



Artificial Intelligence in Vehicular Wireless Networks: A Case Study Using ns-3

Matteo Drago, Tommaso Zugno, Federico Mason,
Marco Giordani, Mate Boban, Michele Zorzi

Workshop on ns-3
June 23rd, 2022

Motivations

AI will be a key component of 6G → Enable efficient and reliable V2X communications

Teleoperated
driving

Autonomous
driving

Platoon
management

HD map collect
and share

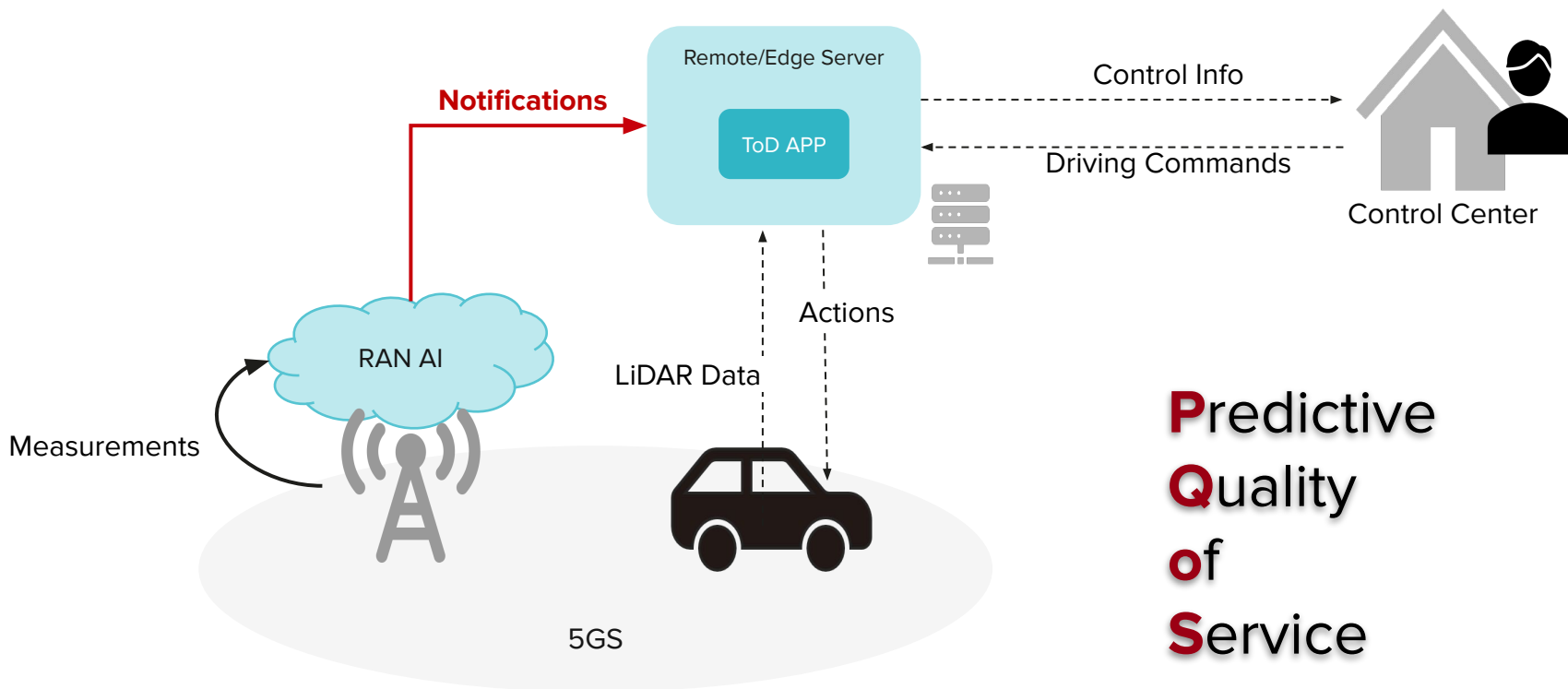
How to train AI algorithms?

Prototypes or real systems yield to accurate results but...

