Future Roundabouts Relying on 5G, Edge Computing and Artificial Intelligence

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Abstract. The paper focuses on the behaviour of cooperative, connected and automated vehicles (CCAVs) with the aim of improving traffic flow and safety and providing adequate comfort to vehicle occupants. The study is part of AI@Edge project, founded by the Horizon Europe framework programme. AI@Edge focuses on leveraging AI and Edge computing to enhance 5G networks. The simulation environment is a single-lane mini-roundabout, calibrated on the basis of experimental measurements to accurately replicate the behaviour of human-driven vehicles. A cooperative Deep Reinforcement Learning (DRL) policy, exploiting Proximal Policy Optimization (PPO), was developed to optimize the behaviour of CCAVs while negotiating the roundabout. To assess the effectiveness of this policy, a dynamic driving simulator coupled with a microscopic traffic simulator and a graphical simulator was employed. This comprehensive approach included both simulated human-driven vehicles (HDs) and CCAVs, alongside a real human driver. Tests indicate that human drivers respond positively to scenarios with a higher percentage of automated vehicles, due to an enhanced sense of safety and comfort. Quantitative analysis of the policy also demonstrates the capability of CCAVs to reduce fuel consumption and optimize traffic flow.

Keywords: CCAM · Artificial intelligence · Deep learning · Edge computing · 5G · Roundabouts · Human driver

1 Reference Scenario and Simulation

The integration of Artificial Intelligence (AI) into autonomous decision-making systems is a fundamental aspect of the multi-service Next Generation Internet. The European project AI@Edge [1] aims to explore the integration of AI-enabled

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platforms in digital infrastructures, including those dedicated to Cooperative, Connected and Automated Mobility (CCAM). This paper focuses on developing a virtual simulation environment, both in terms of digital infrastructure and vehicle replication. It will be employed to test a Deep Reinforcement Learning (DRL) policy that optimizes traffic flow within roundabouts, while safely navigating CCAVs in a mixed traffic situation with humans-in-the-loop. This specific type of intersection is selected as it is known to be a bottleneck for automated driving. The reference scenario for the simulations is a four-leg single-lane mini-roundabout [2], which is based on an actual roundabout located in Milan. The scenario is reported in Fig. 1.

(a) SUMO network. (b) VI-WorldSim network. (c) Actual roundabout

Fig. 1: SUMO and VI-WorldSim networks and the actual roundabout (Maps Data: ©2023 Google)

The introduction of CCAVs is expected to bring significant improvements in traffic flow, safety and emissions [3]. However, the adoption of CCAVs will be gradual and the period of mixed traffic conditions with CCAVs and human-driven vehicles (HDs) sharing the same infrastructure is expected to be long [4]. Microscopic traffic simulators (MTS) are typically employed for analyzing different networks and traffic conditions. However, due to the complexity of the human being, driver models roughly approximate human behaviour. Therefore, computer experiments with SUMO had to be substantiated with a human-in-the-loop. To this end, SUMO (Simulator of Urban Mobility [5]), was coupled with a dynamic driving simulator and the VI-WorldSim [6] graphical environment. This architecture [7,8] allowed for very accurate replication of the real scenario, thus being able to create an effective Digital Twin.

Three types of vehicles were present in the simulation:

1. CCAVs driven by the DRL policy hosted in the Artificial Intelligence Framework (AIF). They communicate with the infrastructure giving and asking for information (e.g. position and speed) about them and all other vehicles.
2. Simulated human-driven vehicles, controlled by a car-following model, specifically an Intelligent Driver Model (IDM) [9], only sending their data.
3. The ego-vehicle driven by the real human driver in the dynamic driving simulator. The 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 infrastructure, with the actual communication delay.

All simulations at the driving simulator were performed in real time. A real-time database was in charge of the synchronization of all involved simulation software.

