EURECOM
Department of Communication Systems
Campus SophiaTech
CS 50193
06904 Sophia Antipolis cedex
FRANCE

Research Report RR-21-345

# On the Traffic Impact of Risk-Aware Autonomous Vehicle Routing Strategies

October $12^{\text{th}}$, 2021
Last update October $12^{\text{th}}$, 2021

Duncan Deveaux and Jérôme Härri

Tel : (+33) 4 93 00 81 00
Email : {duncan.deveaux,jerome.haerri}@eurecom.fr

[1]EURECOM's research is partially supported by its industrial members: BMW Group Research and Technology, IABG, Orange, Principauté de Monaco, SAP, NortonLifeLock.

# On the Traffic Impact of Risk-Aware Autonomous Vehicle Routing Strategies

Duncan Deveaux and Jérôme Härri

**Abstract**

Connected and Autonomous Vehicles (CAV) face a variety of challenging driving situations in ever more complex road infrastructures designed with human drivers in mind. Despite an increasing driving intelligence, a possible answer to complex road infrastructure or the proximity of vulnerable road users may be to alter CAV driving strategies to avoid potential *risky* or complex driving situations. In this paper, we make a first study on the impact of strict *risk-aware* routing strategies on urban traffic. Simulation-based results showed that, if a large amount of CAV are statically routed to avoid *risky* areas, mixed effects on traffic can be observed. While the travel time for human-driven vehicles was reduced, an increased length of queues among the road network led to increased pollutant emissions.

**Index Terms**

autonomous, risk, routing, take-over, traffic, vehicles

# Contents

# List of Figures

# 1 Introduction

Connected and Autonomous Vehicles (CAV) are vehicles meant to drive passengers safely to their destinations without driver or human intervention. Through information exchange, CAV are able to get knowledge of their environment and improve driving safety. Various standards such as the American DSRC or the European ITS-G5 have been developed for information exchange and communication in *vehicular networks*. The ability to communicate for CAV brings a potential for coordination among a fleet of autonomous vehicles, differing from the traditional competitive driving behaviors of human drivers, as introduced in the survey by Tettamanti *et al*. [2].

Even at low penetration rates, the introduction of Connected and Autonomous Vehicles (CAV) on the roads is expected to show significant benefits for the fluidity of traffic. Because CAV are able to exchange information, they are able to coordinate their movements, bringing opportunities for regulating traffic, even mostly composed of legacy human-driven vehicles. According to Wu *et al* [3], a uniform penetration rate of autonomous vehicle as little as 6% of the overall traffic could allow to efficiently stabilize traffic on highways by mitigating shockwaves of slowing down vehicles. Alfaseeh *et al.* [4] suggested an architecture offloading all CAV routing decisions to a centralized controller. By taking educated routing decisions, the approach allowed to improve traffic conditions in a simulation of downtown Toronto in terms of mean travel time and traffic throughput.

Coordination among autonomous vehicle can benefit to the greater number by improving traffic conditions in various situations. However, this assumes cooperation between autonomous vehicles and choices of routing that may in some cases be against the interest of CAVs in terms of self-driving capabilities. An expected key feature of CAV is to be able to use and share the current road infrastructure with traditional human-driven vehicles, two-wheelers, and pedestrians. However, most roads were not designed with autonomous traffic in mind, and CAV must compose with ever more complex road infrastructures requiring implicit cooperation and prediction of the intentions of human drivers and other vulnerable road users.

Some driving conditions have been studied to be difficult to negotiate autonomously in current states of automation [5]. In some situations, the perception algorithms on-board CAVs reach a capacity limit and are not able to accurately interpret a driving scene. In other situations, a road layout may be too complex for the CAV on-board algorithms to compute safe trajectories, e.g., in the case of work zones or temporary ground marks. Notwithstanding, poor visibility may also alter sensor measurements, e.g., occlusion by buildings in city centers or poor weather conditions and be an issue for self-driving capabilities of CAV [6].

Moreover, situations that require active cooperation with humans are known to be difficult to negotiate for autonomous vehicles. Again, the issue comes from both (i) the complex layout of road infrastructures designed for humans drivers, such as unsignalized intersections, i.e., yield-type crossings or roundabouts and

(ii) the need to develop algorithms to understand and impersonate human drivers' implicit behavior and communication methods [7–9].

Combined with loaded traffic conditions, such situations may cause CAVs to return the control to a human supervising driver [10], cruise at a reduced speed, or stop completely. This breaches the autonomous character of the CAV and alters the comfort of autonomous driving for passengers. To identify such situations, risk metrics for autonomous vehicles have been defined, allowing a risk-aware routing of CAVs [11]. In order to maximize the likelihood of being able to drive from $A$ to $B$ in a fully automated manner, CAV can be routed away from *risky* zones that may require take-over from a human driver.

In this paper, we make a first study on the impact on traffic of such a systematic rerouting of CAV to the most "automated-friendly" paths. We summarize the existing literature to understand what road conditions and topologies are challenging to negotiate for CAV. Based on this understanding, we perform a simulation-based study using the SUMO-based city-wide MoST scenario [1] and investigate the effect of such *risk aware* routing on traffic and pollutants emission metrics, to compare it with strategies where autonomous vehicles would operate optimally regardless of the complexity of the road infrastructure.

The rest of this article is organized as follows: Section 2 summarizes the literature for situations known to be challenging to drive autonomously for the current CAVs. Based on this understanding, Section 3 describes a case study applied on a simulated city of Monaco, which investigates the effect for traffic and the environment of rerouting CAV away from a set of predefined *autonomy-challenging* areas. We discuss the results of the case study and lay out future research opportunities in Section 4, while Section 5 summarizes the article.

## 2 A measure of risk for automated features

A scale of automation for vehicles as been defined in the SAE J3016 standard [12] and widely accepted. Levels 0 to 2 refer to partial or no automation, whereas Level 5 refers to full automation, in which case the vehicle does not require a driver at all. Although aiming at Level 5 by the industry, personal vehicles currently being tested or available on the road typically operates at automation Levels 3 or 4, that is: conditional to high automation. In these systems, the vehicle is able to autonomously control the vehicle in a set of known situation, but the presence of a supervising human driver is still required.

For these CAV systems, certain road situations and driving contexts are more difficult or risky to negotiate than others. The objective of CAV at that stage is to minimize the risk of accident for its passenger while maintaining an optimal self-driving feature, that is, maintaining a reasonable driving speed and avoiding the return of the vehicle's control to a human supervisor. Situations where a CAV is not able to handle the driving task and must return the control to a human driver are especially dangerous. Due to the vehicle being at the edge between human driving and full automation, the supervising driver – driver or passenger – is likely to suffer from a lack of attention at critical moments when it is supposed to take back control [13].

