Enhancing safety assessment for fully autonomous vehicles: a role for agent-based modelling

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Abstract: The advent of fully autonomous cars - level 5 automation, according to the Society of Automotive Engineers (SAE) - represents a paradigm shift in the entire mobility landscape. This article explores the critical aspect of safety evaluation for these vehicles, essential for their societal integration. In fact, ensuring passengers, pedestrians, and road users' safety is crucial for adopting this technology. A major challenge for this safety evaluation is selecting suitable modelling tools to assess the complex dynamics of autonomous systems. This research rigorously evaluated various modelling approaches based on accuracy, scalability, and flexibility, finding Agent-Based Modelling (ABM) to be the most effective. Through ABM it is possible to simulate individual agents representing vehicles, pedestrians, and infrastructure, allowing realistic scenario simulations and safety performance evaluations. Analysing this tool, the aim is to highlight the various dynamics of autonomous driving systems and their implications for the future of transportation safety. Insights from this study inform policy, industry practices, and future research on autonomous vehicle safety, contributing to the ongoing discourse on their safety and reliability.

Keywords: Autonomous driving cars, Safety assessment, Agent-based model.

1.Introduction

As we stand on the edge of a new era in transportation, the integration of Autonomous Driving Vehicles (ADVs) promises to reshape the landscape of mobility in profound ways. With advancements in artificial intelligence, sensor technology, and connectivity, these vehicles hold the potential to revolutionize how we move people and goods, offering unprecedented convenience, efficiency, and accessibility. Apart from the excitement surrounding this transformative technology, it is crucial to confront the challenges and the drawbacks that accompany its implementation, particularly concerning safety **(Jafary et al., 2018)**.

While the potential benefits are vast, safety remains a paramount concern. Despite the promise of reducing human error and minimizing accidents, the transition to autonomous driving is not without its risks: the complex interplay of factors such as unpredictable road conditions, technological limitations, and ethical dilemmas underscores the need for rigorous safety standards. Indeed, recent research has highlighted the inherent vulnerabilities and shortcomings of this technology. From cybersecurity threats to the ethical implications of decision-making algorithms, ADVs introduce a new set of challenges that must be addressed to ensure the safety and well-being of passengers, pedestrians, and other road users **(Rezaei and Caulfield, 2021)**. Moreover, as AVs become increasingly integrated into our transportation systems, questions regarding liability, regulatory frameworks, and public acceptance arise.

The transition to autonomous driving represents a paradigm shift in how we conceptualize and regulate transportation, requiring careful consideration of legal, ethical, and societal implications **(de Leo and Miragliotta, 2023)**.

Navigating the complex landscape of road safety requires a comprehensive understanding of the myriad factors influencing traffic dynamics and accident occurrence. From human behaviour to infrastructure design, each component plays a critical role in shaping the safety outcomes on our roadways. The integration of ADVs promises to revolutionize the traditional paradigms of road safety, offering innovative solutions to age-old challenges. Studies have delved into the intricate interplay of factors such as traffic light optimization, pedestrian crossings, and speed limits, employing simulation models to identify optimal parameters for enhancing road safety **(Buivol et al., 2020)**. Moreover, the socioeconomic implications of road accidents underscore the urgency of proactive interventions, with projections indicating that without action, road traffic crashes could ascend to the 7th leading cause of death by 2030 **(Kataria, 2018)**.

The focus on Vulnerable Road Users (VRUs) has emerged as a main point for understanding the social dimensions of road safety, shedding light on the influence of social inequities, habits, and environmental factors on accident occurrence **(Fernandes et al., 2019)**. Furthermore, the development of sophisticated road safety measurement tools has enabled policymakers and researchers to assess the efficacy of interventions and regulatory frameworks, leading to evidence-based decision-making and targeted improvements **(Sutandi, 2015)**.

While the attention was traditionally on driver behaviour and on vehicle efficiency, emerging research highlights the importance of holistic approaches that consider a broader spectrum of factors. From tire-road friction to driver distraction, each variable contributes to the intricate tapestry of road safety dynamics **(Alonso et al., 2018)**. Consequently, the challenge lies not only in identifying these factors but also in developing robust methodologies for measurement and analysis. Retrospective analysis, predictive interventions, and advanced statistical models offer valuable insights into the causal mechanisms driving road accidents, but data quality and validation remain ongoing challenges **(Makarova et al., 2019) (Van Zuylen, 2008)**.

This paper presents just a preliminary design for an ABM aimed at enhancing safety assessments for autonomous vehicles. The detailed technical aspects and concrete implementation proposals will be addressed in future research phases since The model is currently in the design phase, and detailed results and simulations will be presented in future publications as the development progresses.

2. Review of the relevant literature

2.1 ADVs & road safety

Against this backdrop of complexity, ADVs emerge as a promising tool for enhancing road safety. By leveraging on cutting-edge technologies such as artificial intelligence and real-time sensor fusion, autonomous vehicles hold the potential to mitigate human errors and to introduce us in a new era of accident prevention **(Alhajyaseen, 2023)**. Moreover, advancements in vehicle-to-vehicle communication and intelligent road infrastructure management systems offer further avenues for optimizing safety outcomes **(Buivol et al., 2020)**. Embracing the potential of autonomous driving technology, it is imperative to acknowledge and address the challenges and ethical considerations that will follow this paradigm shift: cybersecurity vulnerabilities, moral dilemmas, and regulatory frameworks necessitate careful navigation to ensure the safe and responsible deployment of autonomous vehicles **(Fernandes et al., 2019)**.

