The Impact of Connected and Autonomous Vehicles: A case study of Paris's ring road, the Périphérique

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Abstract

Urban ring roads like Paris's Boulevard Périphérique suffer from chronic congestion, elevated emissions, and complex traffic dynamics. Connected and Autonomous Vehicles (CAVs) have the potential to mitigate these issues, yet their systemic effects remain insufficiently explored. This study assesses the impact of varying CAV penetration rates (0 %, 30 %, 50 %, 70 %, 100 %) on traffic performance through microsimulation in SUMO. Two car-following models—Krauss and IDM—are used to evaluate differences in flow dynamics. Key performance indicators such as mean speed, waiting time, time loss, and stop count are computed for each scenario, both in aggregate and disaggregated by vehicle type. Results show important network-wide improvements with increasing CAV penetration, especially beyond 50 %, though HDVs often experience degraded performance in mixed scenarios under IDM. Additionally, non-linear patterns emerge at intermediate CAV levels, indicating complex interaction effects. The findings highlight the importance of model selection and penetration thresholds and suggest that partial automation could yield suboptimal or even adverse outcomes without careful integration. This work provides some insights for urban mobility planning and phased CAV deployment strategies.

1 Introduction

1.1 General Context

The world of road transport is on the verge of major change as countries like the UK, Japan or the US start to either allow the first SAE level 3 (Conditional automation) in California (2023) or updating their legislation (Japan, 2023 and UK, 2024) to allow driverless cars on their roads in a near future. However, once these authorisations become global, the shift from manned vehicles to autonomous vehicles won't be instantaneous. There will be, for an extended period, mixed traffic on roads. Therefore, a question of "compatibility" between human and robots comes naturally forward. Will the coexistence of almost to completely autonomous vehicles and almost to completely manually driven cars be possible without security issues? How complex would such a system be?

The first question would be a non-technical one: would people actually accept being on the road with autonomous vehicles. The advancement of autonomous vehicle (AV) technology is expected to create systematic changes in modern travel, making human acceptance a critical factor for successful deployment. A thorough review from Zhang, Zhang & Ma, (2023) of 94 studies on the topic from 2016 to 2021 found that the research landscape is dominated by descriptive studies, with questionnaire surveys being the most common method for data collection. This approach has limitations, as participants often have no real-world experience with AVs, meaning their responses may reflect imagined attitudes rather than actual acceptance. Across the body of research, several key factors consistently emerge as important influencers of public acceptance, including trust, cost, age, safety, perceived usefulness, and perceived ease of use. Trust, in particular, has been identified as one of the most critical elements in fostering a positive attitude toward adopting AVs. Ultimately, the development of AVs is currently driven more by technological supply than by consumer demand, which underscores the importance of this research in addressing and improving human acceptance to help ensure the future success of autonomous transportation.

1.2 Paris's périphérique

1.2.1 What is it

The "boulevard périphérique de Paris", commonly known as the "périph", is a 35-kilometer urban ring road encircling central Paris. Officially opened in 1973 after 17 years of construction, it plays a critical role in the city's mobility, handling nearly one-quarter of all Parisian trips daily. The infrastructure is diverse, with 40% of the route in open trench (including covered sections), 30% in tunnels or enclosed with sound barriers, and the remainder at or above ground level. Operationally, it is monitored and maintained through a sophisticated system: 750 traffic sensors, 99 surveillance cameras, and 166 emergency call stations feed real-time data to a centralised control center managed jointly by the Préfecture de Police and the City of Paris ("Ville de Paris" = Paris City Council). This data informs dynamic traffic signs and congestion maps to help drivers avoid incidents. The road is also a focal point for experimental policies, including vehicle counting and carpooling detection at the Porte de Montreuil, and noise-reducing asphalt, which has already reduced perceived sound levels by up to 7 decibels in certain sections. As a vital and complex traffic artery, the périphérique is not only a technical and logistical challenge but also a proving ground for future smart and sustainable mobility initiatives. (Paris city council (Mairie de Paris))

1.2.2 Traffic data

First, it is important to note that the speed limit recently changed from 70 km/h (43.5 miles/h) to 50 km/h (31.07 miles/h). Here is a breakdown of general traffic data from June 2025:

- Mean speed is **33.1 km/h** over an entire day with the lower mean speed being 24.3 km/h between 4pm and 8pm.
- Congestion is **22.1%** over an entire day with the highest being 47.8% between 4pm and 8pm.
- Mean Flow is **7464 veh/h** over an entire day with the highest flow being 9583 veh/h between 11am and 3pm.
- Noise pollution is approximately **77dB** over an entire day near Auteuil, it goes up to 77.9dB between 7am and 10am and drops to 74.8dB between 10pm and 6am.
- Air Pollution is averaging as **90.1µm/m^3** of **NOx** and **28.1µm/m^3** of **PM10**.

(Mobility and Transports Department, Paris Region Institute)

1.3 Research problems and Challenges

This study aims to assess the potential impact of connected and autonomous vehicles (CAVs) on traffic performance along the boulevard périphérique. However, several challenges arise in attempting to simulate and evaluate such a scenario with realism and scientific rigour.
Firstly, the boulevard périphérique presents a highly complex urban traffic system. Its configuration as a ring road with frequent interchanges, high vehicle density, and dynamic lane-changing behaviour makes it difficult to model accurately. The initial attempt to use a full ArcGIS-derived network resulted in an unmanageable and computationally intensive model, highlighting the trade-off between network realism and simulation tractability. A simplified loop network was therefore adopted, which, while abstracted, preserves key characteristics of the périphérique's flow dynamics.
Secondly, the integration of CAVs in a mixed traffic environment introduces uncertainty. Real-world data on CAV behaviour, especially under dense urban conditions, is limited. This creates difficulties in calibrating realistic behavioural parameters for both human-driven vehicles (HDVs) and CAVs. Key differences in acceleration, reaction time, and minimum gap settings must be assumed rather than measured, potentially impacting the validity of simulation outcomes.
The choice of car-following model adds a further layer of complexity. Different models (e.g., Krauss, IDM) produce varying dynamics, and selecting one over another introduces methodological bias. This research therefore includes a comparative analysis of model performance under identical scenarios to investigate this sensitivity.
In addition, the generation of demand and vehicle routing patterns is constrained by data availability. Without access to real-world origin-destination matrices, traffic flows are synthetically generated and may not reflect actual travel behaviours on the périphérique.
Lastly, selecting appropriate performance indicators presents a challenge. While mean speed, waiting time, time loss, and stop count offer useful insights, they must be interpreted carefully, especially when comparing scenarios with different vehicle mixes or car-following models.
These challenges underscore the complexity of conducting meaningful simulation-based assessments of CAV integration in urban environments. They also justify the methodological choices made throughout the study.

1.4 Research aim and Objectives

The objective of this paper is to analyse the impact of the potential implementation of Connected and Autonomous on a high-density network such as Paris's Périphérique, through different simulations. This road is known to be very congested at peak hours, so this study aims to highlights the potential benefits of implementing CAVs on such a network. One of the first benefit would be reducing congestion, thus improving travel time through this network. Then, a lot of other benefit could be analysed from this: Reduced emissions and pollution, reduced noise pollution, increased economic value… .

1.5 Structure of the dissertation

The dissertation will begin with a literature review of different aspects of CAVs, such as Lane-changing, dedicated lanes or safety considerations. A methodology section will then explain which simulations where conducted under which parameters. This will be followed by a first simulation, for 5 different scenarios, on a simple, small network. Then a more complex simulation will take place on a larger and more complex network, this simulation will be decomposed into two simulations, for two different car following models. Finally, the last part will cover the comparison of the different findings, conclusions and discussions for future work on this subject.

2 Literature review

2.1 Traffic

2.1.1 Lane-changing or dedicated lanes

Lane-changing is a known source of traffic oscillations and safety risks. In a mixed traffic environment (with both CAVs and HDVs), the sometimes robotic-like behavior of CAVs can create "mental discomfort" for HDV drivers. This leads to unsafe interactions and further disruptions to traffic. (Liu & Peeta, 2025)

There are 2 control strategies that have been explored to address these problems:

- **Human-like control:** This system aims to make CAVs behave more intuitively and in a more predictable manner for human drivers. Liu & Peeta, (2025) propose a "human-like lane-change control strategy" (HLCS) that integrates the strengths of both "robot driving" and "human driving". Their strategy uses a "Human Lane-Change Model" (H-CLM) developed via imitation learning to replicate natural human driving patterns, which helps adjust the CAV's actions with HDV drivers' expectations. This is combined with a "Robot Lane-Change Model" (R-LCM) that leverages the superior perception and reaction skills of CAVs to ameliorate safety and smoothness. By mixing these models, the HCLS aims to produce manoeuvres that are not only efficient but also intuitive, therefore reducing HDV driver anxiety and overall improving interactions on the road.
- **Robust Optimal Control:** This system focuses on achieving time and energy-optimal manoeuvres that are demonstrably safe and robust to HDV unpredictability. Li, Chavez Armijos & Cassandras, (2025) formulate the CAV-HDV interaction as a bilevel optimisation problem, using an Iterated Best Response (IBR) to model the decision-making process and find an equilibrium. Safety is explicitly guaranteed through the implementation of Control Barrier Functions (CBFs), which ensure the vehicle remains in a safe state even with disturbances from HDVs. A key innovation in their work is a threshold-based criterion that allows a lane-changing CAV to make a strategic decision: either interact with a neighbouring HDV or cooperate with another nearby CAV to create a gap, which can eliminate or greatly reduce the uncertainty of interacting with the human driver.

Another approach to the mixed traffic between CAVs and HDVs is the implementation of dedicated lanes. With such a system, interferences and interactions between human drivers and CAVs is reduced and, it also allows the implementation of other systems that could multiply CAVs efficiency, such as platooning.

