases), and only a small proportion of conflicts results from HDV–CAV interactions.

National road network (N7): In the national road network, only a few conflicts have been observed, as presented in Figure 6. The results in terms of detected conflicts suggest that the interaction in highly mixed traffic (small penetration rates – 2.5% and 7% – scenarios B and C) would lead to a slight conflict increase, and this trend is then reversed by the introduction of higher levels of automation (scenarios D to F). In this scenario, solely the interaction between non-automated vehicles seems to be impacted and the pattern is consistent with the pattern of impact on traffic, as observed in previous section.

Dublin city centre: The Dublin city centre network model features 435 intersections with very complex junction layout and actuated traffic light controllers. This makes it particularly challenging for CAVs to drive through, as the number of interactions with other vehicles is significantly increased. Figure 7 shows the number and location of conflicts detected from PETs during the morning peak hour (8 to 9am).

With the first introduction of CAVs, a slight increase of conflicts occurs (scenario B with results in 8 additional conflicts). From that point on, first a slight reduction in conflicts is observed (at 7% to 20% penetration rates, scenarios C and

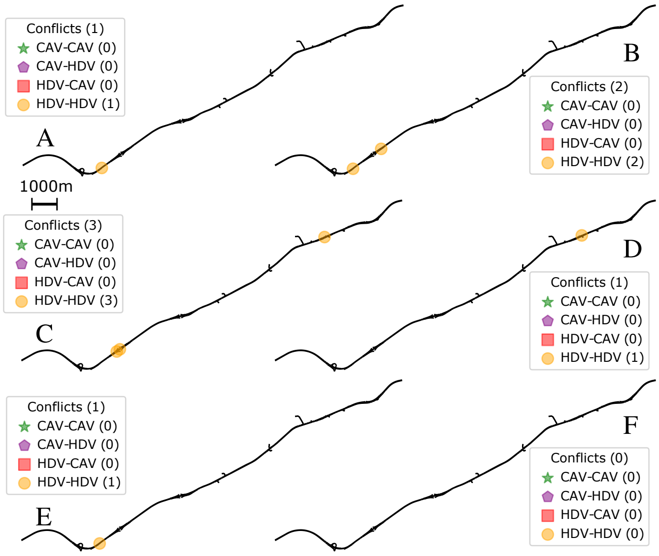

Fig. 6. Recorded conflicts in the national road case study during the morning peak hour (7-8am)

D) and then their drastic reduction (40% to 70%, scenarios E and F). The best improvement is observed with higher number of CAVs (70%, scenario F) and enables a 58% reduction of the number of conflicts compared to the baseline scenario A. Conflicts originating from HDVs are the most observed, but there is also an increase of HDVs that enter in conflict with CAVs, suggesting that CAVs level 2 impact HDV traffic negatively during early deployment (scenario B). These results suggest that CAV might cause adverse effect for small shares of CAVs vs. HDVs and that a wider deployment will be required to achieve safer traffic in cities.

C. *Findings and analysis*

The observed impact of CAVs in our study is consistent with recent findings from the literature [11], [5]. While results differ in each network, some global trends can be extracted.

Our major finding is that the benefits of the introduction of CAVs, both on traffic efficiency but even more so on road safety, would be gradual but not linear. In our study, we captured the long-term positive impact of CAVs, expected to reduce traffic congestion drastically, even in mixed flow situations. The effect on traffic is more visible for high-speed networks and is diminished for the urban network.

The second finding points out the shorter-term scenarios, where a low percentage of CAVs will be mixed with a high number of HDVs. In this context, the benefits of CAVs are, at best, barely visible from the simulation results, and in some cases, we observed more traffic congestion due to the introduction of CAVs. This suggests that the transition phase would be critical for the success of CAV deployment, and that both researchers and decision-makers should primarily focus on this period. CAVs generated only a few additional conflicts and only in the city center network and majority of observed conflicts originated from HDVs. This suggests that the interaction of HDVs with CAVs is the main concern to ensure that safety can be guaranteed, especially at early stage of CAV deployment. Additional training for human drivers to learn how to react to CAVs could be a way to reduce the associated risks.

Comparing safety and traffic results, we can also conclude that in high speed networks (motorway and national network), locations of most conflicts are linked with locations of congestion on the network (this is particularly visible from Figures 2 and 5). However, in the case of urban traffic (Figures 4 and 7, only few among most-used intersections seems to be linked to a higher number of detected conflicts. These observations on interactions between traffic and safety impact of CAVs highlight the need to evaluate impacts of CAVs on both, to observe in which set of conditions they follow the same trends and in which ones does the impact differ.