The integration of autonomous vehicles into the transportation systems will conduct to a transformative era, promising unparalleled advancements in road safety. Conventional vehicles (CVs) have long been associated with numerous drawbacks, including human error, distracted driving, and traffic congestion, leading to a staggering number of injuries and fatalities on the roadways. Instead, emerging research suggests that ADVs possess the potential to revolutionize road safety dynamics, mitigating risks and reshaping the landscape of transportation.

Several studies have underscored the pivotal role of this technology in minimizing the prevalence of accidents and fatalities on our roads, thanks to these vehicles' capacity to avert collisions caused by human errors. Notably, the intersections, which are notorious hotspots for accidents, witness a significant reduction in potential conflicts and rear-end collisions with the advent of this technology **(Khashayarfard and Nassiri, 2021)**. The promise of enhanced safety extends beyond individual vehicle operations, with ADVs showcasing the ability to smooth traffic flow, mitigate stop-and-go patterns, and alleviate travel delays in the event of road failures **(Dong et al., 2022) (Ye and Yamamoto, 2019)**.

The global impact of these vehicles' deployment on road safety is projected to be substantial, with estimates suggesting a potential reduction of accidents by up to 93% at unsignalized intersections **(Calvi et al., 2022)**.

Additionally, while simulation studies indicate substantial safety improvements at high penetration rates of autonomous driving vehicles, lower rates may initially introduce conflicts, necessitating careful navigation through transition phases **(Alozi and Hussein, 2023)**.

In light of these developments, this paper aims to delve into the topic of road safety through the introduction of ADVs.

2.2 Simulation techniques for ADVs

Different simulation techniques vary in their ability to accurately model the complex interactions between autonomous driving cars and their environment. Discrete event simulation focuses on modelling the sequence of events and the time between them, making it suitable for analysing the timing of events like traffic flow. System dynamics simulation, on the other hand, emphasizes feedback loops and the behaviour of the system over time, making it useful for understanding how changes in one part of the system affect the whole, such as traffic congestion dynamics. Agent-based simulation involves modelling individual entities with behaviours and interactions, allowing for a detailed examination of how individual cars interact within the environment, making it ideal for studying the behaviour of autonomous vehicles in a dynamic environment with various agents like pedestrians and other vehicles. Each simulation technique offers unique strengths in capturing different aspects of the interactions between autonomous driving cars and their surroundings, providing valuable insights into the complex dynamics of autonomous driving systems **(Wen et al., 2021)**.

System dynamics and agent-based simulations offer different strengths in modelling autonomous driving systems. In particular, system dynamics are well-suited for analysing high-level dynamics like traffic congestion and the impact of policy changes on the transportation network. System dynamics can provide insights into how changes in one part of the system, such as the number of autonomous vehicles, affect the whole.

In contrast, agent-based simulations model the individual autonomous vehicles as autonomous agents with their own behaviours and decision-making rules **(Achachlouei and Hilty, n.d.)**.

This allows agent-based models to capture the complex interactions between individual vehicles, pedestrians, and other elements of the environment in a more granular way **(Taillandier et al., 2021)**. Agent-based simulations are better able to simulate emergent behaviours that arise from these micro-level interactions. For this reason, agent-based modelling provides a more detailed, bottom-up perspective on the complex behaviours and interactions between individual autonomous vehicles and other actors **(HÖrl, 2017)**.

Finally, studies by **(Bastarianto et al., 2023)** and **(Ljubovic, 2009)** highlight the effectiveness of agent-based models in simulating complex traffic environments demonstrating the potential of agent-based modelling in enhancing safety assessments for fully autonomous vehicles, providing a solid foundation for our proposed approach.

3.Aims and objectives

The primary aim of this paper is to explore the role of agent-based modelling in assessing safety for fully autonomous vehicles.

Through an examination of various modelling techniques, the objective of this section is to clearly motivate the selection of ABM for modelling ADVs and their complex environments, highlighting the benefits for the safety evaluation (especially for what concern VRUs), also presenting a preliminary design framework for an ABM and proposing a possible enrichment of the model thanks to the Markov chains to enhance the understanding of ABM dynamics.

3.1 Why Agent-Based Modelling?

First, agent-based models are advanced in terms of flexibility, extensibility, and capability to realize heterogeneity **(Li et al., 2021)**. This tool is widely employed in the field of crowd dynamics, in which the agents, having personalized characteristics, form a complex crowd dynamic system **(Chen, 2012)**. This makes the agent-based models suitable for modelling the pedestrian flow considering pedestrian characteristics and their interactions with other VRUs and with the vehicles **(Sinha and Rajasekar, 2020)**.

