Cooperative Connected and Automated Mobility in a Roundabout

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Abstract

Roundabouts are intersections at which automated cars seem currently not performing sufficiently well. Actually, sometimes, they get stuck and the traffic flow is seriously reduced. To overcome this problem a V2N-N2V (vehicle-to-network-network-to-vehicle) communication scheme is proposed. Cars communicate via 5G with an edge computer. A cooperative machine-learning algorithm orchestrates the traffic. Automated cars are instructed to accelerate or decelerate with the triple aim of improving the traffic flow into the roundabout, keeping safety constraints, and providing comfort for passengers on board of automated vehicles. In the roundabout, both automated cars and human-driven cars run. The roundabout scenario has been simulated by SUMO. Additionally, the scenario has been reconstructed into a dynamic driving simulator, with a real human driver in a virtual reality environment. The aim was to check the human perception of traffic flow, driving safety and driving comfort. The hardware for letting cars communicate via 5G (telematic box) has been developed and tested in the virtual reality environment of the dynamic driving simulator. Human drivers require relatively low jerk but feel safe and comfortable driving with the automated cars instructed by the cooperative machine learning algorithm.

Introduction

Roundabouts have become increasingly popular in recent years as a traffic control measure that offers several benefits over traditional signalized intersections. They have been shown to improve traffic flow, reduce fuel consumption and car accidents in case of moderate traffic [1, 2]. However, the increasing use of automated vehicles has raised new challenges for roundabout design and operation. In particular, current automated vehicles struggle to navigate roundabouts efficiently [3]. On the other hand, the correct introduction of Cooperative, Connected and Automated Vehicles (CCAVs) can boost the roundabout key performance indicators, since they can be aware of traffic conditions in real-time and analyze them, and pursue cooperative objectives, such as global fuel-saving [4, 5]. To address this issue, this paper proposes a novel Vehicle-to-Network-Network-to-Vehicle (V2N-N2V) communication scheme, which makes use of both Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) protocols. Furthermore, this communication scheme, as well as proving to be an effective solution for traffic management in complex networks such as the roundabout, allows to reduce the operation and maintenance costs for both the vehicle and the infrastructure. A cooperative Deep Reinforcement Learning (DRL) policy is used to orchestrate the traffic into the roundabout, providing instructions to CCAVs on when to accelerate or decelerate and, therefore, acting as a traffic orchestrator. Proximal Policy Optimization (PPO) is used to update policy weights during the iterations. The policy aims to improve traffic flow, maintain safety constraints, and provide driving comfort for passengers on board of CCAVs. The proposed approach is developed within the European project AI@EDGE [6], which leverages the latest advancements in wireless communication technology to enable real-time communication and support a diverse range of AI-enabled applications, such as Cooperative, Connected and Automated Mobility (CCAM) [7]. The V2N-N2V protocol is enabled by a 5G mobile network capable of ensuring high-speed data transfer and low-latency communication, which is essential for CCAVs in real-time traffic conditions. To evaluate the proposed approach, the roundabout scenario has been simulated using SUMO (Simulator of Urban MObility) [8], a Microscopic Traffic Simulator (MTS). Additionally, the scenario has been reconstructed in VI-WorldSim [9], a graphical simulator, coupled with the dynamic driving simulator at the DriSMi Laboratory of Politecnico di Milano [10], which is crucial to account for a human-in-the-loop. The dynamic driving simulator also permits the study of human perception in a policy-driven vehicle in perfect safety, thus being able to truly optimize CCAVs from the perspective of driving comfort. The combination, albeit complex, of these three simulators resulted in a Digital Twin of the real network, capable of returning reliable outcomes. The aim of the research was to assess the human perception of traffic flow, safety, and driving comfort when navigating in a network with a mixed traffic situation, in which both CCAVs and Human-Driven Vehicles (HDs) are present. These latters are driven using a car-following model, namely an Intelligent Driver Model (IDM), whose parameters have been obtained by calibrating the traffic in the real roundabout. The resulting simulation scenario has been tested with a panel of drivers to assess both qualitatively and quantitatively the DRL policy's ability to drive in the roundabout.

The paper is structured as follows. At first, the simulation environment is outlined considering the specific roundabout chosen and the communication scheme between vehicles and the three simulators employed. Secondly, the dynamic driving simulator and the digital infrastructure are described. Then, the policy is presented, considering the PPO algorithm and the comfort optimization using a *Replay* scenario. Finally, experimental tests and results are reported.