To mitigate the risk of requiring a human driver's take over, CAVs could consider the possibility to avoid areas and situations that are known to be risky or challenging to the continuous capability of the CAV to drive in an automated manner. We perform a summary of the literature in order to determine which areas imply such risk or perturbation for current automated vehicles. We consider the problem from two approaches, namely:

1. Technical risk, areas that may be prone to technical failures of the on-board sensors and algorithms of the automated vehicle, leading to risk.

2. Human Interaction risk, which involves areas where complex interaction with human beings is required.

Moreover, in complex situations involving various factors of risk, CAVs may be unable to pursue autonomous driving. As a consequence, a take-over might be triggered by the CAV, in which a supervising human driver is asked to take back control of the vehicle. In a third subsection, and to consolidate the summarized risk factors, we summarize the literature for situations that are specifically known to involve a risk of take-over of a CAV by a supervising human driver.

## 2.1 Technical Risk

Pink *et al.* [5] surveyed the various challenges that automated vehicles face while driving on public roads. One of the main features required for automated driving is *perception* by a CAV of its driving environment. CAVs come equipped with various sensors built for that purpose, such as cameras, lidars, and radars. Then, perception algorithms fuse the sensed information with external sources, e.g., map data, in order to properly classify the sensed objects and understand the current driving scene. Such understanding of the scene and recognition of other vehicles, pedestrians or obstacles is essential to a safe and continued automated driving by a CAV. The paper suggests a list of situations that challenge the technical quality of the retrieved sensor data or the proper accomplishment of perception algorithms.

On the one hand, technical issues may appear at the sensor information acquisition level. As studied independently by Zang *et al.* [6], poor weather conditions, such as rain, snow or fog can significantly alter sensor data quality, in turn altering the perception capabilities of the CAV. Occlusion is another scenario in which a part of the scene is hidden, e.g., by a building or another vehicle. Pink *el al.* give the example of driving next to a lumbertruck. Recent works have studied the impact of occlusion for self-driving vehicles [11, 14].

On the other hand, issues may arise in the scene understanding algorithm, even with good sensor data quality. Pink *el al.* use the example of driving in construction zones, where temporary road markings – unexpected by the CAV – overlap with the original marks. The lack of training of highly automated vehicles' scene recognition algorithms for temporary construction zones situations may lead the vehicle to temporarily return control to a human supervisor.

### 2.2 Human Interaction Risk

Communication with human beings is a key issue and challenge for the development of autonomous vehicles. Mechanisms to efficiently understand human drivers' intents and communicate the machine intentions' back to them must be implemented for a successful transition from human-driven vehicles to autonomous vehicles. Even with a high penetration rate of autonomous vehicles, the human factor can never be completely eliminated, as pedestrians and two-wheelers must still be considered.

[15] defines *safety-critical events* for CAVs. Erratic behavior from other road actors or unplanned events such as pedestrians on roads at unexpected places are listed. The unpredictability of human road actors makes their interaction with CAV challenging. In turn, situations where interaction with human drivers is unavoidable can be risky for CAVs and force them to return control to a human driver. In unsignalized intersections, i.e., yield type stops, give-way, or roundabouts, particularly in loaded traffic conditions, negotiation with humans is necessary to proceed.

Rasouli *et al.* [7] have surveyed the challenges and papers dedicated to autonomous vehicle interaction with pedestrians. The main difficulties and open issues that arise include understanding and predicting pedestrian behavior. What is more, it is reasonably expected that pedestrians, as well as human drivers, might adopt a different behavior when facing and recognizing an automated vehicle as opposed to in a traditional situation. Few studies have investigated this issue, raising uncertainty in current stages for autonomous driving in areas of high pedestrian occupancy.

Another identified challenge is defining means of communicating with road users. This requires not only estimating their intentions, as studied by Fisac *et al.* [8] or Zyner *et al.* [9], but also defining means of communicating the CAV's intentions to human drivers. Until these issues are addressed in further details and studies, areas of high-pedestrian concentration, especially featuring unsignalized pedestrian crossings as studied by Chen *et al.* [16], can challenge the ability of CAV to drive autonomously. Similarly, unsignalized intersections, i.e., yield type, stop intersections or roundabouts, require communication with human drivers as well as behavior understanding and prediction and may trigger a human supervisor's take-over.

### 2.3 Risk and Human Take-over

Xin *et al.* [10] surveyed the literature for reasons that are typically considered to trigger a take-over of the CAV, i.e., the CAV returns control to a human supervising driver. They are found to be linked to a capacity limit of the scene perception algorithms on board highly automated vehicles. In the studied systems, a capacity limit can be reached when one or more of the following conditions are met:

- Complex driving situation, e.g., lane change.
- Weather conditions affecting visibility.
- Occlusion, e.g., caused by road-side buildings.
- Large number of vehicles and objects on the road.

The authors give a list of example situations in which such conditions are likely to be met, and trigger a take-over by a human driver. Work zones are challenging to navigate for CAV for several reasons. The lack of ground marks or the presence of temporary ground marks overlapping with permanent marks can be ambiguous and thus challenging for the perception algorithms of autonomous vehicles. This is especially true for those that have not been trained or designed to recognize overlapping temporary ground markings. What is more, the temporary road layout in work zones is typically unexpected by the CAV, as map data possessed by the vehicle may not immediately incorporate the updated topology.

Complex driving situations that can cause human driver take-over include lane change or lane merging situations, or situations of packed traffic where the number of neighboring vehicles to consider is high. The paper also quotes irregular driving behaviors of other road drivers that can be encouraged by unclear ground markings. Finally, the interaction with pedestrians and small vehicles such as nonmotorized vehicles or two-wheelers can trigger a take-over. This is caused by the potentially unexpected trajectories they take, for example, in high pedestrian density areas or unsignalized pedestrian crossings.

# 3 Case Study: Urban Driving in Monaco

To study the impact on traffic and the environment of routing CAV away from a set of identified *autonomy-challenging* areas, we develop a case study applied to the city state of Monaco. After identifying a set of such areas in Monaco, we use a microscopic traffic simulation tool to investigate the effects of rerouting a gradually more important proportion of vehicles away from them.

## 3.1 Autonomy challenges in Monaco

Based on the literature review, we define a list of the most challenging-to-drive intersections and areas for CAV in the city state of Monaco. We especially consider (i) the nature of the area, e.g., roundabout or yield type, (ii) the presence of occlusion in the area, (iii) the presence of unsignalized pedestrian crossings, (iv) the clarity of ground marks, e.g., typically poor in a work zone, (v) the presence of a lane merging and (vi) the typical traffic conditions in the studied morning rush-hour period. Figure 1 illustrates the location of the selected areas, and Table 1 summarizes their addresses and characteristics.