VI. CONCLUSIONS AND FUTURE WORK

This paper presents a comprehensive microsimulation study evaluating the impact of various penetration levels of CAVs with various levels of automation on traffic flows and safety, on 3 different road network types, for 3 different sets of traffic conditions each.

The study resulted in several main findings. Firstly, we identified that the effects of CAVs on safety and efficiency would be gradual but not linear. We observed that a penetration rate of around 20% to 40% (depending on the type of network and traffic conditions) could be sufficient to reach near-maximum benefits. In addition, the motorway scenario seemed to be the most positively impacted, as the behaviour of CAVs is less constrained by the network. Secondly, results tend to show that short-term deployment scenarios (*i.e.*, with low CAV penetration rates could be of main concern as we observed an increase in both traffic congestion and conflicting situations in some regions of the networks. This confirms that this period would be critical for the success of CAV deployment and that research should primarily focus on improving interaction between human-driven and autonomous cars. Finally, since our study allows to compare safety and traffic efficiency impacts, results tend to show that limiting congestion can be linked to a reduction of conflicting situations, but at the same time safety concerns can mainly arise from the characteristics of the network which CAVs alone can not address. Connected infrastructure might be one of the answers for this problem, but further research needs to be done in evaluating how current infrastructure is suitable for CAVs or will need to be adapted.

While this paper presents a quite comprehensive study, the work relies on some assumptions that might affect results for the long-term scenarios. One important factor is the expected reliability of CAV technologies: while we modelled a failure rate for sensors that probably generated additional conflicts in the simulation, further development of microscopic models are expected to better capture real CAV sensing or decision limits (*e.g.*, computer vision classification errors). Another important factor seems to be the evolution of

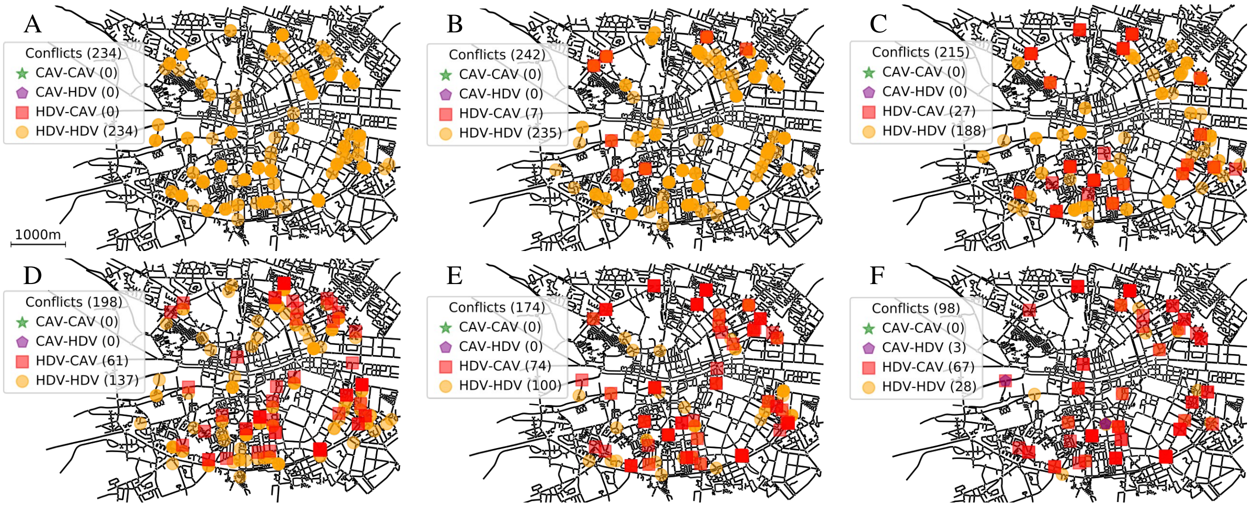

Fig. 7. Recorded conflicts in the urban case study in the morning (8-9am)

car ownership that should be impacted by CAV deployment. This is particularly sensitive for urban networks, where we assumed that private CAVs would replace privately-owned HDVs. Therefore, an interesting future work direction would be to investigate the impact of CAVs as used in a shared autonomous mobility-on-demand fleet [23], and to study how the mix of transportation modes (private CAVs, shared autonomous taxis, autonomous public transportation, etc.) would affect CAV impact.

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