Simulation environment

The first step of the study coincides with the definition of the simulation environment characteristics and the communication scheme between the vehicles present inside the road network. These two features are required to build all the simulation architecture and understand which software to adopt.

The roundabout

The reference scenario for the simulations is a four-leg single-lane mini-roundabout, which is based on an actual roundabout located in Milan. This roundabout has been chosen since it represents a common roundabout in European urban areas [11] and shows medium-high traffic, thus being a challenging simulation environment for CCAVs and yielding results of general significance. The intersection has been geometrically reproduced in SUMO and VI-WorldSim and the networks obtained have been aligned so that they can be used simultaneously without applying any geometric transformation. In Fig. 1 it is possible to see the real roundabout and the two networks built.

a) Roundabout in Milan b) VI-WorldSim network c) SUMO network

Figure 1. Reference scenario for the simulation. a) shows the real roundabout in Milan, b) and c) the two networks built in VI-WorldSim and SUMO, respectively.

While replicating the roundabout geometry, the human-driven vehicles have been measured and reproduced using an Intelligent Driver Model (IDM). Specifically, an experimental calibration of the scenario was undertaken to validate the accuracy of the roundabout model in comparison to data obtained from the real-world roundabout. Firstly, measurements were taken for the maximum queue length, upstream and downstream flows for each leg, considering road vehicles, pedestrians, and bicycles on the actual roundabout. This process was repeated for six consecutive time slots, each lasting 10 minutes. From this dataset, the Origin/Destination (O/D) matrix of the roundabout has been built and employed for the subsequent calibration of the model. A calibration procedure has been implemented in SUMO by comparing the outputs of the simulation with the acquired data while varying the most relevant parameters of the IDM driver model. At the end of the calibration, the set of parameters minimizing the difference between the simulated and measured data has been identified.

Communication scheme

Two different types of communication must be outlined and developed. The first communication scheme refers to the logic implemented between all CCAVs to exchange data and let the DRL policy make decisions during the simulation. The second one is related to the simulators used and the implementation of their connection, needed to ensure the correct flow of data during the simulation.

Vehicles communication

CCAVs exploit a specific configuration scheme called Vehicle-to-Network-Network-to-Vehicle (V2N-N2V). This scheme leverages both Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) protocols, enabling vehicles to exchange information between them and with a piece of digital infrastructure, the MEC/Edge node. It contains the Artificial Intelligence Framework (AIF) in which the policy resides and acts as a regulator of the traffic entering the intersection. The scenario considers a mixed traffic situation in which both CCAVs and human-driven vehicles are present. 20% and 80% of CCAVs are considered as market penetration rates to study their effect in the intersection. Specifically, three types of vehicles are present:

1. CCAVs driven by the DRL policy hosted in the AIF. They communicate with the infrastructure, exchanging information such as position and speed with other vehicles.
2. Simulated human-driven vehicles controlled by a car-following model, specifically an IDM.
3. The ego-vehicle driven by a real human driver in the dynamic driving simulator. The vehicle's cockpit is equipped with a telematic box that reads data from the ego-vehicle and transmits it to a 5G radio platform connected to the digital infrastructure, with an actual communication delay.

The digital infrastructure is installed ideally in the centre of the roundabout and receives data from all the vehicles involved in the scenario, i.e., both conventional and automated ones. It sends via 5G to the automated vehicles the instructions to accelerate or to brake. By hypothesis, the human-driven vehicles just send data to the network but they do not receive any instruction to control their respective accelerations. This can be implemented in a real scenario by mounting sensors able to retrieve data from HDs unable to send their information. The ego-vehicle allows to consider a human-in-the-loop. This is trivial to analyse the interaction between automated vehicles and real non-simulated ones.

Simulators communication

The simulation considers three different simulators. A Microscopic Traffic Simulator (MTS) is used to analyse vehicle interaction in the network implemented and drive human-driven vehicles using an IDM. To account also for the human-in-the-loop, computer experiments with SUMO had to be coupled with a dynamic driving simulator and the VI-WorldSim graphical environment. During the simulation, these three entities must communicate to correctly visualize all vehicles, apply policy actions, and retrieve vehicles' responses. Specifically, a Transmission Control Protocol (TCP) is used to obtain data from all vehicles in the SUMO simulation, except for the ego-vehicle, and manipulate them to consider the VI-WorldSim different references. Thereafter, a User Datagram Protocol (UDP) is employed to send this information to the dynamic driving simulator and display vehicles in the VI-WorldSim network. Finally, again through a UDP protocol, the ego-vehicle's new position and speed is retrieved from VI-WorldSim and sent, using TCP, to SUMO to correctly move the vehicle driven by the human-in-the-loop. This communication architecture ensures a perfect replication of the real scenario, in which automated vehicles are driven by a DRL policy, human-driven vehicles reproduce a real behaviour employing an IDM and a real human driver interacts in the virtual environment. Complex as it is, such a scheme makes it possible to develop a functioning Digital Twin [12, 13], which is necessary to obtain reliable results crucial to the development of this technology.