**Round-point Du Portier** The roundabout *Du Portier* is, at the time of writing, undergoing construction works, and ground marks have been mostly removed. This adds to the difficulty of driving for CAV, combined with the presence of unsignalized pedestrian crossings at every arm of the roundabout and the need for cooperation with human drivers, due to a high traffic at rush hour.

**Place d'Armes** Some arms of the roundabout of *Place d'Armes* are occluded by buildings. Pedestrian activity is high combined with several unsignalized crossings.

**Boulevard des Moulins** The roundabout of *Boulevard des Moulins* features very congested traffic at rush hour. Moreover, it lacks ground marks clearly identifying lanes, and some of its smaller arms are occluded by surrounding buildings.

**Boulevard d'Italie** In the vicinity of *Boulevard des Moulins*, the roundabout of *Boulevard d'Italie* suffers from similarly congested traffic at peak times, as well as unclear ground markings for lane separation.

**Avenue de la Madone** Near the heart of the busy Monte Carlo area, the intersection between the Casino Square and *Avenue de la Madone* is highly congested at peak times. It is a yield-type intersection, requiring negotiation with human drivers, as well as with many pedestrians coming from the nearby Square and *Jardin de la petite Afrique* park. The left-hand side of the intersection is occluded by a building. Finally, the intersection features an unsignalized pedestrian crossing.

**Avenue de France** Located at the East border with France, the intersection at *Avenue de France, 1* connects two-lane roads on the French side with single lane roads in Monaco. It is implemented by a set of yield-type intersections, requiring active negotiation with human drivers, especially at peak times, when the traffic is congested. Unsignalized pedestrian crossings are located near the intersection.

**Pont Sainte-Dévote** Similarly to *Avenue de France*, the *Sainte-Dévote* bridge is a yield-type intersection with several lane merging areas. It requires active negotiation with human drivers under congested traffic conditions at peak times.

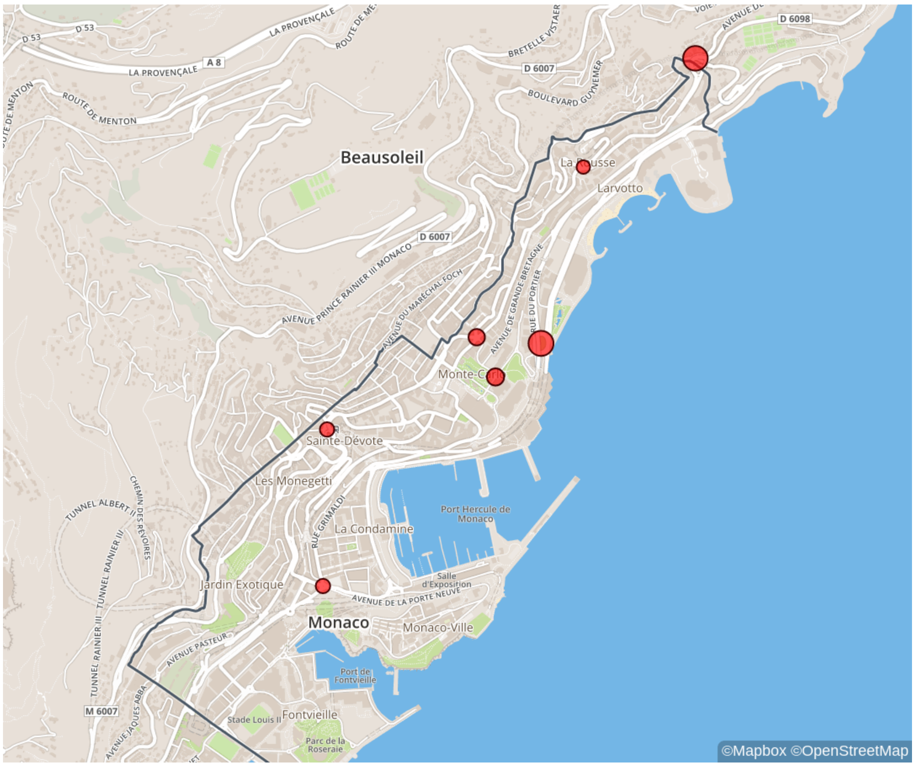


Figure 1: Difficult zones considered for CAV in Monaco

Table 1: Summary of the considered risky zones

| | Type | Occlusion | Pedestrian Crossings | Lane merging | Marks clarity | Rush-Hour Traffic |
|---|---|---|---|---|---|---|
| **Rond point du portier** | Roundabout | | ✗ | | Work zone | ++ |
| **Rond point Place D'armes** | Roundabout | ✗ | ✗ | | | ++ |
| **Boulevard des moulins** | Roundabout | ✗ | ✗ | | Low | +++ |
| **Boulevard d'Italie** | Roundabout | | | | Low | +++ |
| **Avenue de la Madone** | Yield | ✗ | ✗ | | | +++ |
| **Avenue de France** | Yield | | ✗ | ✗ | | ++ |
| **Pont Sainte-Dévote** | Yield | | | ✗ | | ++ |

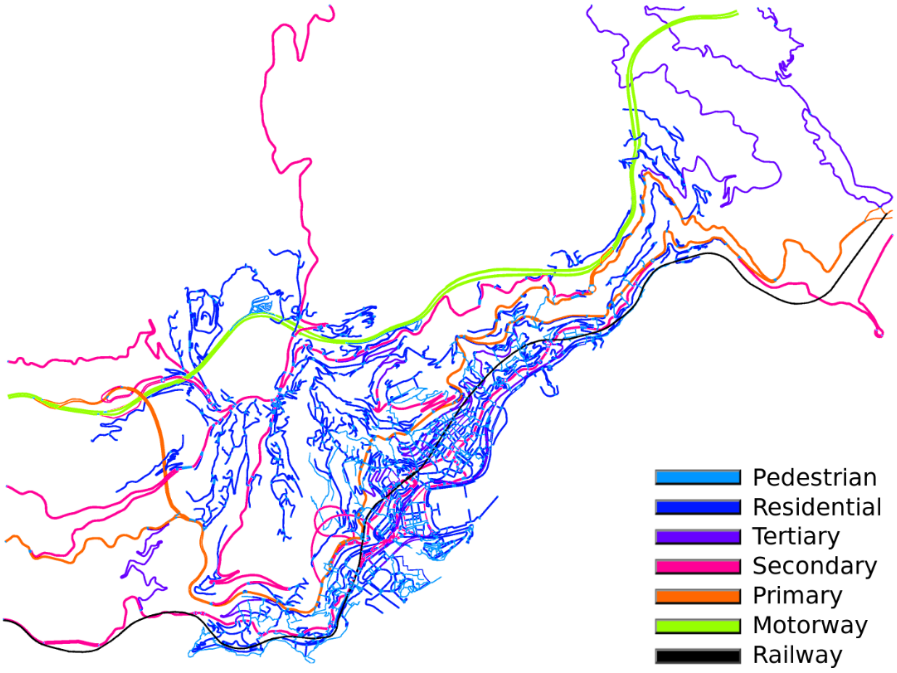


Figure 2: Overview of the MOsT scenario [1]