The DriSMi laboratory of Politecnico di Milano [10] conducted the tests using a state-of-the-art cable-driven driving simulator, called DiM400 [11]. The motion is provided by a multi-stage system with redundant degrees of freedom and very low latency. Its cockpit features active seat belts and brake. Noise and Vibration Harshness (NVH) frequencies are reproduced using eight shakers. For more details, please refer to [12].

2 Digital Infrastructure and AI Policy for CCAVs

The reference scenario described in the previous section 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. 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). Since roundabouts represent a critical situation for AI, Edge computing and 5G [13], this scenario provides a challenging real-world problem to assess the performance of the AI@Edge project's technologies.

2.1 Communication Protocol

The connect-compute platform contains the digital infrastructure to run the mobile Edge computing applications [14] and represents one of the most important innovations of the AI@Edge project. In particular, this platform will be used to implement an innovative communication protocol, called Vehicle-to-Network-to-Vehicle (V2N2V). In this protocol, all vehicles are connected to the cloud via a 5G connection. A Multi-access Edge Computing (MEC) server, located near the roundabout and also connected to the network, collects all the provided information and run the DRL policy. As a result, the user is brought closer to the edge of the digital infrastructure. V2N2V combines Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) protocols, optimizing both and reducing the operation and maintenance costs for the vehicle and the infrastructure.

2.2 DRL Policy

CCAVs choices are guided by a DRL policy. The Proximal Policy Optimization (PPO) method [15] is used to learn policy parameters. PPO is an algorithm that is based on the Trust Region Policy Optimization (TRPO) algorithm [16], but it offers improved flexibility at the cost of increasing the computational complexity. Both PPO and TRPO optimize policies efficiently by iteratively adjusting their parameters while maintaining stability during the learning process. PPO employs a dual-step process, involving 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 selected actions are relative to expected outcomes. Policy improvement is performed through several epochs of optimization, during which PPO computes surrogate objectives that quantify the change in the policy's performance with respect to the previously considered set of policy parameters. These surrogate objectives facilitate the optimization of the policy by promoting positive action shifts while limiting the extent of any update to improve stability during learning. The objective of the policy is to improve traffic flow and minimise fuel consumption while ensuring safety for any vehicle in the network. Furthermore, the AVs also accounted for the driving comfort of vehicle occupants to also take into consideration the real acceptability of such technology. To this end, the computed advantages are obtained as a function of the lateral and longitudinal jerks, for which thresholds are defined based on experimental data. This led to a comprehensive and functioning motion planning algorithm.

3 Experimental Tests

Some experimental tests have been conducted to validate the digital infrastructure architecture and the AI policy. A panel of drivers has been asked to drive in the reference roundabout scenario presented in Sect. 1. Before conducting the tests, 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. The calibration procedure has been implemented in SUMO by comparing the simulation outputs with the acquired data while varying the most relevant parameters of the IDM driver model. At the end of the calibration, the set of driver parameters minimizing the difference between the simulated and measured data has been identified. The panel of participants chosen for the experimental tests consisted of ten drivers without prior subject experience with driving simulators. The panel included 5 female and 5 male, 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 safety and general preferences. 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 1, 2, 3 and 4. Specifically, Table 1 and Table 2 report the qualitative results derived from participants' responses, while Table 3 and Table 4 show the quantitative results obtained by evaluating the policy's effectiveness in relation to traffic flow and fuel consumption. Considering quantitative results, the fuel consumption data have been retrieved considering a simulation lasting 3600 s to better appreciate their behaviour over time.

Table 1: Answers to the first 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 2: Answers to the second question of the survey.

Globally, which of the two scenarios did you prefer?	Number of answers
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 3: Normalized consumption and emission scores given a penetration rate of CCAVs, considering a simulation of 3600 s. 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		HD			
	consumption	emission	consumption	emission	# CCAVs	# HDs
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

On the other hand, crossing time, defined as the time interval between departure and arrival for every vehicle, has been retrieved during simulations with humans-in-the-loop lasting 100 s.