Zhang et al. (2025) assess the effectiveness of dedicated lanes using a modified Cell Transmission Model (CTM), a mesoscopic model that can adequately simulate large-scale traffic dynamics. Their model incorporates the fundamental diagrams of heterogeneous traffic flows, capacity drop phenomena, and specific driving rules for DLs. Their research provides several key insights:

- **Effectiveness is Conditional:** The greatest benefits from DLs are realised under conditions of high traffic demand and low CAV penetration rates. In low-density scenarios, DLs can be detrimental to overall traffic throughput.
- **Optimal Placement Varies:** The best location for a DL depends on traffic conditions. Under high density, placing a DL on an edge lane is recommended to avoid obstructing general traffic flow. In scenarios where lanes have different speed limits, placing the DL

on the high-speed lane is generally more adequate, as it maximises the advantages of CAVs.

- **Partial vs. Full-Length DLs:** The optimal length of a DL is also dependent on traffic demand. While full-length DLs are recommended for high-density conditions, a partial-length DL can be a more cost-effective solution for moderate densities or to manage recurring bottlenecks. When dealing with bottlenecks, placing a partial DL adjacent to or downstream of the congestion point is most efficient at reducing delays.

2.1.2 Car-following models

Car-following models (CFMs) describe how a vehicle reacts to the behaviour of the vehicle in front. These models are fundamental in microscopic traffic simulation as they define longitudinal dynamics and influence the accuracy of outputs such as congestion patterns, emissions, and energy consumption. Various CFMs have been proposed, ranging from rule-based to data-driven approaches, each with specific assumptions and parametrisation.

The Krauss model is the default in SUMO and emphasises collision avoidance by calculating a safe speed v_{safe} at each timestep, taking into account the reaction time, braking deceleration, and gap distance. Although simple, this model tends to underestimate real-world time headways and can lead to higher collision rates if not calibrated properly (Schrader et al., 2024).

$$v_{safe}(t) = v_l + \frac{g(t) - v_l(t) \cdot \tau}{\frac{v_f}{b \cdot v_f} + \tau}$$

With:

- $g(t)$, the gap to the leading vehicle
- τ, the reaction time
- b, the comfortable breaking deceleration

Then, the desired speed, $v_{des}(t)$ is found with the following equation:

$$v_{\text{des}}(t) = \min\left[v_{\text{safe}}(t),\ v_f(t) + a,\ v_0\right]$$

With:

- a, the driver's preferred maximum acceleration
- b, the maximum deceleration

(Schrader et al., 2024)

The model allows the user to fine tune a, b and τ as we'll see later, as it is the model that we will use in this study.

The Intelligent Driver Model (IDM) defines acceleration as a function of current speed, desired speed, gap, and relative velocity. It is more realistic in modelling both free-flow and congested conditions and has shown high performance in reproducing real-world trajectories, especially when calibrated on spacing, velocity, and acceleration simultaneously (Schrader et al., 2024). In particular, the IDM showed the lowest RMSE in both spacing and velocity and provided the most realistic acceleration profiles in calibrated SUMO simulations.

The Wiedemann 99 model incorporates psychological aspects of driving, such as perception thresholds and decision regimes. It can simulate more nuanced behaviours like defensive or aggressive driving styles, but its calibration is complex, and it may introduce unrealistic acceleration patterns when improperly tuned (Schrader et al., 2024).

Gipps (1981) proposed a behavioural car-following model based on physical limits and driver behaviour assumptions. It includes explicit constraints on acceleration, braking, and desired speed, with parameters that are interpretable and tied to driver psychology. Its formulation allows for smooth transitions between free-flow and car-following states, and it has been validated to replicate observed speed-flow relationships and platoon stability.

More recently, data-driven and generative models have emerged. For instance, Zhang et al. (2022) introduced a generative CFM using neural networks conditioned on individual driving styles. This approach allows the model to adapt to varying behaviours and can outperform traditional models in reproducing complex trajectories, although it requires large datasets and training time.

A comparative evaluation by Kim & Heaslip, (2023) examined the suitability of several CFMs (including IDM, Krauss, Wiedemann, and Gipps) for simulating automated vehicles on highways. The study emphasised the importance of model selection based on traffic context (urban vs. highway) and vehicle type (HDV vs. CAV), noting that parameter sensitivity varies substantially between models. It also highlighted the need for careful calibration when simulating mixed traffic environments with varying automation levels.

Overall, the choice of car-following model and its calibration has an important impact on the accuracy of traffic simulation, especially when modelling energy consumption and emissions in networks with CAV penetration.

2.2 Safety considerations

2.2.1 Safety validation and penetration rates

Validating the safety of CAVs is a real challenge, indeed, real-world testing is expensive, slow and hazardous. This has led to the development of sophisticated, large-scale simulation environments to assess performance. Xu et al. (2025) explored the relationship between CAV penetration rates and accidents rates, with a high-fidelity co-simulation framework. Their findings challenge the assumption that more CAVs means more safety.

While an increase in CAVs generally leads to a reduction in collisions, the study identified an optimal safety performance at a 70% penetration rate, which resulted in an 86% reduction in accident rates compared to scenarios with no CAVs. Counterintuitively, as the penetration rate increased beyond this point (from 80% to 100%), the accident rate began to rise again. This suggests that in complex urban environments, the homogeneity of an all-CAV system could introduce new risks, such as more aggressive and less forgiving interactions with vulnerable road users like pedestrians and cyclists. Even at the optimal 70% penetration rate, important conflicts persisted, particularly at roundabouts and signalised intersections, which accounted for over 70% of conflicts involving CAVs (Xu et al., 2025) .

2.2.2 Behavioural impacts in mixed traffic

The interaction between CAVs and human-driven vehicles (HDVs) is a critical factor in overall road safety. The smooth, predictable behaviour of CAVs appears to have a calming effect on the human drivers around them. A driving simulator study by Wei & Shao, (2024a), found that HDV drivers who were following a CAV exhibited less driving volatility in their speed and acceleration compared to when they followed another HDV.

This increased stability translates directly to improved safety metrics. The study observed a remarkable improvement in Time-to-Collision (TTC), a key surrogate safety measure, for HDVs following CAVs. The minimum and mean TTC values increased a lot, indicating a lower risk of rear-end collisions. This suggests that the presence of even a moderate number of CAVs can help stabilise traffic flow and reduce the likelihood of crashes by influencing human drivers to adopt safer, less erratic driving patterns (Wei & Shao, 2024a).

2.2.3 Impact of CAV Breakdowns

While CAVs may operate flawlessly in ideal conditions, the risk of technological failure presents a serious safety challenge. The breakdown of a CAV, particularly one leading a platoon, can have substantial negative impacts on traffic flow and safety.

A study by Wu, Postorino & Mantecchini, (2024) investigated the consequences of a lead vehicle in a CAV platoon breaking down on a highway. The sudden stop and resulting platoon dispersion were found to reduce traffic capacity by approximately 20%. The analysis of conflict frequency, using TTC, showed that while higher CAV penetration rates generally augment safety even in breakdown conditions, the size of the platoon is a critical factor. The study suggests that platoon sizes should be limited to four vehicles, as larger platoons struggle to disperse efficiently, leading to an increase in probable conflicts and a greater risk to traffic safety (Wu, Postorino & Mantecchini, 2024).

2.3 Environmental impact of autonomous mobility

2.3.1 Direct impact on fuel consumption and emissions

At the most basic level, the operational characteristics of CAVs can lead to important environmental benefits. Their ability to maintain steady speeds and shorter, more consistent headways, eliminates much of the inefficient "stop-and-go" driving, typical of human drivers. Here is a breakdown of what has been found in recent years concerning this:

- **Traffic smoothing effect:** The predictable and stable movement of CAVs has a positive ripple effect on the surrounding traffic. Research by Wei & Shao, (2024b) demonstrates that even conventional human-driven vehicles (HDVs) exhibit less volatile driving when following a CAV, resulting in lower fuel consumption and fewer pollutant emissions for the HDV. This calming effect suggests that the introduction of CAVs can improve the environmental performance of the entire traffic stream, not just the autonomous vehicles themselves.
- **The Role of Technology (ICE vs. EV):** The type of powertrain is a fundamental determinant of environmental impact. A comparative analysis by Huang et al. (2024) shows that Electric Vehicles (EVs) can reduce carbon emissions by as much as 70-90% compared to traditional gasoline vehicles (GVs) during urban rush hours. When CAV technology is applied to an electric platform, the benefits are compounded. Their study indicates that an electric CAV can be 35-50% more efficient than an electric vehicle

driven by a human, showcasing the synergistic relationship between electrification and automation.

2.3.2 Impact of platooning and dedicated lanes

- **Dedicated lanes:** To mitigate the negative interactions between CAVs and HDVs, dedicated lanes are often proposed. A study by Wang et al. (2024) evaluates various lane management strategies and finds that their effectiveness is highly dependent on traffic demand and the CAV penetration rate. For instance, strategies that separate CAVs and HDVs can improve operating speeds and reduce fuel consumption, but these benefits diminish as traffic demand increases. Their work highlights that there is no one-size-fits-all solution; the optimal strategy depends on the specific traffic context.
- **Platooning and Its Trade-offs:** The ability of CAVs to form electronically coupled platoons is a key source of efficiency, reducing aerodynamic drag and enabling smoother flow. However, Wang et al. (2024) also note that increasing platoon size does not always lead to lower fuel consumption. While platooning could improve traffic efficiency (speed), if that increased speed pushes vehicles beyond their optimal energy consumption range (e.g., above 109 km/h in their model), fuel consumption can increase. This reveals a possible trade-off between maximising traffic throughput and minimising environmental impact.