## 3.2 Simulation Framework

Simulation of Urban MObility (SUMO) [17] is a free software general-purpose microscopic traffic simulator that includes various tools to model traffic mobility. The Traffic Control Interface (TraCI) APIs allow complex interactions with the simulations, making the implementation of various scenarios possible. In this paper, we use Monaco SUMO Traffic (MoST) scenario [1], a realistic model of the city of Monaco and its traffic during a typical morning rush hour from 5:00 to 12:00.

MoST is a 3D model of the city state of Monaco, including elevation data. Due to the geographical position of the city close to the Alps mountain chain, the elevation of various roads differs greatly as well as their slope. In order to accurately model the emissions of the vehicles simulated in the SUMO MoST environment, we use the *PHEMLight* [18] emissions model. PHEMLight is a simplified version of the *Passenger Car and Heavy Duty Emission Model* developed by TU Graz. It takes the current road slope into account when estimating emissions, making it suitable for our study.

### 3.3 Evaluation setup

We run several MoST simulations, each simulating a typical morning rush hour in Monaco. The simulation includes various modes of transportation in addition to passenger cars, such as buses, trains, VTC, pedestrians, or two-wheelers. In total, about $22700$ passenger vehicles are inserted in a simulation, each with their own itinerary made of a departure point, potential stops, and a final destination point. However, the routing of each passenger vehicle is not fixed once it has been computed. It is dynamically reevaluated based on the current traffic conditions every P=300s of simulated time. If a new path with a shorter estimated trip time is found, the vehicle is routed to follow the shortest available path to its destination, computed using the Dijkstra algorithm. The costs of possible paths are computed as their overall distance divided by the current mean speed of vehicles driving them, thus taking the current traffic conditions into account.

What is more, in each simulation, we divide passenger vehicles into two categories: Each passenger vehicle is either flagged as a *Human-driven* vehicle or as a *CAV*.

- *Human-driven* vehicle's behavior is left unchanged. Their goal is to reach their destination through the fasted possible route among the available routes in the network. As explained earlier, their route is reevaluated every P=300s of simulated time to take current traffic conditions into account.

- Vehicles flagged as *CAV* take *risk* into account when computing routes to their destination. In this study, risk is a simplified static and binary value. At all times in the simulation, the seven areas of Monaco that we defined in Table 1 are considered *risky* to navigate for *CAV*. As a consequence, vehicles flagged as *CAV* are systematically routed away from these *risky* areas.

  Routing of vehicles flagged as *CAV* in each simulation is dynamically recomputed every P=300s of simulated time, taking traffic *and risk* into account. *CAV* take the fastest route to their destination that does not involve crossing any of the aforementioned *risky*, autonomy-challenging areas of Monaco.

In each simulation, a random subsection of $\{N \in [0, 10, 20, 35, 50, 60]\}\%$ of the *passenger cars* are flagged as *CAV* vehicles. They are dynamically routed to reach their destination while avoiding the aforementioned autonomy-challenging areas of Monaco. The objective of this evaluation is to study the potential impact on traffic and the environment of systematically routing CAV away from risky, autonomy-challenging areas.

Various metrics and statistics are collected from each completed simulations, including:

- General statistics on the traffic flow conditions at each step of the simulation, e.g., the mean speed of vehicles.
- Statistics on queues forming in the road network and their length.
- The trips data of each car, including their trajectories, trip duration, fuel consumption.
- The emissions' statistics of each car in the simulation, including $CO_2$, CO and $NO_x$ gases, $PM_x$ particles and hydrocarbon emissions. The extracted emissions data take the elevation and the slope the car is driving at into account.

After running several simulations for $\{N \in [0, 10, 20, 35, 50, 60]\}\%$ of CAV, i.e., rerouted passenger cars in the MoST scenario, we analyze the results on the impact on the environment and traffic of rerouting a gradually greater amount of CAV away from autonomy-challenging areas.

## 3.4 Evaluation Results

### 3.4.1 Routes

We notice a clear separation between routes taken by CAV and human-driven vehicles. Figure 3 illustrates on a map the routes taken by both types of vehicles for a proportion of 50% of CAV and 50% of human-driven vehicles. For each road, the difference between the number of CAV and the number of human-driven vehicles that have been driving it during a complete simulation is computed and normalized into the interval [-1,1]. The blue colors indicate lanes where the number of CAV was superior to the number of human drivers, whereas the red colors indicate lanes mostly occupied by human drivers.

Primary roads leading to the city-centre and Monte Carlo are overwhelmingly occupied by human-driven vehicles, especially from the south border with France. *Boulevard du Jardin Exotique*, leading to the *Sainte-Dévote* area where CAV do not drive, until the main artery *Boulevard des Moulins* to *Boulevard d'Italie* are the primary roads that human drivers occupy more, benefiting from a shift of CAV to secondary roads. CAV shift on parallel roads in the French side, such as the *Avenue Paul Doumer*. Although they are less risky to drive autonomously, they typically increase the route length and can feature lower speed limits and traffic throughput than those of the primary roads of Monaco.

Furthermore, we notice that human drivers favor primary roads even more as the proportion of CAV increases. Fig. 4 shows the difference in preferred roads chosen by human drivers (i) in the absence of CAV and (ii) with a proportion of 60% of CAV on the roads. In each case, a normalized value of the most driven roads