- ☹️ Low scalability
- ☹️ Low flexibility
- ☹️ High costs

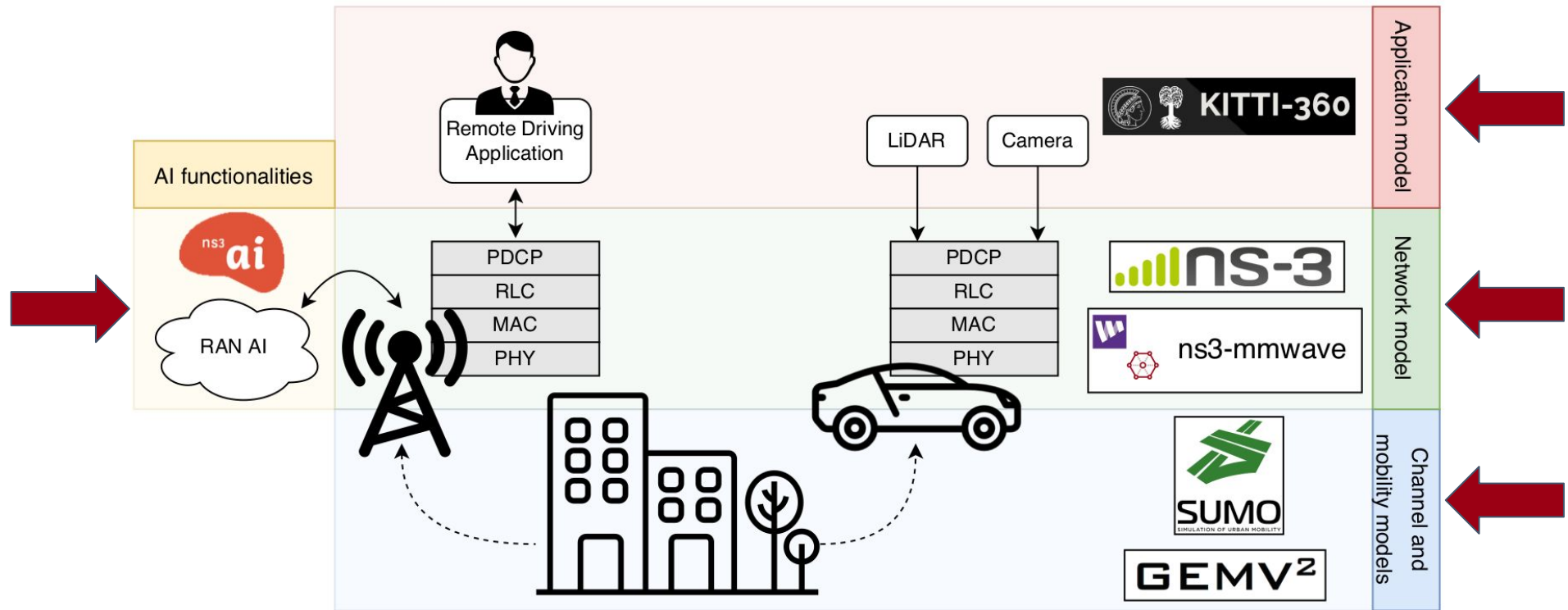


Reference Scenario



Simulation Framework

Available at <https://github.com/signetlabdei/ns3-ran-ai>



Channel and Mobility Models



Open Street Map yields a representation of the area of interest → in our case, Bologna downtown



SUMO
SIMULATION OF URBAN MOBILITY

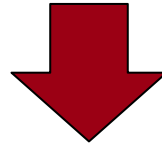
generates vehicles' mobility traces

GEMV²

calculates the channel components from the OSM map and the SUMO trajectories (pathloss values are used as input and parsed from ns-3)

Key ns-3 class: `GemvPropagationLossModel`

Network Model




Extended to include sub-6GHz capabilities and to accept the GEMV²-based propagation model

Key ns-3 methods: `InstallSub6GnbDevice()` and `InstallSub6UeDevice()` of the class `MmWaveHelper`

Application Model

Scenario: Host Vehicle (HV) is controlled by a remote driver through an ad hoc driving application installed on a remote or edge server.

Trace-based application → We implemented a new module to generate this traffic flow based on  and as a function of:

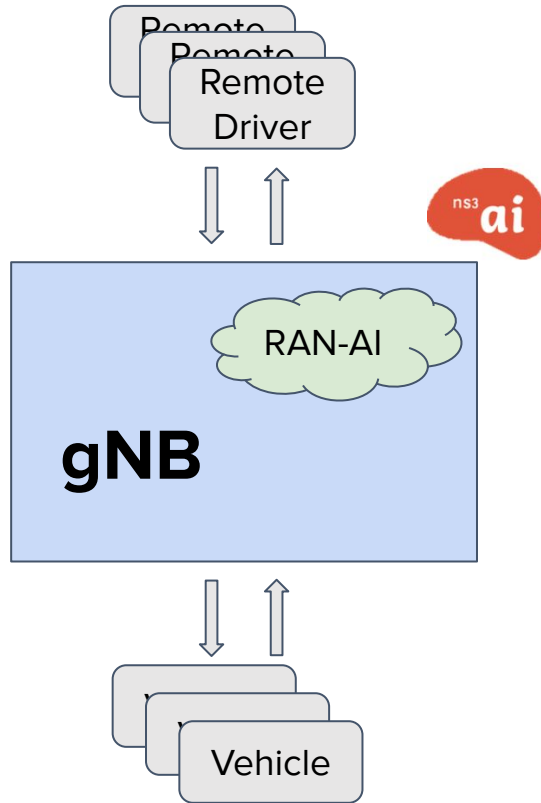
1. Size of input sensor data (in bytes).
2. Update sensor time (typically fixed to 100 ms for LiDARs).
3. The level of compression/segmentation for the sensor data, based on Draco and RangeNet++.

For this work we consider a fixed value of compression and three distinct levels of segmentation:

1. **Raw (R):** Raw LiDAR acquisition is considered.
2. **Segmentation Conservative (SC):** Data points associated to road elements are removed.
3. **Segmentation Aggressive (SA):** Data points associated to buildings, vegetation, traffic signs, and the background are also removed, keeping only the most critical items in the scene.

Key ns-3 classes: `KittiTraceBurstGenerator`, `BurstyApplication`, `BurstSink()` and `BurstyAppStatsCalculator()`

Intelligent Network Controller

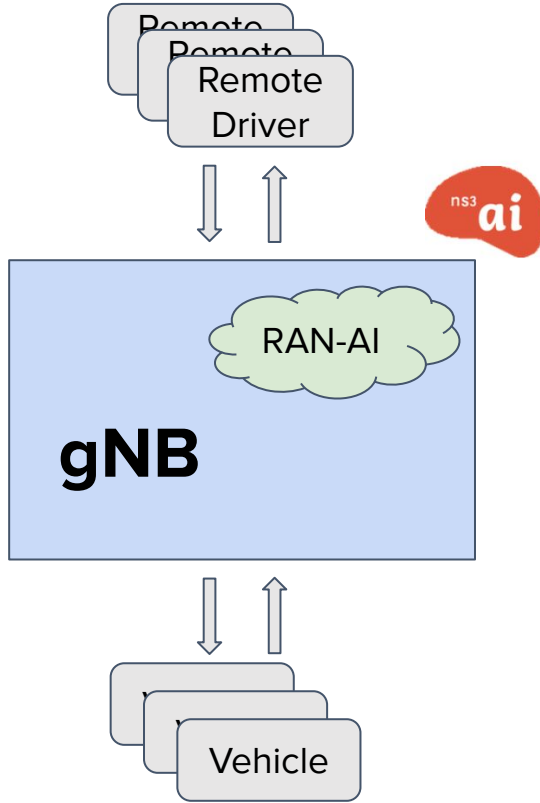


RAN-AI tasks:

1. Collecting metrics from the gNB and end users.
2. Running AI algorithms using as inputs the collected metrics
→ AI-agnostic framework.
3. Determining the actions to take in order to maximize the network performance.
4. Communicating the actions to the relevant entities so that they can tune their behavior accordingly.

In this work the RAN-AI controls the end users applications, but the framework does not prevent other countermeasures/actions from being considered.

Intelligent Network Controller



KILLER FEATURE:

Easy to adapt to different problems, as the API to exchange the data are scenario-independent.

Developer choices:

How to use the data available at the RAN-AI and how to disseminate the output.

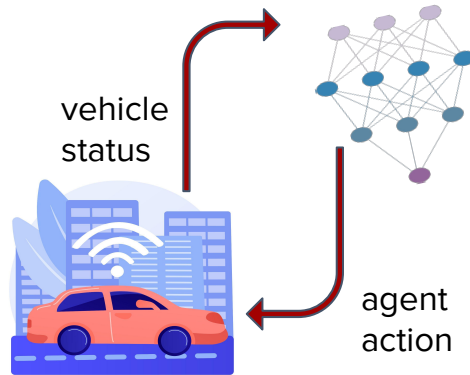
Key ns-3 classes and methods: `ReportMeasures ()` of the class `RanAi`, and `InstallRanAi ()`, `SendStatusUpdate ()` of the class `MmWaveEnbNetDevice ()`

Our case study

We focus on **Predictive Quality of Service paradigm**, to provide advanced notifications in case of upcoming QoS changes.