2.3.3 The Human factor: Passenger compliance

A critical and often-overlooked factor is how human passengers interact with and accept CAV technology. The theoretical benefits of optimised CAV platooning can be quickly undone if passengers do not comply with the system's operation.

A study by Xu et al. (2024) used a virtual reality environment to assess the impact of passenger compliance. Their findings are stark: non-compliant behaviour, where a passenger decides to intervene and manually override the CAV's control, disrupts the stability of the entire vehicle fleet. This single act can increase vehicle emissions by over 20% compared to a scenario with full compliance. This research underscores that public acceptance and trust are not just social issues but have direct and measurable environmental consequences. The full eco-driving aptitude of CAVs can only be realised if passengers allow the system to operate as designed.

2.3.4 Use of Renewable Energies

The ultimate environmental benefit of electric CAVs is inextricably linked to the source of their power. An analysis by Huang et al. (2024) incorporates a lifecycle perspective on electricity generation. They find that even with a power grid where only 30% of electricity comes from renewable sources, those renewables account for just 2.5% of the total carbon emissions. When the share of renewable energy reaches 50%, the emissions from the non-renewable half are 17 times higher. This demonstrates that the true "green" potential of electric CAVs is directly dependent on the decarbonisation of the power grid. A fleet of autonomous EVs running on coal-fired power plants simply shifts the emissions problem from the tailpipe to the smokestack.

2.4 Knowledge Gap

There is a limited amount of research on how HDV-CAV interactions influence congestion. We have seen in this paper that there may be more to congestion than just the penetration rate of CAVs/HDVs.

Many works focus on highway environments, with limited application to dense urban ring-road networks such as the one seen in this paper. Also, no case study has been done for this particular ring road.

3 Methodology

3.1 Study area

The study area is, as previously stated, the Périphérique. It was initially planned to use actual road data to create a realistic network in Sumo, however the network rapidly appeared to be far too large and complex to be usable in the short timeframe that was available for this research project. It was then decided to draw a simplified version of the périphérique directly on netedit (sumo's tool to edit networks).

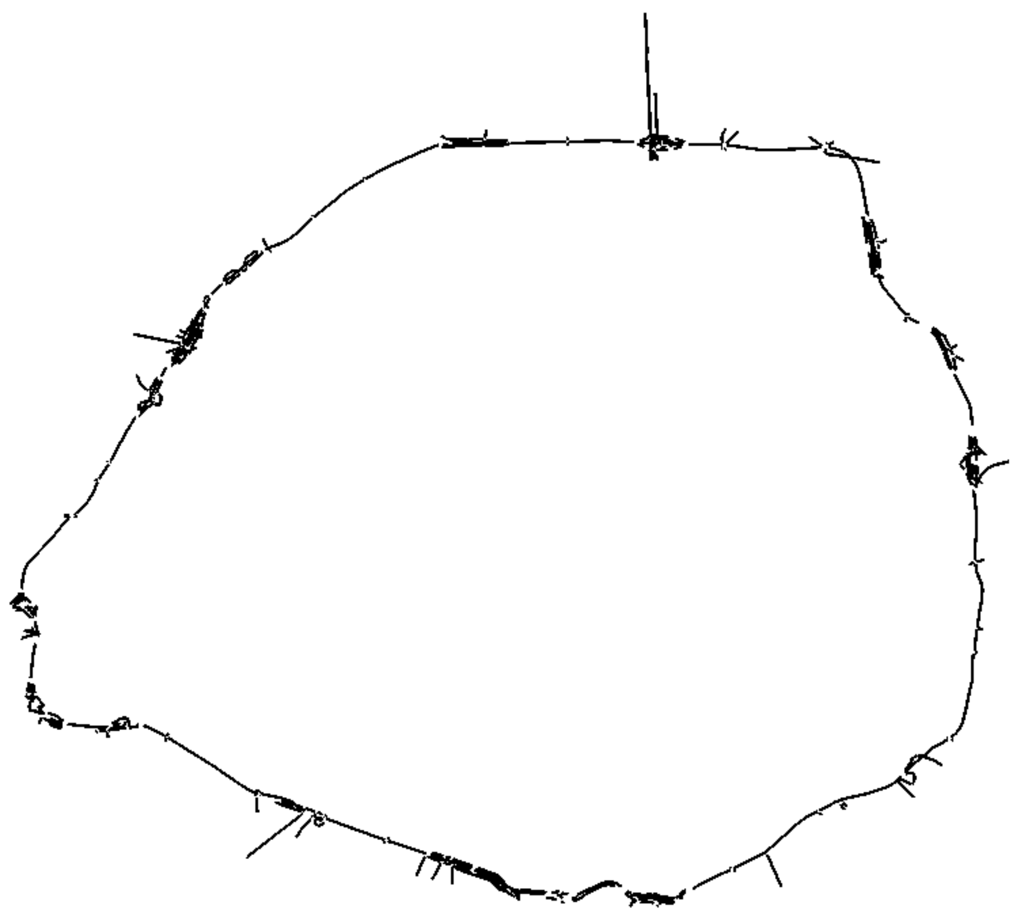


Figure 1 - Initial network, too large and complex

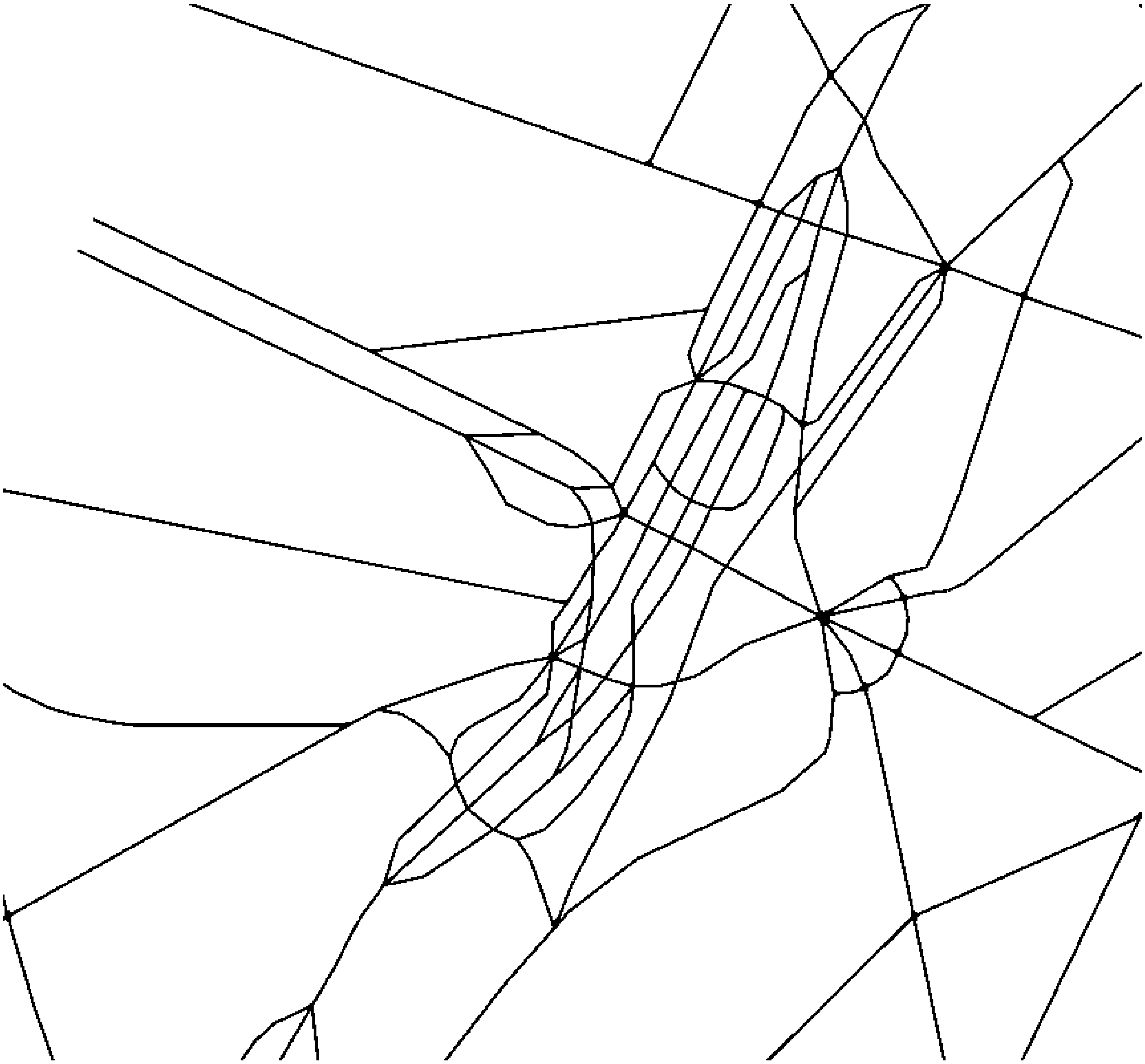


Figure 2 - Example of Porte Maillot, west side of the périphérique

You can see above a good example of the road complexity; this is situated on the West side of the city.

3.2 Traffic simulation

Traffic on this network was modeled using sumo's built in tool, randomTrips.py. This generates a set of random trips for a given network. The script simulates traffic by:

- randomly choosing source and destination edges,
- respecting constraints like trip distance or network permissions,
- and writing the resulting trips to a ".trips.xml" file.