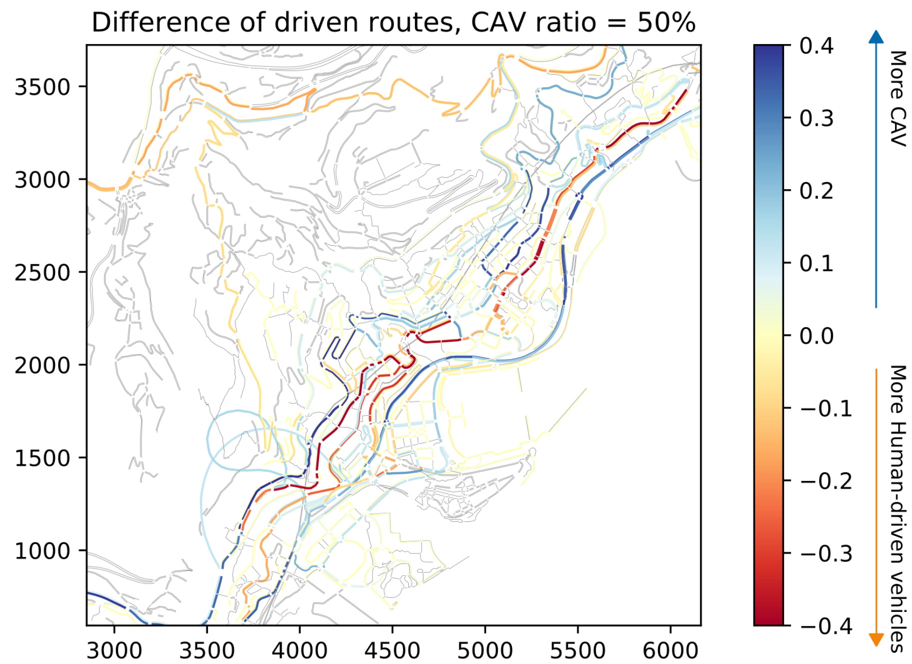


Figure 3: Difference of routes between CAV and human-driven Vehicles for a ratio of CAV of 50%

by human drivers is computed in the range [0,1], with 0 being a road that no human vehicle has taken during a simulation, and 1 the most frequented road by human drivers. The roads are colored by the difference of those normalized most driven road values for a ratio of 60% and 0% of CAV. The blue colors indicate roads that were preferred by human drivers when 60% of the overall vehicles where CAV. The red colors indicate the roads taken by vehicles with no CAV in the road network.

As the proportion of CAV increases, human drivers favor the primary roads we listed earlier even more. We argue that this is caused by the space freed on those roads by CAV choosing other, secondary roads. This could indicate an improvement in the traffic conditions on primary roads. In the next section, we analyze further results on traffic conditions in the road network.

### 3.4.2 Trip duration

We investigate on the effect of such different routing of CAV and Human-driven vehicles on their respective mean trip duration and mean speed. Figure 5 shows the evolution as the proportion $r_{CAV}$ of CAV increases of the mean trip duration during a simulation of (i) CAV in blue, (ii) Human-driven vehicles in orange and (iii) all vehicles. For each value of $r_{CAV}$, we perform $n = 10$ distinct simulations with a different random choice of vehicles flagged as CAV. The 97.5%

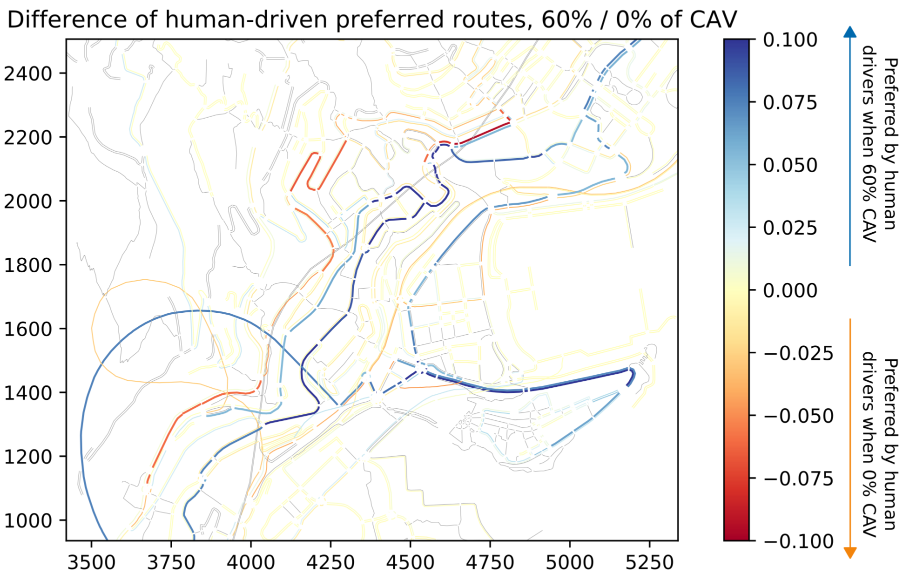


Figure 4: Difference of preferred routes by human-driven vehicles for 0 and 60% of CAV

confidence intervals are computed using a Student $t$-distribution with $t = 2.262$, for the corresponding $n = 10$ sample size.

We observe that an increased rate of CAV resulted in an increase of the travel duration for CAV, compensated by a significant reduction of the travel time for human-driven vehicles. All vehicles considered, the trip duration does not vary. This confirms the benefits on trip time for human drivers as the occupancy of primary, faster roads decreases in favor of secondary roads, mostly occupied by CAV.

Similarly, Figure 6 shows the evolution as $r_{CAV}$ increases of the mean speed of different types of vehicles during a simulation. The mean speed of vehicles remains stable regardless of the amount of CAV vehicles on the road. We notice that the mean speed of human-driven vehicles however increases with $r_{CAV}$. In parallel, the mean speed of CAV decreases as their number increases. This can be explained by a difference of speed limits in the secondary roads taken, or potentially by the formation of longer queues in those paths, due to an increased presence of CAV. In the next section, we investigate on the evolution of queues length and mean speed during a simulation.

### 3.4.3 Queues and congestion

Figure 7 shows the evolution of the combined length of queues on the road every 5 minutes of a simulation, for different ratios of CAV, with a confidence interval of 95%. We notice an increase of approximately 1km of the overall queue