→ AI agent **based on Reinforcement Learning** and **trained according to the Double Q-learning (DQL) algorithm**.

→ **GOAL:** identify the optimal application mode for the end users when transmitting sensor data.

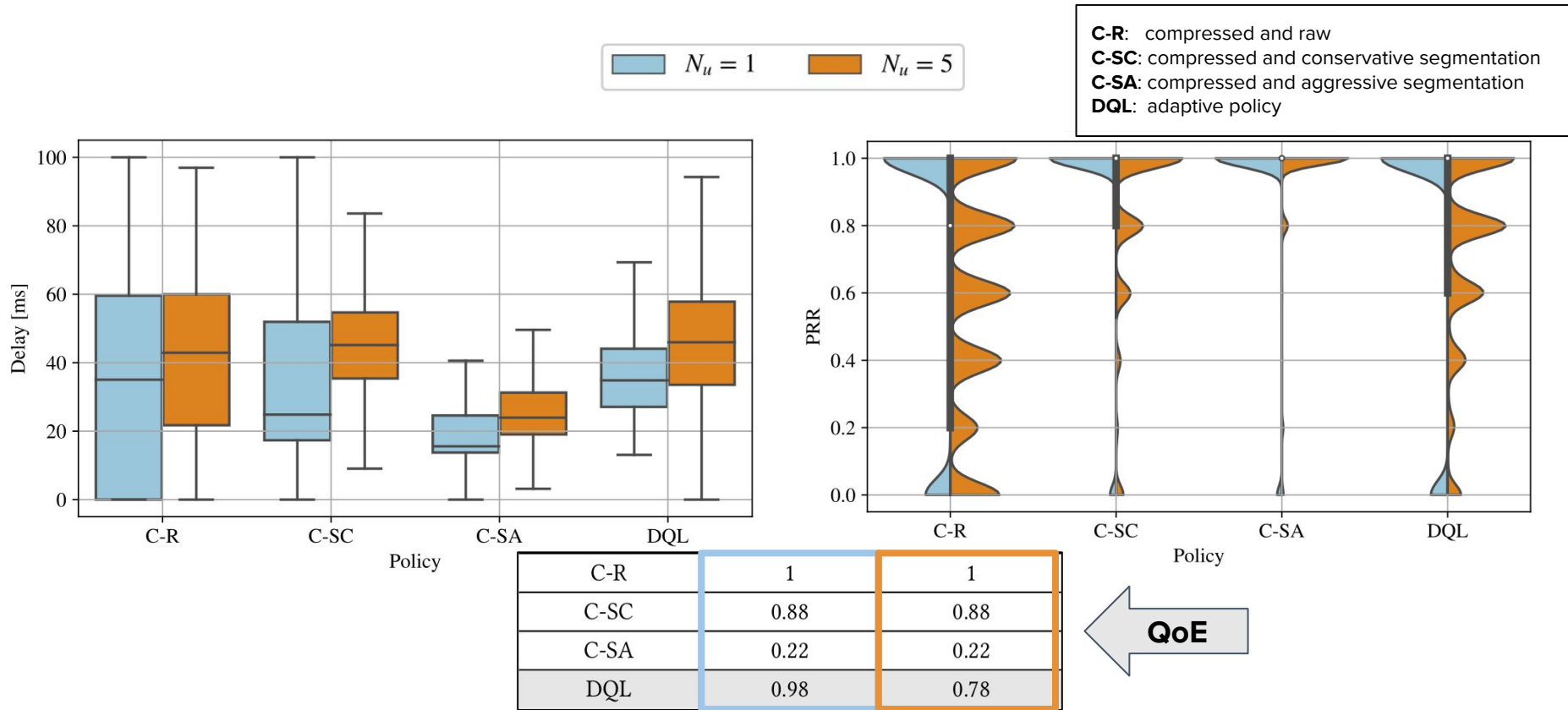


Reward Function

$$R(t) = (1 - \alpha) \frac{\delta_m - \hat{\delta}_t}{\delta_m} + \alpha \frac{CD_{\text{sym},m} - \hat{C}D_{\text{sym},t}}{CD_{\text{sym},m}}$$