Dynamic Driving Simulator

The tests were conducted at the DriSMi Laboratory of Politecnico di Milano, which is equipped with a high-fidelity cable-driven driving simulator. The simulator features a multi-stage system with redundant degrees of freedom and very low latency, providing realistic motion. The cockpit is equipped with active seat belts and brakes, ensuring maximum safety during the tests. To reproduce Noise and Vibration Harshness (NVH) frequencies, eight shakers are used. The driving simulator is depicted in Fig.2, and its performance is summarized in Table 1. For more information on the driving simulator, please refer to [14].

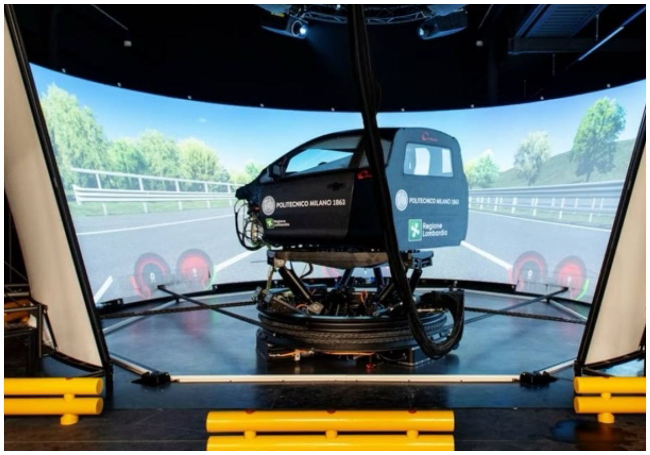

Figure 2. Dynamic Driving Simulator at DriSMi Laboratory of Politecnico di Milan

Table 1. Dynamic driving simulator main properties.

Physical quantity	Values
Longitudinal acceleration of the base	1.5 g
Lateral acceleration of the base	1.5 g
Vertical acceleration of the cockpit	2.5 g
Longitudinal travel	4.2 m
Lateral travel	4.2 m
Vertical travel	± 298 mm
Yaw angle	± 62°
Roll angle	± 15°
Pitch angle	± 15°

Digital Infrastructure

The reference scenario described is part of the use case #1 of the AI@EDGE project. AI@EDGE aims to realize a connect-compute platform for creating resilient and secure end-to-end slices [15]. Within AI@EDGE broad system architecture, there is a layer, called "network and service automation platform". This platform automates the management of various orchestrators, provides non-real-time intelligence, and ensures the low latency required for the Artificial Intelligence Framework (AIF). The connect-compute platform contains the digital infrastructure to run the mobile Edge computing applications and represents one of the most important innovations of the AI@EDGE project. In particular, this platform is used to implement the innovative communication protocol previously described, namely V2N-N2V. All vehicles are connected to the cloud via a 5G connection. A Multi-access Edge Computing (MEC) server collects all the provided information and runs the DRL policy. The Edge communicates with the cloud in which all data are stored, extending the capabilities of cloud computing powered by 5G. Consequently, the user is brought closer to the edge of the digital infrastructure.

DRL policy

Autonomous Vehicles (AVs) are guided by a Deep Reinforcement Learning (DRL) policy that uses the Proximal Policy Optimization (PPO) [16] method to learn policy parameters. PPO is an algorithm based on the Trust Region Policy Optimization (TRPO) algorithm [17] but with improved flexibility and computational complexity. Both PPO and TRPO optimize policies efficiently by iteratively adjusting their parameters while maintaining stability during learning. PPO uses a dual-step process of policy evaluation and policy improvement. During policy evaluation, data is gathered by executing the current policy within the environment, and advantages are computed to measure how favourable the chosen actions are relative to expected outcomes. In this regard, it is possible to define:

- A value function $V_{\pi\theta}$ associated with the policy π, that represents the expectation for a generic state of the environment *s*.
- An action-value function $Q_{\pi\theta}(s,a)$, which indicates the expected cumulative discounted rewards obtained by following policy π over an infinite horizon, starting from state *s* and performing as a first action a.