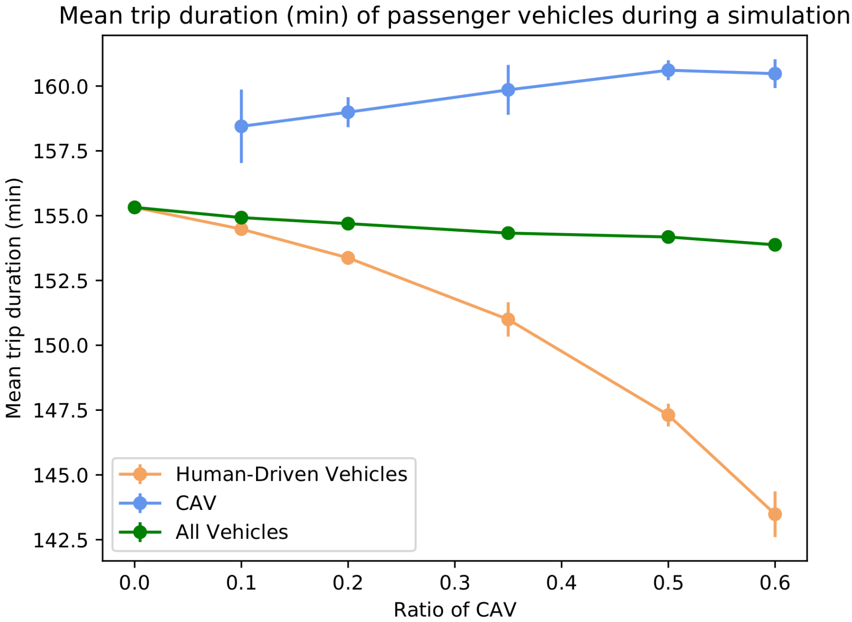


Figure 5: Mean trip duration of vehicles during a simulation

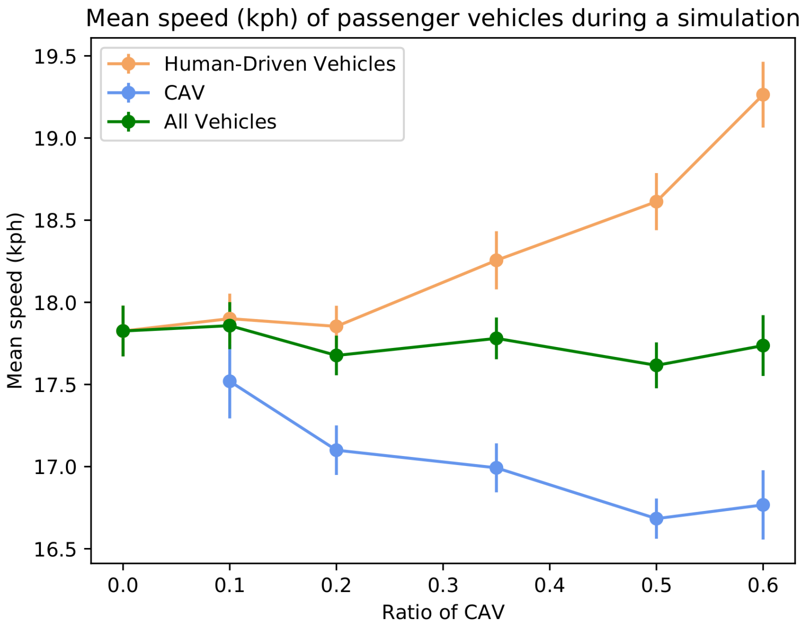


Figure 6: Mean speed of vehicles during a simulation

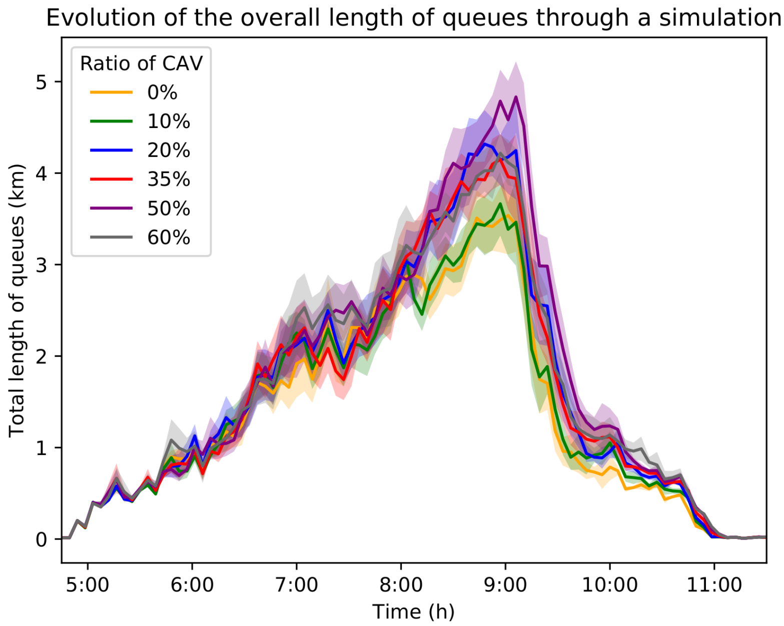


Figure 7: Evolution of the overall queues length through a simulation

length at peak time – 8:30 to 9:00 – starting from a proportion of 20% of connected vehicles on the road.

Figure 8 illustrates the evolution of the mean speed of passenger vehicles (both Human-Driven and CAV) every 5 minutes of the simulation, depending on the proportion $r_{CAV}$ of CAV in the simulation. The shown values are mean speeds relative to the roads' limit speeds, in the interval [0,1], 1 representing a vehicle driving at the limit speed. This graph comforts the analysis on the evolution of queue lengths, as we notice a similarly less significant mean speed reduction for vehicles at peak time for r = 0 and 10%.

Longer queues leading to lower relative mean speeds and greater delays can be observed in the road network for $r_{CAV} > 10\%$. This suggests an important role of CAV rerouting in the formation of queues. Starting from a threshold of $r_{CAV}$ located between a proportion of 10 and 20% of CAV, secondary roads become congested, affecting the trip times of CAV, and potentially increasing pollutants emissions during peak time.

#### 3.4.4 Pollutant emissions

Figure 9 shows with a 97.5% confidence interval the evolution as $r_{CAV}$ grows of the mean $CO_2$ emissions of vehicles by driven distance in $g/km$, provided that