The script also uses *optparse* to handle a wide set of command-line options, such as:

- --net-file: Path to the SUMO network. (used)
- --output-trip-file: Output XML file for generated trips. (used)
- --begin / --end: Simulation time window for vehicle departures. (used)
- --period: Spacing between departures (controls flow rate). (used)
- --allow-fringe: Whether to allow entry/exit on fringe edges. (used)
- --min-distance / --max-distance: Optional constraints on trip length. (not used)
- --flows: Generate <flow> elements instead of individual trips. (not used)

Example of the command used to create the route files for simulation in part 5:
python randomTrips.py -n net.net.xml -o trips.trips.xml -b 0 -e 14400 -p 0.25 --fringe-factor 5.0 --validate

net.net.xml is the network designed for the simulation, -b 0 and -e 14400 specify the beginning and the end of the simulation (from 0 to 14400 seconds, i.e. 4 hours), -p 0.25 specify the period between departures (0.25 seconds) –validate ensures that each trip has a valid route.
The duration of 14400 seconds, or 4 hours was chosen to simulate a typical peak-hour period. They can very often be as long as 4 hours on this road, from 7am to 11am for example.

3.2.1 Scenarios

It was decided to analyse 4 different scenarios and compare them with a base case:

SCENARIO	% CAVS	% HDVS	OUTPUT
BASE CASE	0%	100%	Mean Speed, Waiting Time, Time loss, Stop Count
SCENARIO 1	30%	70%	Compare KPIs
SCENARIO 2	50%	50%	""
SCENARIO 3	70%	30%	""
SCENARIO 4	100%	0%	""

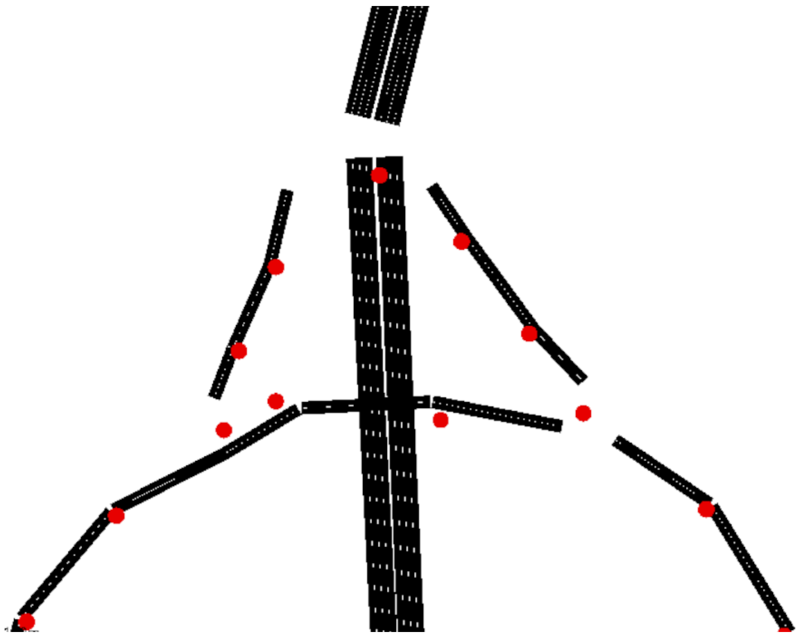
3.3 Data Sources

It was first decided to use GIS data from the official data.gouv.fr website, but the network was hand-drawn for more simplicity. Some traffic and emissions data were used, from the website Mobility and Transports Department, Paris Region Institute (2025).

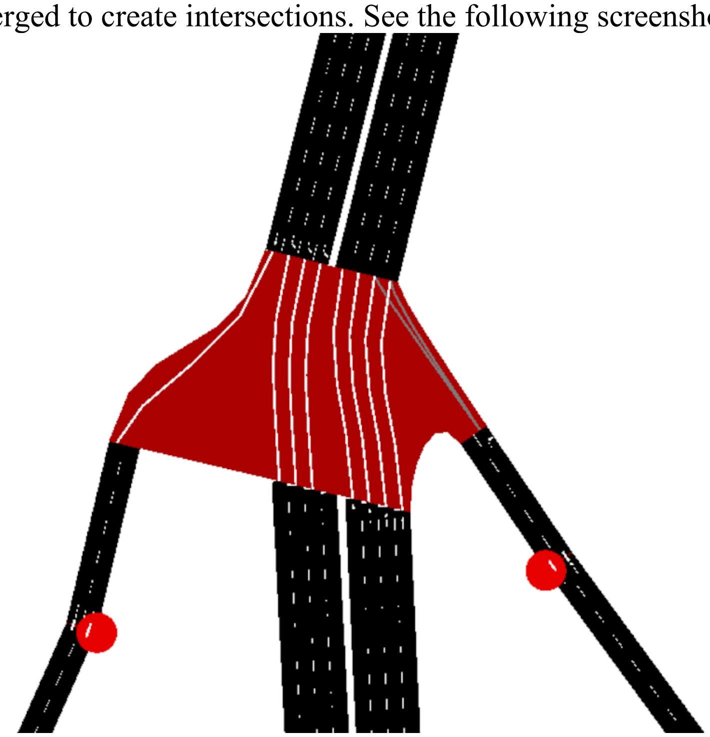
3.4 Network Modelling and Simulation Setup

The networks were modelled with sumo's built-in tool Netedit. The method followed was:

- Draw the main ring first
- Draw interchanges
- Adjust nodes at interchanges (merge nodes to create the intersections)



Above is an example from part 4, with the simplified network. The red dots are the nodes. Nodes can be merged to create intersections. See the following screenshot:



3.5 Evaluation Metrics (KPIs)

The chosen evaluation metrics are the following:

- Mean speed: This is a good indicator of overall congestion, easily comparable between scenarios and vehicle types
- Waiting Time: The time in which the vehicle speed was below or equal 0.1 m/s (scheduled stops do not count) (as defined in the Sumo documentation)

- Time Loss: The time lost due to driving below the ideal speed. (ideal speed include the individual speedFactor; slowdowns due to intersections etc. will incur timeLoss, scheduled stops do not count) (as defined in the Sumo documentation)
- (unscheduled) Stop Count: The average number of times each vehicle type stopped due to congestion, for each scenario.

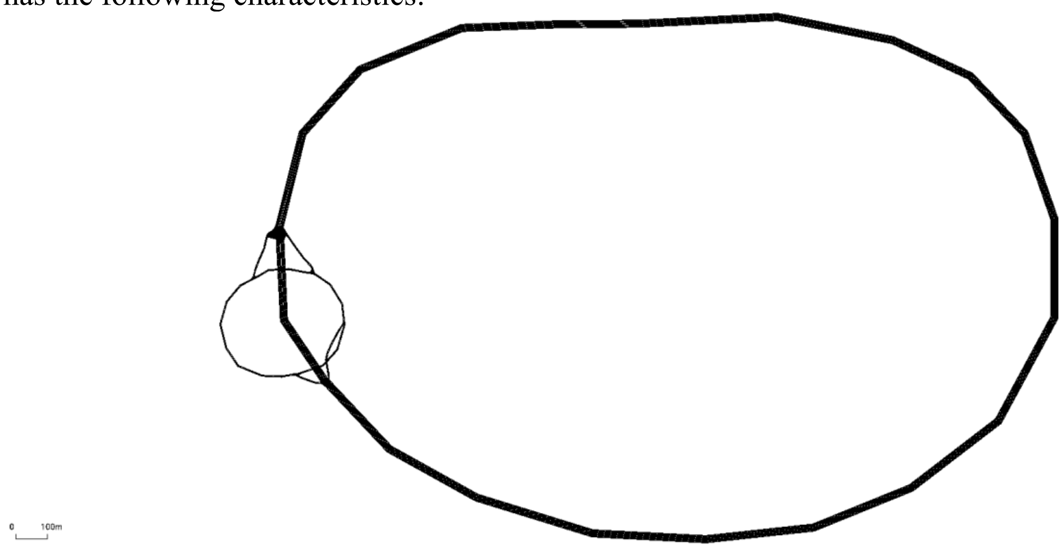
4 Preliminary study, simplified network

4.1 Objectives

Before implementing a detailed simulation on a realistic network of the Paris Périphérique, a preliminary study was conducted using a highly simplified model. The main objective of this initial experiment was to explore general trends in traffic performance under increasing shares of Connected and Autonomous Vehicles (CAVs). It also served to validate the SUMO simulation setup.

4.2 Study area

To approximate the geometry of the Périphérique while maintaining computational efficiency, a minimalistic ring road was manually constructed in SUMO's NetEdit. The simplified network has the following characteristics:



- The shape is a large, closed ring road with a roundabout which purpose is to allow vehicles to change directions.
- The main ring is **4 lanes per direction**, consistent with the typical cross-section of the real infrastructure.
- Pedestrians are prohibited
- Max speed is **50 km/h**
- The main loop is approximately **6.6 km long, 18.9%** of the length of the Boulevard périphérique.
- A calculated flow of 1410 veh/h (calculated from Mobility and Transports Department, Paris Region Institute (2025))

This abstracted network intentionally omits complex junction geometries, elevation changes, and heterogeneous demand patterns to isolate the influence of traffic composition on fundamental traffic performance indicators.

4.3 Simulation Scenarios

Five scenarios were simulated, all under identical demand conditions of **1410 vehicles per hour**, based on recent flow data from the Mobility and Transports Department of the Paris Region Institute. The scenarios varied only in the proportion of CAVs in the traffic stream:

SCENARIO	% CAVS	% HUMAN-DRIVEN VEHICLES (HDVS)
BASE CASE	0%	100%
SCENARIO 1	30%	70%
SCENARIO 2	50%	50%
SCENARIO 3	70%	30%
SCENARIO 4	100%	0%

Each scenario was simulated over a one-hour period in SUMO, and detailed tripinfo output files were collected for analysis.
The simulation was done over 3600 seconds (1h).