This results in the following definition of advantages over iterations.

$$A_{\pi\theta}(s,a) = Q_{\pi\theta}(s,a) - V_{\pi\theta}(s)$$

Policy improvement is performed through several epochs of optimization, where PPO computes surrogate objectives that quantify the change in the policy's performance concerning the previously considered set of policy parameters. These surrogate objectives facilitate the optimization of the policy in a manner that promotes positive action shifts while limiting the extent of these updates to maintain stability during learning. The objective of the DRL policy is to improve traffic flow and minimize fuel consumption while ensuring safety and driving comfort for human drivers in the network. Furthermore, cooperative behaviour is obtained during the training phase by giving positive rewards if the policy improves the state of all the vehicles involved and not only their own. To evaluate the efficacy of the learned policy, simulation data is collected and analyzed for each vehicle entering and exiting the circulatory roadway. From the simulation, all vehicle data, such as fuel consumption, pollutants, and time intervals, are retrieved.

Comfort analysis

The dynamic driving simulator allows to deeply evaluate the comfort perceived by a real human passenger in a vehicle driven by the policy. This can be done by considering a specific test called *Replay*. A VI-CarRealTime driver is used to replicate a CCAV's position and speed over time. The result is used to move the dynamic driving simulator within which there is a human passenger, yielding important information on perceived driving comfort. Initially, the policy was trained without considering any limit on accelerations and jerks in the lateral direction. The result of this training is a policy which can optimize the traffic in terms of fuel consumption and traffic flow, but due to high lateral accelerations and jerks, could not be used in a real environment. Fig. 3 reports the lateral and longitudinal accelerations during a generic simulation.

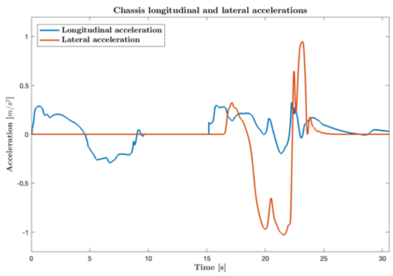

Figure 3. Lateral and longitudinal accelerations of a CCAV during a generic simulation.

As can be seen, the absolute lateral acceleration value becomes higher than 1g, making the vehicle greatly uncomfortable. Longitudinal accelerations are coherent with the limit imposed by the IDM model. Consequently, a second policy has been trained considering also limits on jerks and accelerations obtained from experimental tests [18]. The result of this implementation is presented in Fig. 4.

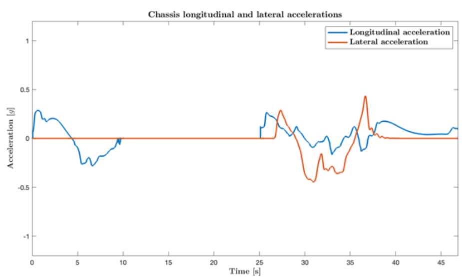

Figure 4. Lateral and longitudinal accelerations of a CCAV during a generic simulation, considering limits on jerks and acceleration in the training process.

The simulation lasted longer since the vehicle reached lower speed values. This second policy reaches absolute lateral acceleration values below 0.5g and also satisfies the limits on jerks. Passengers tested this solution and rated it as satisfactory considering driving comfort, thus obtaining CCAVs fulfilling accelerations and jerks requirements and being a valid daily alternative in a real-world application.

Experimental Tests

Some experimental tests have been conducted to validate the digital infrastructure architecture and the DRL policy. A panel of drivers has been asked to drive in the reference roundabout scenario. The panel of participants chosen for the experimental tests consisted of ten drivers without prior subject experience with driving simulators. The panel included 5 females and 5 males, aged between 22 and 33, with driving experience ranging from 1 to 15 years. At the conclusion of each test, the drivers' perceptions were gathered. Following the test, each participant was requested to complete a form aimed at gauging their preferences regarding the proportion of CCAVs in the network, with respect to traffic flow, safety, and general preference. It should be noted that, due to the limited number of participants, these findings are preliminary, and a larger group of drivers should be considered to obtain more accurate information. The results of the preliminary tests are presented in Tables 2, 3, 4, 5 and 6. Specifically, Tables 2, 3 and 4 report the qualitative results derived from participants' responses, while Table 5 and Table 6 show the quantitative results obtained by evaluating the policy's effectiveness in relation to traffic flow and fuel consumption.