Parameter	Description	Value
f_c	Carrier frequency	3.5 GHz
B	Total bandwidth	50 MHz
P_{TX}	Transmission power	23 dBm
T	RAN-AI update periodicity	100 ms
τ_s	Simulation time	80 s
N_u	Number of vehicles	{1, 5}
λ	Discount factor	0.95
ζ	Learning rate	10^{-4}
ϵ	Weight decay	10^{-3}
α	QoS/QoE weight	1
δ_M	Max. tolerated delay	50 ms
PRR_m	Min. tolerated PRR	1
$CD_{\text{sym},m}$	Max. tolerated Chamfer Distance	45
Layer size (inputs × outputs)		$8 \times 12 \rightarrow 12 \times 6 \rightarrow 6 \times 3$

Impact of number of users

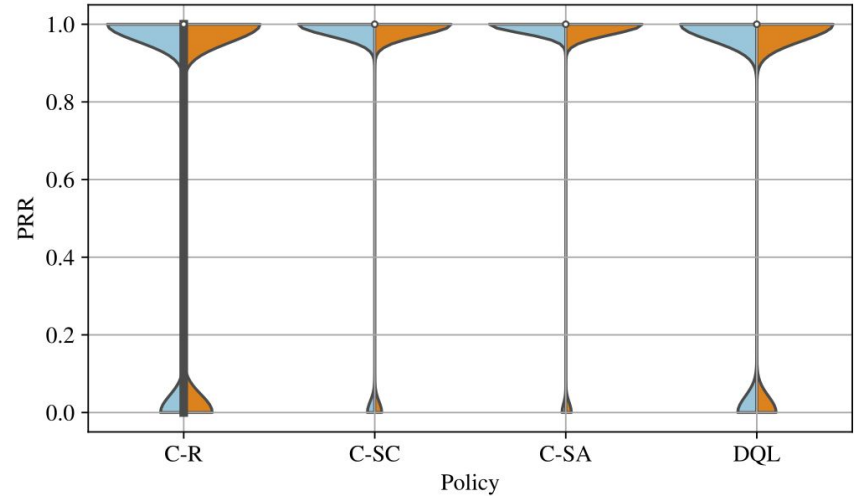
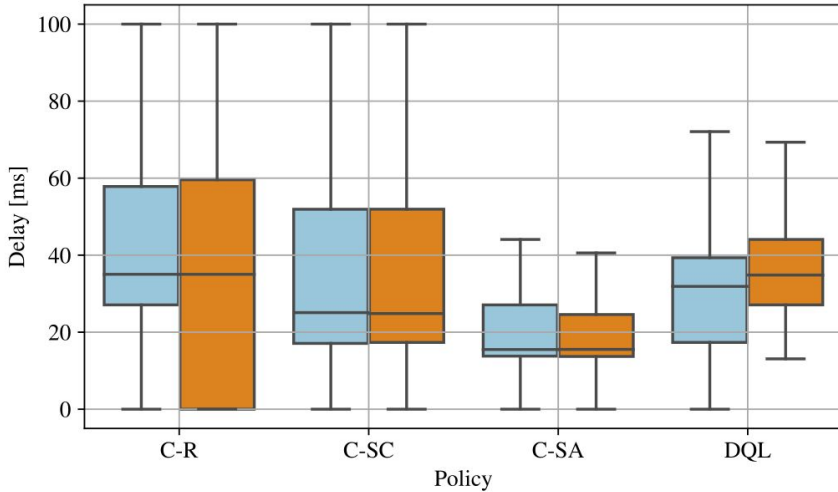


Impact of actions notification

C-R	1	1
C-SC	0.88	0.88
C-SA	0.22	0.22
DQL	0.98	0.94



C-R: compressed and raw
C-SC: compressed and conservative segmentation
C-SA: compressed and aggressive segmentation
DQL: adaptive policy



GOAL: study the overhead impact

Ideal notification → a callback is fired to change the application mode

Real notification → a packet with the information is actually sent through the network

Ideal notification Real notification

Conclusions

New framework to study the performance of AI algorithms in next-generation networks scenarios!

Future developments will include:

- more extensive simulation campaign (higher number of vehicles orchestrated by the same RAN-AI)
- test different learning tools such as federated learning for vehicular networks or QoS prediction based on the vehicles' positions on the map

Our work has been publicly released at <https://github.com/signetlabdei/ns3-ran-ai>

Further results can be found here: F. Mason, M. Drago, T. Zugno, M. Giordani, M. Boban, and M. Zorzi, "A Reinforcement Learning Framework for PQoS in a Teleoperated Driving Scenario," IEEE WCNC Workshops, 2022.



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