4.4 Vehicle types and behavioural parameters

Two distinct types of vehicles were defined in the simulation to represent the contrasting behaviours of **Connected and Autonomous Vehicles (CAVs)** and traditional **Human-Driven Vehicles (HDVs)**. These were implemented as separate vehicle classes in SUMO with differing microscopic parameters to capture their expected operational characteristics. The following code is an example from the 100% CAV scenario (hence the “probability=1” for vType id=”AutoV”):

```
<vTypeDistribution id="vehDist">

        <vType id="HumanV" accel="2.6" decel="4.5" sigma="0.5" length="5.0"
minGap="2.5" maxSpeed="13.9" tau="1.2" color="1,0,0" probability="0"/>

        <vType id="AutoV" accel="2.8" decel="4.5" sigma="0.1" length="5.0"
minGap="1.0" maxSpeed="13.9" tau="0.6" color="0,1,0" probability="1"/>

</vTypeDistribution>
```

4.4.1 CAVs

CAVs were modelled to reflect their advanced control efficiency, cooperative adaptive cruise control, and faster reaction times. The following key parameters were set:

PARAMETER NAME	VALUE	IMPACT
ACCEL	2.8	The acceleration ability of vehicles of this type [$m.s^{-2}$]
DECEL	4.5	The deceleration ability of vehicles of this type [$m.s^{-2}$]
SIGMA	0.1	Car-following parameter
TAU	0.6	Car-following parameter
LENGTH	5.0	The vehicle's **netto**-length [m]

MINGAP	1.0	Empty space after leader [m]
MAXSPEED	13.9	The vehicles" maximum technical speed. Here at 50 km/h to simplify the configuration of the model
COLOR	0,1,0	Vehicles' colour on the gui
PROBABILITY	[0;0.3;0.5;0.7;1.0]	The penetration rate.

(P. A. Lopez et al., 2018)

4.4.2 HDVs

HDVs were modelled with parameters based on typical driver behaviour variability:

PARAMETER NAME	VALUE	IMPACT
ACCEL	2.6	The acceleration ability of vehicles of this type [$m.s^{-2}$]
DECEL	4.5	The deceleration ability of vehicles of this type [$m.s^{-2}$]
SIGMA	0.5	Car-following parameter
TAU	1.2	Car-following parameter
LENGTH	5.0	The vehicle's **netto**-length [m]
MINGAP	2.5	Empty space after leader [m]
MAXSPEED	13.9	The vehicles" maximum technical speed. Here at 50 km/h to simplify the configuration of the model
COLOR	1,0,0	Vehicles' colour on the gui
PROBABILITY	[0;0.3;0.5;0.7;1.0]	The penetration rate.

(P. A. Lopez et al., 2018)

4.4.3 Differences

Tau is the reaction time, in seconds:

- HDV: tau=1.2
  - Realistic human driver response time
  - Slower to accelerate and brake, creating more stop and go waves
- CAV: tau=0.6
  - Reacts faster to changes ahead
  - Smoother flow

Sigma represents driver imperfection or variability, it introduces randomness in acceleration, lane-changing and car-following:

- HDV: sigma=0.5
  - Human drivers don't maintain perfect distances, may brake unexpectedly and lane change less precisely.
  - Causes instabilities, inefficient gaps and waves of slowing.

- CAV: sigma=0.1
  - Highly stable and predictable driving behaviour
  - CAVs maintain optimal following distance and avoid unnecessary braking

4.5 Performance indicators

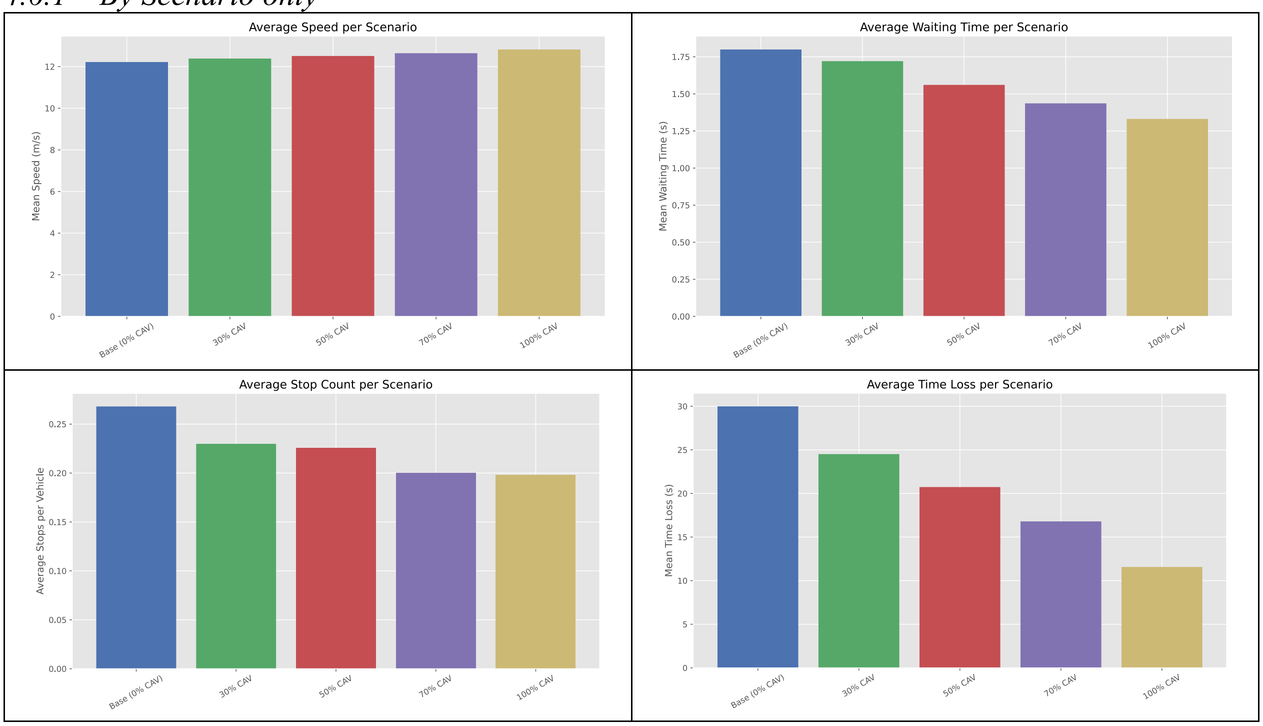
The key performance indicators (KPIs) extracted from the simulation results include:

- **Mean waiting time (s):** average time vehicles spent at standstill.
- **Mean time loss (s):** additional time compared to a free-flow trip at maximum speed.
- **Mean speed (m/s):** calculated as total distance travelled divided by total trip duration
- **Average number of stops:** directly given by the simulation output

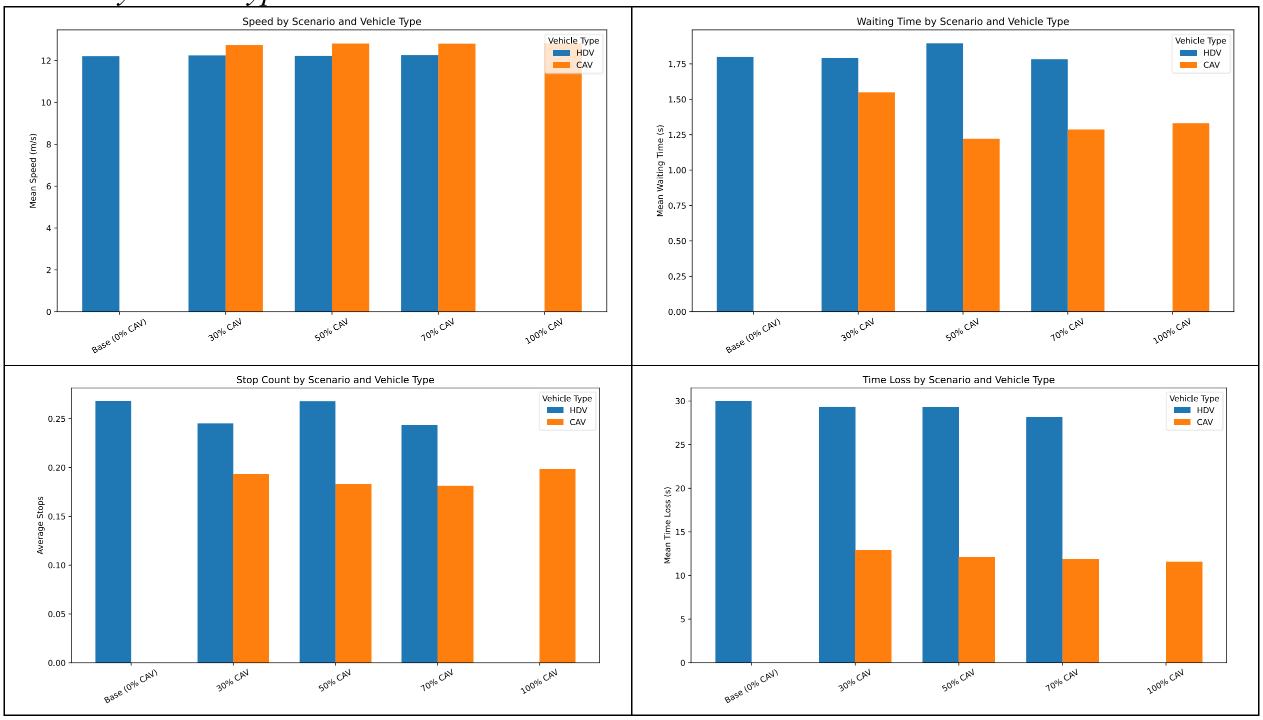
4.6 Findings

The output of each simulation scenario is a tripinfo.xml file that describes each trip that was made during the timeframe of the simulation, these xml files were then computed with python to produce the following graphs:

4.6.1 By Scenario only



4.6.2 By vehicle type and scenario



Scenario	vType	Mean Waiting Time (s)	Mean Time Loss (s)	Mean Stop Count	Mean Speed (m/s)
0% CAV	HDV	1.8	29.99	0.27	12.21
30% CAV	CAV	1.55	12.89	0.19	12.74
	HDV	1.79	29.35	0.25	12.24
50% CAV	CAV	1.22	12.09	0.18	12.81
	HDV	1.9	29.27	0.27	12.22
70% CAV	CAV	1.29	11.89	0.18	12.81
	HDV	1.78	28.15	0.24	12.26
100% CAV	CAV	1.33	11.57	0.2	12.82

4.6.3 Comparison

The results from Sections 4.6.1 and 4.6.2 provide complementary perspectives on how increasing the proportion of CAVs influences traffic performance in the simplified ring road network. While the aggregate indicators show expected improvements, the disaggregated data reveal more nuanced dynamics.