According to the qualitative results, 80% of the participants perceived the scenario with 80% CCAVs to be safer. Additionally, 70% of the participants preferred the scenario with 80% CCAVs. Moreover, as the number of CCAVs increased, both CCAVs and HDs reduced their fuel consumption and emissions on average, and the average crossing time decreased.

Table 4: Crossing time and number of vehicles that completed their path as a function of the percentage of CCAVs, considering a simulation of 100 s.

	0% CCAVs	20% CCAVs	80% CCAVs
Average crossing time [s]	56.26	54.49	49.01
Maximum crossing time [s]	87.53	83.32	79.66
N. vehicles [-]	35	39	41
Reduction of crossing time	ref.	3.15%	12.88%

4 Conclusion

This paper presents a co-simulation between SUMO and a dynamic driving simulator to investigate the interaction between HDs and CCAVs in a mixed traffic situation. An innovative communication configuration called V2N2V is used to manage data flow. The study focuses on a mini-roundabout and uses a DRL policy to control CCAVs. Preliminary tests show that human drivers preferred and were safer with more CCAVs. Furthermore, CCAVs reduced fuel consumption, enhanced traffic flow, provided adequate driving comfort and boosted the efficiency of HDs. These results validate the test bed employed and give an understanding of future applications, regarding complex traffic administration by AVs. Future research paths include the analysis of more complicated road networks and the use of physiological sensors to subjectively assess the driver.

References

1. AI@Edge project. https://aiatedge.eu/ Accessed 01 Sep 2023
2. Montella, A., Turner, S., Chiaradonna, S., Aldridge, D.: International overview of roundabout design practices and insights for improvement of the Italian standard. Can. J. Civ. Eng. **40**, 1215–1226 (2013)
3. Li, S.E., et al.: Dynamical modeling and distributed control of connected and automated vehicles: challenges and opportunities. IEEE Intell. Transp. Syst. Mag. (2017)
4. Zhao, X., et al.: Co-Simulation platform for modeling and evaluating connected and automated vehicles and human behavior in mixed traffic. In: SAE International Journal of Connected and Automated Vehicles (2022)
5. Lopez, P., et al.: Microscopic traffic simulation using SUMO. IEEE Intell. Transp. Syst. Conf. (ITSC) (2018)
6. VI-WorldSim https://www.vi-grade.com/en/products/vi-worldsim/ Accessed 01 Sep 2023
7. Previati, G., Mastinu, G.: Sumo roundabout simulation with human in the loop. SUMO Conf. Proc. **4**, 29–40 (2023)
8. Previati, G., et al.: Roundabout traffic: simulation with automated vehicles, AI, 5G, edge computing and human in the loop. In: Proceedings of the ASME 2023 (2023)
9. Treiber, M., Kesting, A.: Car-following models based on driving strategies in Traffic flow dynamics. Springer, pp. 181–204 (2013)

10. DriSMi: Driving Simulator Politecnico di Milanohttps://www.drismi.polimi.it/?lang=it Accessed 01 Sep 2023 Accessed 01 Sep 2023
11. DiM400 https://www.vi-grade.com/en/products/cable-driven_dim_dynamic_simulator/Accessed 01 Sep 2023
12. Previati, G., Mastinu, G., Gobbi, M.: Influence of the inertia parameters on a dynamic driving simulator performances society of allied weight engineers 81st annual conference. Savannah, Georgia (2022)
13. Cuenca, G., et al.: Machine Learning Techniques for Undertaking Roundabouts in Autonomous Driving. Sensors (2019)
14. ETSI GR MEC 017. Mobile Edge Computing (MEC) (2018)
15. Schulman, J., Wolski, F., Dhariwal, P.A., Radford, Klimov, O.: Proximal policy optimization algorithms. CoRR, vol. abs/1707.06347 (2017)
16. Schulman, J., Levine, S., Moritz, P., Jordan, M.I., Abbeel, P.: Trust region policy optimization. CoRR, vol. abs/1502.05477 (2015)