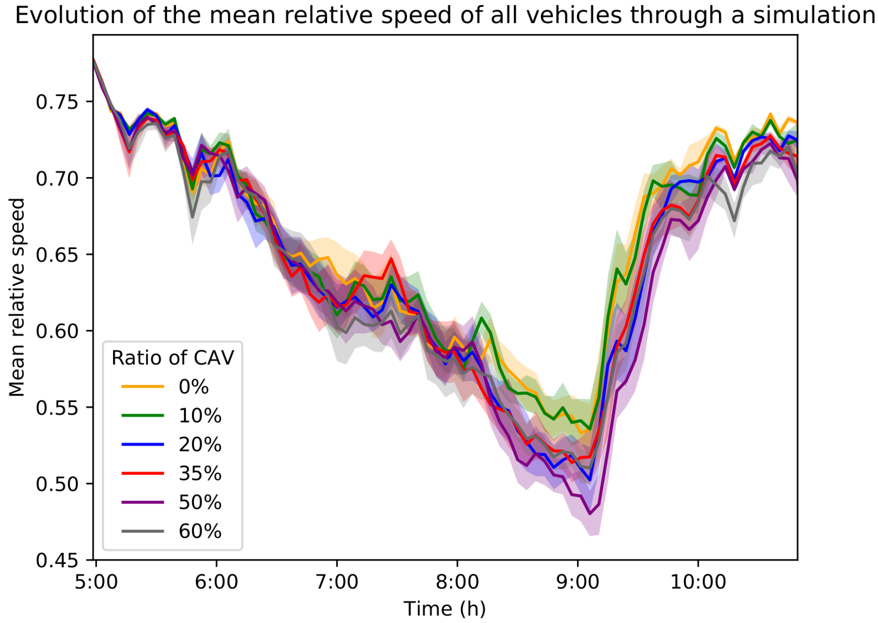


Figure 8: Evolution of the mean relative speed of vehicles through a simulation

both CAV and human-driven vehicles are gasoline-powered and follow the EURO 4 emission standard. We observe a stable increase of about 5% of $CO_2$ emitted by kilometer for CAV compared with human-driven vehicles. The amount of emissions for CAV and human-driven vehicles taken separately are stable, potentially growing slightly. All vehicles considered, the growth of the number of CAV leads to an increase in the emissions. We get similar results for other pollutants, with CAV emitting 7% more $NO_x$ gases, 6% more CO gases and HC hydrocarbons, 5% more $PM_x$ particles, and burning 5% more fuel than human-driven vehicles per kilometer. Although some emissions could be mitigated by a shift to electric or hybrid vehicles, these results demonstrate an increase in energy consumption by CAV by kilometer, most likely linked to their presence in queues and more elevated secondary roads.

What is more, we observe an increase in the global pollutants emissions during simulations as $r_{CAV}$ increases. Figure 10 shows the evolution of the total $CO_2$ emissions by Human-driven vehicles and CAV in metric tons depending on $r_{CAV}$ with 97.5% confidence intervals. We observe an increase of 4%, i.e., about 2 metric tons of globally emitted $CO_2$ every morning rush-hour in Monaco between $r_{CAV} = 0$ and $r_{CAV} \geq 50\%$. The increase is especially significant between $r_{CAV}$ = 10 and 20%, as well as between $r_{CAV}$ = 35% and 50%. When looking into the total emissions separated by vehicle type, we notice that CAV proportionally emit more $CO_2$ than human-driven vehicles. The dark blue bars represent the proportional

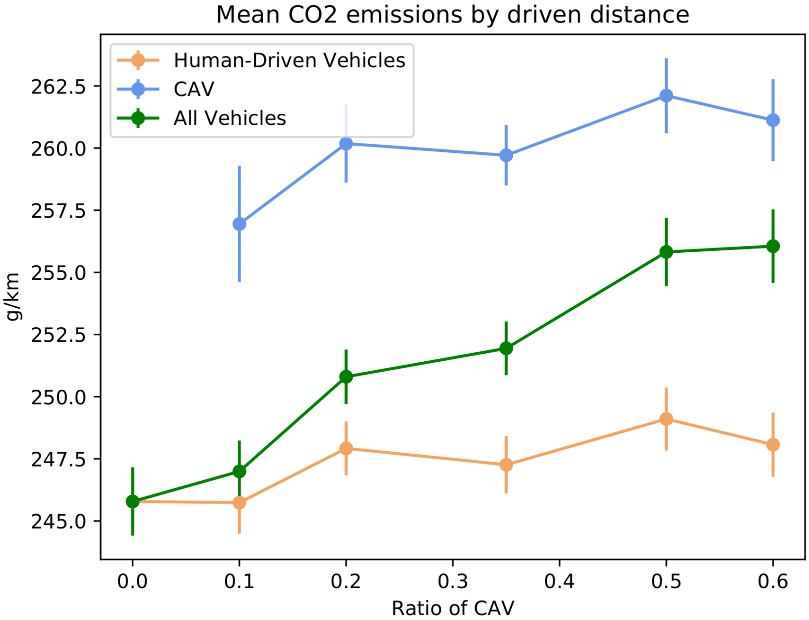


Figure 9: Evolution of the emissions of $CO_2$ by driven distance by vehicle type

exceeding of $CO_2$ emissions of CAV with regard to their representation in the road network.

We obtained similar results for the overall emissions of other pollutants by vehicle type. Total emissions of $NO_x$ and $CO_2$ as well as total fuel consumption grow by steps between 10-20% and 35-50%, whereas emissions of CO gases, $PM_x$ particles and Hydrocarbons grow linearly with $r_{CAV}$.

# 4 Discussion

We investigated the effects of routing CAV away from a set of predefined *risky* areas hypothetically tagged as potentially likely to challenge the ability of the CAV of undisturbed automated driving. Conducted on a city-wide simulation of the SUMO MoST scenario, and although considering hypothetical risky situations, this first study brought light on the impact on traffic and the environment of potential CAV risk-aware routing strategies.

The first noticeable effect is that, as their proportion increases, CAVs are increasingly redirected on secondary roads. Human-driven vehicles benefit from an increasingly reduced occupancy on primary, faster roads, allowing them to reduce their mean travel duration. On the contrary, the mean trip duration of CAV decreases as their proportion grows. There seems to exist a threshold in the propor-

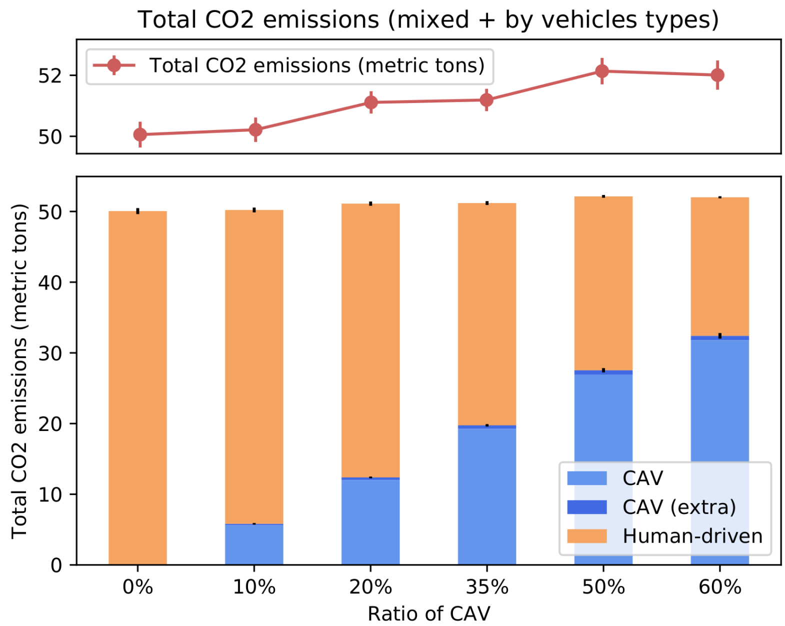


Figure 10: Total $CO_2$ emissions by vehicle type in a simulation

tion of CAVs choosing a static risk-aware routing strategy starting from which the secondary roads they favor get saturated, located in the case of Monaco between 10 and 20% of vehicles. After this threshold, longer queues form, reducing the relative mean speed of vehicles and increasing the emission of pollutants.