Table 2. Answers to the first question of the survey

Regarding traffic flow, which of the following statements do you agree with the most?	Number of answers
Traffic with 20% of CCAVs was definitely smoother	1
Traffic with 20% of CCAVs was partially smoother	3
Traffic with 20% of CCAVs was partially less smooth	4
Traffic with 20% of CCAVs was definitely less smooth	1
I did not perceive differences	1

Table 3. Answers to the second question of the survey

Regarding safety perception, which of the following statements do you agree with the most?	Number of answers
Traffic with 20% of CCAVs was definitely safer	0
Traffic with 20% of CCAVs was partially safer	2
Traffic with 20% of CCAVs was partially less safe	2
Traffic with 20% of CCAVs was definitely less safe	6
I did not perceive differences	0

Table 4. Answers to the third question of the survey

Globally, which of the two scenarios did you prefer?	Number of
I definitely preferred the scenario with 20% CCAVs	0
I partially preferred the scenario with 20% CCAVs	3
I partially preferred the scenario with 80% CCAVs	3
I definitely preferred the scenario with 80% CCAVs	4
I cannot say which scenario I preferred	0

Table 5. Normalized consumption and emission scores given a penetration rate of CCAVs, considering a simulation of 3600 seconds. The worst-performing and best-performing vehicles are used as normalising factors, generating a score between 0, lower fuel consumption and 1, worst performance, for each vehicle.

% CCAVs	CCAV		Human-driven vehicles		#CCAV	#HDs
	Consumption	Emission	Consumption	Emission		
0	–	–	0.74	0.69	0	1540
20	0.61	0.56	0.64	0.58	308	1232
80	0.46	0.38	0.49	0.44	1232	308
100	0.43	0.36	–	–	1540	0

Table 6. Crossing time, defined as the time interval between departure and arrival for every vehicle, and the number of vehicles that completed their path as a function of the percentage of CCAVs, considering a simulation of 100 seconds.

	0% CCAVs	20% CCAVs	80% CCAVs
Average crossing time [s]	56.26	54.29	49.01
Maximum crossing time [s]	87.53	83.32	79.66
# vehicles [-]	35	39	41
Reduction of crossing time	Ref.	3.15%	12.88%

Based on the qualitative results, 80% of the participants believed that the scenario with 80% CCAVs was safer. Furthermore, 70% of the participants favoured the scenario with 80% CCAVs. In addition, as the number of CCAVs increased, both CCAVs and HDs reduced their fuel consumption and emissions, and the crossing time, on average. With regard to traffic flow, qualitative results show that participants did not strongly perceive a difference between the two scenarios. Quantitative results support this outcome since they show a maximum reduction equal to 12.88% and, therefore, difficult to be perceived by the user committed to correctly navigate inside the roundabout. Overall, the policy has been capable of reaching all of its objectives outperforming the roundabout without CCAVs.

Conclusion and future work

This paper presents a novel approach to consider CCAVs in a complex urban network. A real four-leg single-lane mini-roundabout in Milan has been completely replicated, both from a geometric point of view and calibrating the traffic to tune an IDM. A Digital Twin of the real scenario has been built coupling an MTS, SUMO, a graphical simulator, VI-WorldSim and the dynamic driving simulator at the DriSMi Laboratory of Politecnico di Milano, introducing a human-in-the-loop. Furthermore, an innovative communication protocol, called V2N-N2V is considered to manage data exchanged by vehicles in the simulation. CCAVs are driven using a DRL policy which aims to optimise traffic flow, safety and driving comfort perceived by human passengers. The dynamic driving simulator has been crucial to optimize driving comfort provided by the policy, considering a *Replay* simulation. Experimental tests have been carried out on a panel of human drivers. Both qualitative and quantitative results have been obtained to completely assess the policy objectives. Tests show that human drivers preferred and were safer in the scenario with the higher percentage of CCAVs. Furthermore, from simulation results, CCAVs not only reduced fuel consumption and enhanced traffic flow but also provided adequate driving comfort and boosted the efficiency of HDs. Future research work will consider more complex networks, such as multi-lane roundabouts, and more comprehensive objective functions for the DRL policy, with the aim of improving the cooperative behaviour of CCAVs. Furthermore, state-of-the-art sensors to quantitative analyse the human response will be used. Examples are Eye Tracking (ET), Electroencephalography (EEG), Electromyography (EMG), Electroencephalogram (ECG), Skin Conductance (SC), and unique Instrumented Steering Wheel (ISW) for sensing forces and moments at each hand.

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