At the aggregate level (Section 4.6.1), the simulations exhibit a clear monotonic improvement in all key performance indicators with rising CAV penetration. Mean speed increases steadily from 12.21 m/s to 12.82 m/s between 0 % and 100 % CAV, while mean waiting time, time loss, and stop count all decline. This trend confirms the general efficiency gains associated with CAV integration, even in a simplified traffic context.

However, when disaggregated by vehicle type (Section 4.6.2), the findings become more intricate. CAVs consistently outperform HDVs across all metrics, as expected, due to their shorter reaction time, lower randomness (sigma), and more stable driving profiles. However, the benefits are not evenly distributed across scenarios, nor do they always scale linearly.

For instance, **CAV performance improves only marginally with penetration**: from 1.55 s to 1.33 s in waiting time, and from 12.89 s to 11.57 s in time loss between 30 % and 100 % CAV scenarios. Similarly, the stop count remains relatively flat (0.19–0.2), and mean speed plateaus around 12.81–12.82 m/s, suggesting that performance gains for CAVs saturate early in this simplified environment.

Conversely, **HDVs show surprising stability** across the entire range of scenarios. Their mean waiting time remains around 1.78–1.9 s, time loss stays near 29 s, and stop count oscillates between 0.24 and 0.27. These limited variations indicate that the presence of CAVs in this context exerts little influence on HDV behaviour. The lack of improvement in HDV metrics reinforces the notion that CAVs do not meaningfully "calm" or stabilise traffic for human drivers in this constrained and uniform loop configuration.

A final point of interest is the **compositional effect**. Overall network-level improvements seen in Section 4.6.1 are not the result of improved HDV dynamics, but simply reflect the increasing share of better-performing CAVs. For example, the average stop count drops from 0.27 to 0.20, but this is driven by the decreasing number of HDVs rather than any reduction in their individual stop frequency.

In summary, this disaggregated analysis reveals that CAV benefits in a simplified loop are mostly internal: they improve their own performance importantly, but offer minimal positive spillovers to HDVs. This contrasts with more complex network setups, where CAV presence may more directly stabilise HDV behaviour. These findings underline the importance of network topology in shaping the system-wide impact of CAV integration.

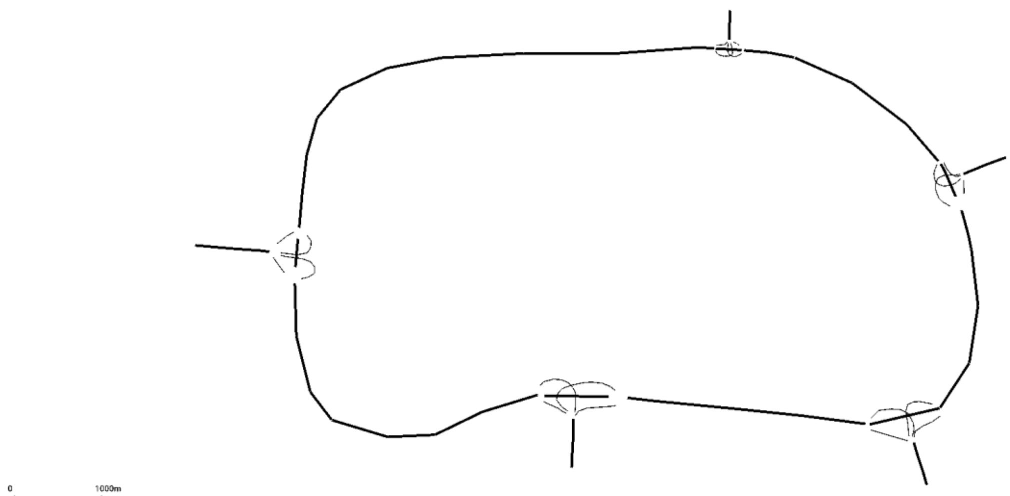
5 More in-depth study on a more complex network

5.1 Objectives

As the first simulation's purpose was to get simple trends (increase or decrease of waiting time for example), the objective of this part is to get actual data that could be applied in a real-world situation. The goal is also to analyse the impact of the car following model on the results.

5.2 Study area

In this part, we are trying to replicate in a more realistic way the Périphérique as it is in the real world. So, a longer network has been designed, with more interchanges, located roughly where the (main) real ones are:



- The shape is an uneven ring road with 5 major interchanges
- The main ring is **4 lanes per direction**, consistent with the typical cross-section of the real infrastructure.
- Pedestrians are prohibited
- Max speed is **50 km/h**
- The main loop is approximately **50% as long as the real-world infrastructure.**

This network has been hand drawn with netedit; sumo's built in editing tool.

5.3 Simulation Scenarios

Five scenarios were simulated, all under demand conditions of approximately 2600 veh/h. This flow was the maximum allowable flow on this particular network, as it was tried to generate a larger flow with Randomtrips.py, a lot of errors came up. The scenarios varied only in the proportion of CAVs in the traffic stream. Two different sets of simulations will be implemented: one set with the default Krauss model and a second set with the IDM (Intelligent Driver Model).

5.4 Vehicle types and behavioural parameters

5.4.1 CAVs

See part 4.4.1.

5.4.2 HDVs

See part 4.4.2.

5.4.3 Differences

See part 4.4.3.

5.5 Performance indicators

See part 4.5.

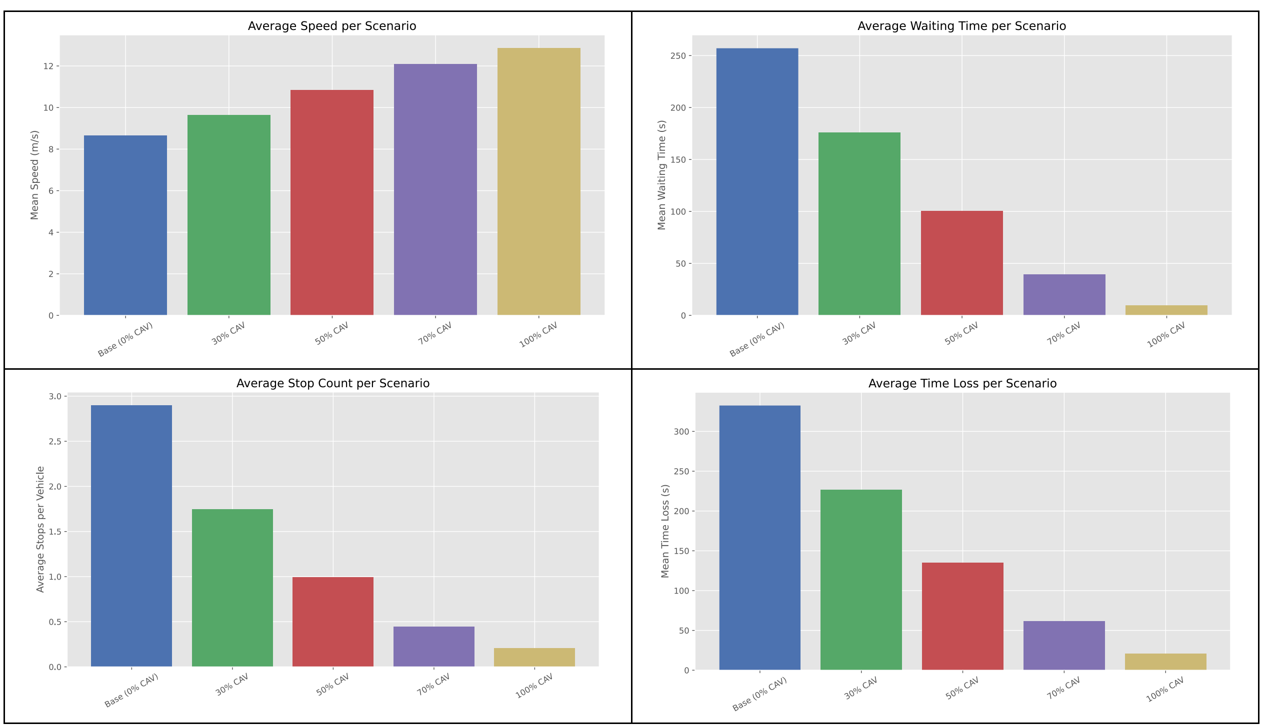
5.6 Findings

The output of each simulation scenario is a tripinfo.xml file that describes each trip that was made during the timeframe of the simulation, these xml files were then computed with python to produce the following graphs:

5.6.1 Krauss Model

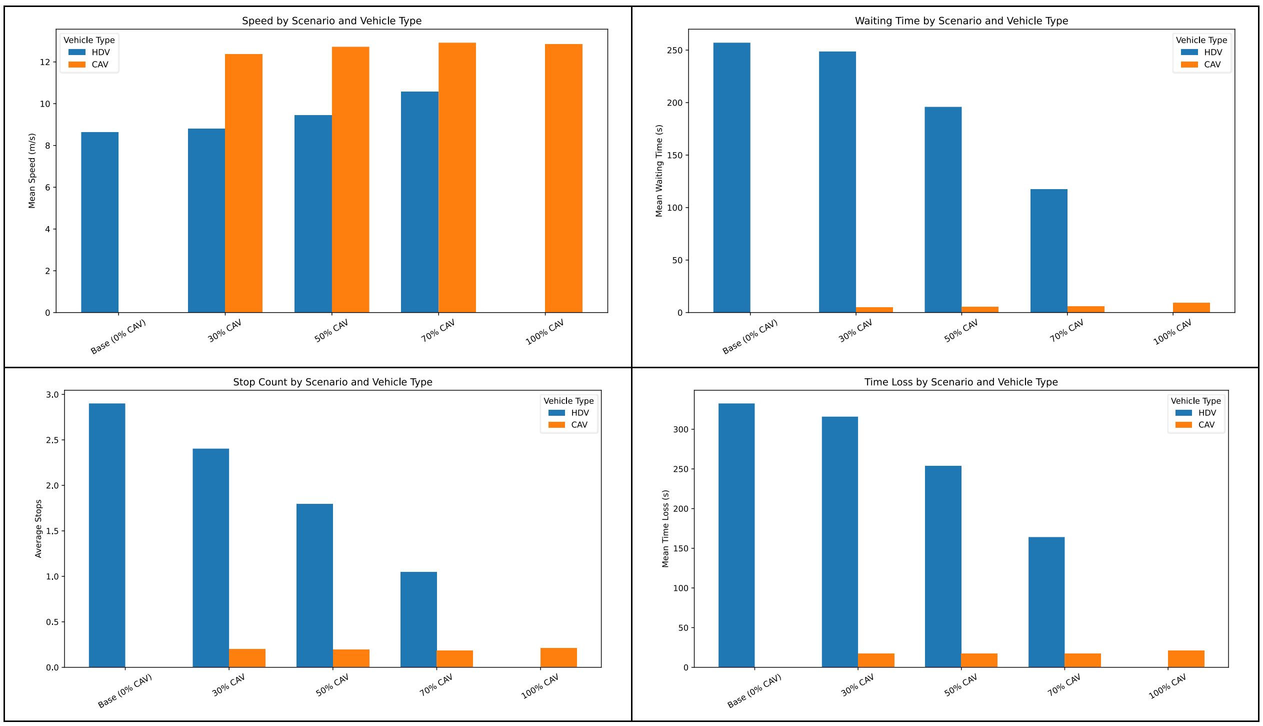
5.6.1.1 By Scenario only

Scenario	**Mean Waiting Time (s)**	**Mean Time Loss (s)**	**Mean Stop Count**	**Mean Speed (m/s)**
0% CAV	257.06	332.51	2.9	8.64
30% CAV	175.85	226.52	1.75	9.63
50% CAV	100.31	135.04	0.99	10.85
70% CAV	39.26	61.41	0.44	12.1
100% CAV	9.53	20.84	0.21	12.85



5.6.1.2 By vehicle type and scenario

Scenario	vType	Mean Waiting Time (s)	Mean Time Loss (s)	Mean Stop Count	Mean Speed (m/s)
0% CAV	HDV	257.06	332.51	2.9	8.64
30% CAV	CAV	5.12	17.09	0.2	12.38
	HDV	248.69	315.88	2.4	8.79
50% CAV	CAV	5.36	17.23	0.2	12.73
	HDV	195.92	253.66	1.8	9.44
70% CAV	CAV	5.81	17.42	0.19	12.92
	HDV	117.35	164.12	1.05	10.57
100% CAV	CAV	9.53	20.84	0.21	12.85



5.6.1.3 Comparison

The simulation results presented in Sections 5.6.1 and 5.6.2 reveal a clear trend: all key performance indicators (KPIs) improve consistently with increasing CAV penetration. Across the five scenarios, there is a marked decrease in average waiting time, time loss, and number of stops, accompanied by a corresponding increase in average speed.

While these overall tendencies align with the patterns observed in Part 4 (simplified network), the magnitude of the improvements is considerably greater in this realistic network configuration. This contrast highlights how increased network complexity and interaction density amplify the advantages of integrating CAVs.

When disaggregating the data by vehicle type (Section 5.6.2), several important insights emerge:

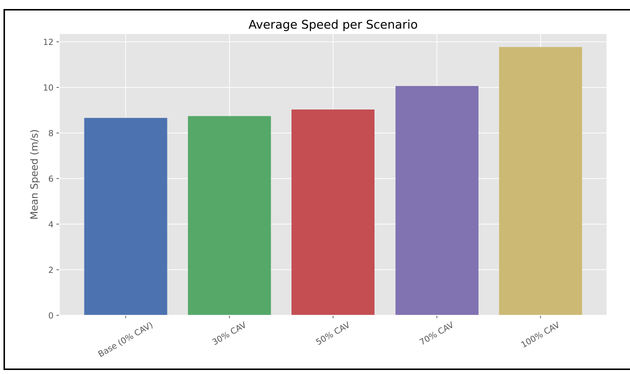
- **CAVs consistently outperform HDVs** across all evaluated metrics. Their enhanced acceleration profiles, shorter reaction times, and reduced behavioural variability (as modelled through lower τ and σ values) enable smoother flow, higher speeds, fewer stops, and lower time losses.
- **HDVs also benefit from the increasing presence of CAVs**. Unlike in the simplified network where HDV performance remained largely static, the realistic network shows measurable improvements for HDVs as CAV penetration increases. This suggests that CAVs contribute to traffic stability by dampening stop-and-go oscillations and facilitating smoother vehicle interactions, even for human-driven vehicles.
- **Time loss dynamics illustrate a more nuanced picture**: for CAVs, time loss throughout the scenarios is increasing by a few percent (from 17.09 s at 30% CAV to 20.84 s at 100% CAV). For HDVs, the decrease is uniform and important (from 315.88s at 30% CAV to 164.12s at 70% CAV), a 48% decrease - further supporting the idea that CAV-induced flow stability positively affects surrounding traffic, particularly in denser environments.
- **The number of stops per vehicle drops sharply** for HDVs while remaining stable for CAVs. The presence of more predictable and efficient CAVs appears to reduce the likelihood of abrupt braking and unnecessary stops for HDs, which are common in heterogeneous traffic.

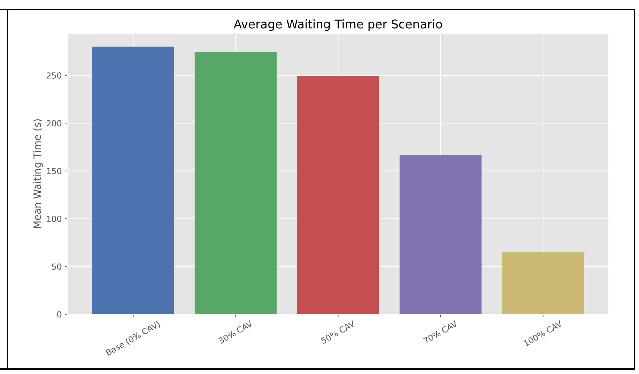
In summary, the findings from this section confirm and reinforce the conclusions drawn in Part 4: a higher proportion of CAVs leads not only to substantial performance gains for the autonomous vehicles themselves, but also to system-wide improvements that benefit HDVs. Crucially, these effects are more pronounced in complex, realistic urban networks, suggesting that even moderate levels of CAV deployment could yield notable benefits in real-world traffic systems.

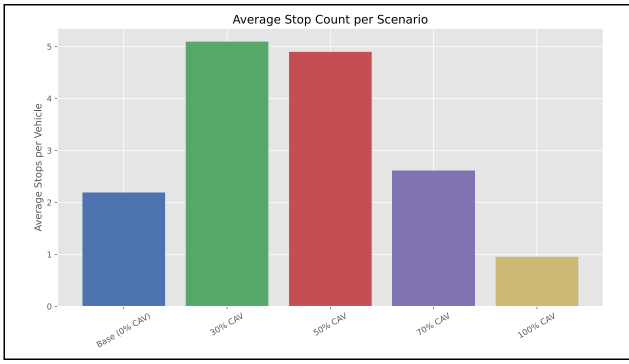
5.6.2 IDM Model

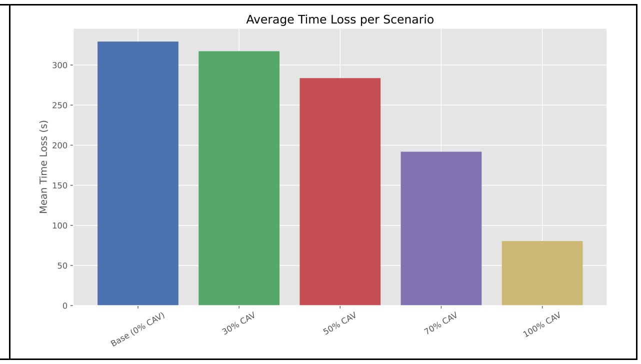
5.6.2.1 By scenario only

Scenario	Mean Waiting Time (s)	Mean Time Loss (s)	Mean Stop Count	Mean Speed (m/s)
0% CAV	280.03	329.28	2.19	8.66
30% CAV	274.65	317.24	5.09	8.74
50% CAV	249.46	283.67	4.9	9.03
70% CAV	166.78	191.87	2.61	10.06
100% CAV	64.77	80.48	0.95	11.77