The energy consumption and pollutants emissions of CAV by kilometer have been measured as high as around 5% increased compared with human-driven vehicles. What is more, the overall $CO_2$ emissions have increased by about 4%, i.e., 2 metric tons when switching from a proportion of 0 to 50% of CAV. This is a significant increase in daily morning rush emissions.

Although such mechanisms of independently routing CAV away from risky zones has been beneficial for human-driven vehicles in terms of mean speed and trip duration, it is negatively balanced by equivalent losses for CAV. Moreover, the increasing proportion of CAV has worsened the environmental footprint of the Monaco road network. The routing of CAV away from predefined *risky* zones has created longer queues on secondary roads, arguably moving the risk for CAV, e.g., of rear-end crashes from primary to secondary roads.

This opens the need for a finer risk-level assessment algorithm based on the characteristics of roads. The creation of knowledge about risky zones by connected vehicles and its exchange in vehicular networks in order to take educated routing decisions based on the current *risk* in various road areas could improve the traffic conditions and environmental impact of CAV while minimizing the risk of automated driving perturbations.

# 5 Conclusion

CAVs are expected to improve traffic throughput and reduce congestion, provided they cooperate in their routing choices to control traffic. However, at current levels of automation, certain road infrastructures and driving situations are difficult to negotiate autonomously for CAV without requiring the intervention of a supervising human driver. A strategy to mitigate the risk of human take-over is to systematically route CAV to the most *autonomous-friendly* paths. As a first study on the impact of risk-aware routing for CAV, we first summarized the literature for the road structures and situations that are likely to disrupt a CAV's automated driving ability. We identified a list of such roads in the city-state of Monaco and set up a SUMO simulation using the MoST scenario to explore the impact on traffic and on the environment of systematically and unconditionally rerouting CAV away from these autonomy-challenging zones. While an increased proportion of CAV reduced the travel time of legacy human-driven vehicles, the traffic conditions worsened for CAV as longer queues formed in secondary roads, their mean speed dropped and trip duration raised. Moreover, the global pollutants emissions raised by up to 4% and 2 metric tons of $CO_2$ as the proportion of risk-based routed vehicles grew from 0 to 50%. This emphasizes both a need for further study on autonomous vehicles' routing algorithms taking risk into account, but also the potential negative impact on traffic of the ever more complex road infrastructures designed for humans without considering autonomous vehicles. As a future work, a cooperative knowledge creation and exchange mechanism by connected vehicles regarding the level of risk of road areas will be studied. Taking educated routing decisions based on the current distribution of risk in a given city could elevate CAV to their full potential of traffic and environmental impact reduction, while reducing the driving risk.

# References


[1] L. Codeca and J. Härri, "Monaco SUMO Traffic (MoST) Scenario: A 3D Mobility Scenario for Cooperative ITS," in *SUMO User Conference*, Berlin, GERMANY, 05 2018.

[2] T. Tettamanti, I. Varga, and Z. Szalay, "Impacts of autonomous cars from a traffic engineering perspective," *Periodica Polytechnica Transportation Engineering*, vol. 44, pp. 244–250, 10 2016.

[3] C. Wu, A. M. Bayen, and A. Mehta, "Stabilizing traffic with autonomous vehicles," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 2018, pp. 6012–6018.

[4] L. Alfaseeh, S. Djavadian, and B. Farooq, "Impact of distributed routing of intelligent vehicles on urban traffic," in *2018 IEEE International Smart Cities Conference (ISC2)*, 09 2018, pp. 1–7.

[5] O. Pink, J. Becker, and S. Kammel, "Automated driving on public roads: Experiences in real traffic," *it - Information Technology*, vol. 57, pp. 223–230, 07 2015.

[6] S. Zang, M. Ding, D. Smith, P. Tyler, T. Rakotoarivelo, and M. A. Kaafar, "The impact of adverse weather conditions on autonomous vehicles: How rain, snow, fog, and hail affect the performance of a self-driving car," *IEEE Vehicular Technology Magazine*, vol. 14, no. 2, pp. 103–111, 06 2019.

[7] A. Rasouli and J. K. Tsotsos, "Autonomous vehicles that interact with pedestrians: A survey of theory and practice," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–19, 2019.

[8] J. F. Fisac, E. Bronstein, E. Stefansson, D. Sadigh, S. S. Sastry, and A. D. Dragan, "Hierarchical game-theoretic planning for autonomous vehicles," in *2019 International Conference on Robotics and Automation (ICRA)*, 05 2019, pp. 9590–9596.

[9] A. Zyner, S. Worrall, and E. Nebot, "A recurrent neural network solution for predicting driver intention at unsignalized intersections," *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 1759–1764, 07 2018.

[10] X. Xin, M. Zhao, M. Zhou, S. Lu, Y. Liu, D. Guan, Q. Wang, and Y. Zhang, "A literature review of the research on take-over situation in autonomous driving," in *International Conference on Human-Computer Interaction*, 07 2019, pp. 160–169.

[11] M. Yu, R. Vasudevan, and M. Johnson-Roberson, "Occlusion-aware risk assessment for autonomous driving in urban environments," *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 2235–2241, 2019.

[12] "Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles."

[13] S. M. Casner, E. L. Hutchins, and D. Norman, "The challenges of partially automated driving," vol. 59, no. 5.

[14] S. G. McGill, G. Rosman, T. Ort, A. Pierson, I. Gilitschenski, B. Araki, L. Fletcher, S. Karaman, D. Rus, and J. J. Leonard, "Probabilistic risk metrics for navigating occluded intersections," *IEEE Robotics and Automation Letters*, vol. 4, no. 4, pp. 4322–4329, 10 2019.

[15] A. Reschka and M. Maurer, "Conditions for a safe state of automated road vehicles," *it - Information Technology*, vol. 57, pp. 215 – 222, 2015.

[16] B. Chen, D. Zhao, and H. Peng, "Evaluation of automated vehicles encountering pedestrians at unsignalized crossings," in *2017 IEEE Intelligent Vehicles Symposium (IV)*, 06 2017, pp. 1679–1685.

[17] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, "Recent Development and Applications of SUMO - Simulation of Urban MObility," *International Journal On Advances in Systems and Measurements*, vol. 5, no. 3&4, pp. 128–138, December 2012.

[18] S. Hausberger and D. Krajzewicz, "Colombo deliverable 4.2: Extended simulation tool phem coupled to sumo with user guide," Tech. Rep., 02 2014.