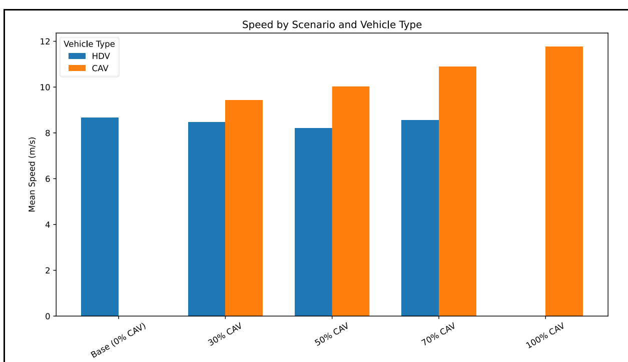


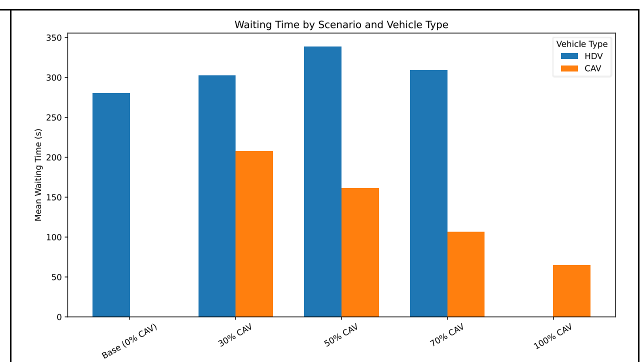


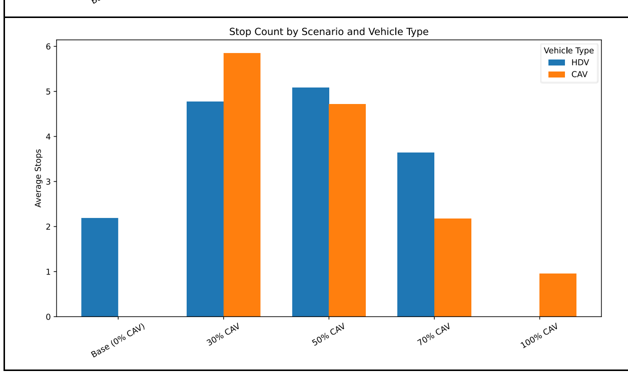


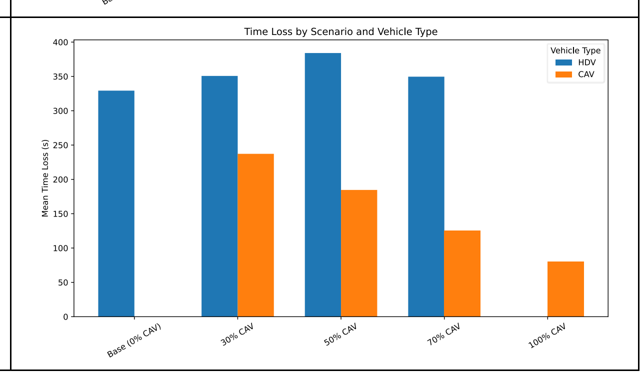
5.6.2.2 *By scenario and vehicle type*

Scenario	vType	Mean Waiting Time (s)	Mean Time Loss (s)	Mean Stop Count	Mean Speed (m/s)
0% CAV	HDV	280.03	329.28	2.2	8.66
30% CAV	CAV	207.55	237.23	5.9	9.44
	HDV	302.73	350.72	4.8	8.48
50% CAV	CAV	161.48	184.63	4.7	10.03
	HDV	338.64	384.07	5.1	8.2
70% CAV	CAV	106.62	125.29	2.2	10.88
	HDV	309.32	349.61	3.6	8.57
100% CAV	CAV	64.77	80.48	1	11.77









5.6.2.3 Comparison

The IDM-based simulation reveals different dynamics from the Krauss-based results. While the aggregated trend remains – increasing CAV penetration improves network performance – the progression is no longer linear or uniform across indicators and vehicle types.

At the aggregate level (5.6.2.1), three of the four performance indicators improve as CAV penetration rises. Mean speed increases from 8.66 m/s at 0 % CAV to 11.77 m/s at full automation. Simultaneously, mean waiting time and time loss drop from 280.03 s and 329.28 s respectively to just 64.77 s and 80.48 s in the 100 % CAV scenario. Stop count has a different evolution, with a maximum for 30% CAV penetration rate. This confirms that the IDM model, with its more aggressive but smooth driving behaviour, increases traffic fluidity at high CAV shares.

However, the disaggregated (5.6.2.2) results reveal several unexpected patterns:

- **At 30 % CAV**, HDVs perform worse than in the 0 % baseline. HDVs experience increased waiting time (from 280.03 s to 302.73 s) and stop count (from 2.2 to 4.8), while CAVs reach the highest stop count across all scenarios (5.9). This suggests that limited CAV presence may create turbulence rather than stability under IDM, especially if cooperative benefits are not fully realised at low penetration.
- **From 30 % to 70 %**, CAV performance improves a lot. Mean waiting time drops from 207.55 s to 106.62 s, time loss from 237.23 s to 125.29 s, and stop count from 5.9 to 2.2. HDVs however seem to get almost no benefit from the increased CAV penetration rate, with time loss going from 350.72 s to 349.61 s and time loss going from 302.73 s to 309.32 s.
- **At 50 % CAV**, however, HDVs exhibit their worst performance in the entire set, with the highest time loss (384.07 s) and lowest mean speed (8.20 m/s). This asymmetry suggests that IDM-based CAVs may inadvertently disrupt HDV dynamics under certain mix ratios, possibly due to tighter following distances or inconsistent merging behaviours.
- By **70 % and 100 % CAV**, system performance becomes increasingly stable. CAVs demonstrate near-optimal operation, with minimal stop counts (2.2 and 1.0 respectively) and high mean speeds (10.88 and 11.77 m/s). The drop in HDV stop counts (from 5.1 to 3.6) and waiting times also confirms that a high share of IDM-driven CAVs exerts a strong stabilising effect.

In conclusion, the IDM model yields sharper contrasts across penetration levels. While it provides superior performance at full automation, partial CAV integration—particularly at 30–50 %—can temporarily degrade performance due to incompatible interaction patterns. These findings underscore the importance of careful calibration and deployment strategies when transitioning to mixed IDM-based traffic environments.

6 Discussions and conclusions

6.1 Summary of Findings

This study aimed to evaluate the impact of Connected and Autonomous Vehicle (CAV) penetration on traffic dynamics within a simplified model of Paris's Boulevard Périphérique. Through a series of simulations with varying proportions of CAVs, using both the Krauss and IDM car-following models, we analysed key traffic indicators including mean speed, waiting time, time loss, and stop count—both in aggregate and disaggregated by vehicle type.

Key findings include:

- A general improvement (at the aggregated level) in traffic performance as CAV penetration rate increases, notably in scenarios above 50% CAV.
- In mixed traffic, Human-Driven Vehicles (HDVs) consistently performed worse than CAVs in terms of time loss and waiting time.
- Non-linear behaviours emerged, particularly at intermediate penetration levels (30–50%), where HDVs exhibited elevated stop counts and time losses.
- Comparisons between Krauss and IDM revealed differing sensitivity to CAV penetration, with IDM scenarios generally producing less benefit for HDVs at mixed traffic scenarios (30, 50 and 70% CAV penetration rates).

6.2 Discussion

The results demonstrate that CAV integration has the potential to improve urban traffic flow. Metrics such as mean speed and time loss improved progressively with increasing CAV penetration, particularly beyond 50%. However, disaggregated results revealed that this improvement is not uniformly distributed across vehicle types.

HDVs were notably disadvantaged in mixed scenarios—especially at 30% and 50% CAV—where their time loss and waiting times peaked (for the IDM model). This suggests that early-phase CAV integration may create traffic heterogeneity that penalises non-automated drivers, potentially due to mismatched behavioural dynamics and differing acceleration/gap-keeping characteristics.

The car-following model also played an important role. Krauss exhibited greater efficiency across scenarios compared to IDM, yielding shorter waiting times and lower stop counts in the aggregated results. However, the performance gap between HDVs and CAVs was smaller under IDM, suggesting that the smoother acceleration and more anticipative behaviour of IDM CAVs may reduce traffic disturbances, even in mixed fleets.

The observed non-linearity - such as the unexpected peak in stop count at 30% CAV - is likely the result of complex interactions between vehicle types, route patterns, and the stochastic nature of the simulation. These trends indicate that optimal benefits from automation might only be realised once a critical mass of CAVs is reached, and that sub-optimal configurations could temporarily degrade network performance for some users.

6.3 Limitations

While the findings offer useful insights, several limitations must be acknowledged:

- The network used was a simplified abstraction of the Périphérique, lacking features such as bottleneck, complex interchanges or complex merges.
- Vehicle behaviours were modelled using fixed parameters, without adaptive or learning mechanisms.
- External disruptions, lane-changing dynamics, and multi-modal interactions were not considered.
- Only two car-following models were tested; the behaviour of more recent or cooperative models (e.g. CACC, RL-based) remains unexplored.

6.4 Future Work

To deepen the understanding of CAV integration, future work could explore:

- The use of more realistic networks with calibrated demand data and multimodal elements.

- Testing a wider array of car-following models, including those featuring cooperation, communication, or reinforcement learning.
- Investigating the impact of adaptive behaviours, traffic signal control, and dynamic lane management.
- Coupling traffic performance with environmental outputs, such as emissions and fuel consumption, to assess the sustainability impact of CAVs.

6.5 Final Conclusion

This study confirms the potential for CAVs to improve traffic performance on urban ring roads, but also underscores the complexity of the transition phase. While full automation yields the most consistent improvements, intermediate levels of penetration can produce non-trivial and sometimes adverse effects, especially for HDVs. Moreover, the choice of car-following model influences the outcome, reinforcing the importance of model selection in simulation-based research. Overall, these results highlight the need for careful policy design and infrastructure planning to support a smooth and equitable transition toward automated mobility.

7 Acknowledgement

I acknowledge the use of ChatGPT 4o (OpenAI, https://chatgpt.com/) for the following:

- Generate outlines for the abstract and some parts of the literature review
- Double check the simulation results for part 4 and 5.
- Generate python code to create the tables and plots in part 4 and 5

I confirm that the work presented is this paper is therefore not AI generated and is my own work.

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