ABM can be used to evaluate the safety of autonomous driving vehicles by simulating the interactions between autonomous vehicles and other road users, such as pedestrians and conventional vehicles. It can help in predicting pedestrian trajectories around an autonomous vehicle, which can be useful to understand how pedestrians react to autonomous vehicles and how to improve the safety of these interactions. This aspect was highlighted in the review by **(Mehdizadeh et al., 2022)**.

In the study by **(Prédhumeau et al., 2022)**, an agent-based model was developed to predict pedestrian trajectories around an autonomous vehicle in a shared space. The model was used for both conventional vehicles and autonomous vehicles, showing its flexibility.

In conclusion, ABM can be a valuable instrument for evaluating the safety of autonomous driving vehicles by simulating the interactions between autonomous vehicles and other road users **(Jing et al., 2020)**. By predicting pedestrian trajectories around an autonomous vehicle and understanding how automated vehicles can cooperate and share information about the environment, ABM can help in evaluating the safety of autonomous driving vehicles.

3.2 Benefits of the ABM for the safety evaluation

ABM has several benefits for evaluating the safety of autonomous driving vehicles:

a. Predictive accuracy, ABM can predict pedestrian trajectories around an autonomous vehicle, helping to understand how pedestrians react to autonomous vehicles and how to improve the safety of these interactions.

b. Simulation of interactions, ABM can simulate the interactions between autonomous vehicles and other road users, such as pedestrians and conventional vehicles. This can help in delineating how autonomous vehicles cooperate and share information about the environment to complete tasks quickly and safely.

c. Scalability, ABM can handle the complexity of multiple interacting virtual vehicles with a variety of capabilities and have them all operate simultaneously. This can help in analysing how automated vehicles operate in a cooperative network.

d. Realistic scenarios, ABM can simulate realistic scenarios, such as an enclosed area with random obstacles, to assess the performance of automated vehicles. This can describe the way in which autonomous vehicles behave in real-world environments.

e. Team formation, ABM can enable the formation of teams based on the individual capabilities and location of autonomous vehicles. This can help in understanding how autonomous vehicles may cooperate and assist with tasks, such as classification and refuelling, to complete missions.

f. Simulation of human behaviour, ABM can simulate the behaviour of human drivers and pedestrians in mixed traffic scenarios. This highlights how autonomous vehicles can operate in mixed traffic and improve the safety of these interactions.

g. Design of traffic simulations, ABM can help in designing traffic simulations with adequate human driver models that cover the heterogeneity of human behaviour. This enhances the adherence of the simulation to real-world traffic scenarios.

h. Handling uncertainty and complexity, ABM can handle uncertainty and complexity in multi-agent simulation and modelling for autonomous vehicles. This ensures that the simulations are accurate, reliable, and scalable.

The benefits listed in this section are based on a thorough review of the existing literature on autonomous vehicle safety assessments as well as insights from our expertise in the field. Notable studies contributing to this understanding include **(Blom et al., n.d.)** and **(Zhao et al., 2019)**.

In summary, ABM can help in evaluating the safety of autonomous driving vehicles by simulating the interactions between autonomous vehicles and other road users, predicting pedestrian trajectories around an autonomous vehicle, understanding how automated vehicles can cooperate and share information about the environment, improving the safety of autonomous driving vehicles through collaborative mapping, enabling team formation based on individual capabilities and location, simulating human behaviour in mixed traffic scenarios, designing traffic simulations with adequate human driver models, and handling uncertainty and complexity in multi-agent simulation and modelling for autonomous vehicles.

3.3 Generical explanation of the framework structure

It is possible to design the ABM following the 4 steps synthesized in **Figure 1 (Huang et al., 2022)**.

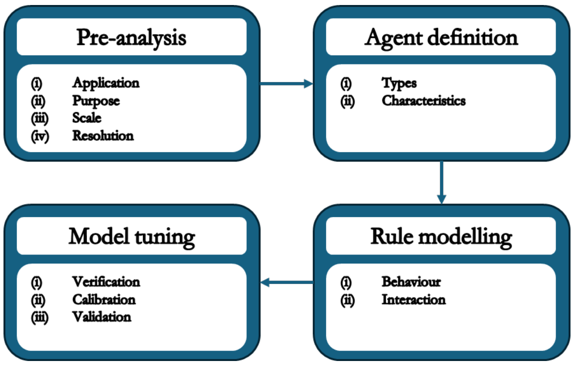

Figure 1 - Agent-based model structure.

Step 1. Preliminary analysis entails delineating the specific application scenario, objectives, and scale of the agent-based model for assessing the safety of autonomous driving vehicles. This involves defining the problem to be addressed, desired outcomes, and whether the focus is on describing, observing, or analysing a particular aspect of the transport system. The scale of the ABM dictates the scope of agent mobility and interaction, as well as the number of agents involved. Simulation resolution is aligned with the characteristics of the ADV system and its environment, ranging from detailed motion-level modelling to broader macroscopic perspectives.

Step 2. Agent specification involves identifying and categorizing heterogeneous entities (agents) within the ADV system environment based on their roles and characteristics. Agents may include various types such as reactive agents simulating law enforcement personnel or disrupters like weather and accidents. Drivers, as adaptive and mobile agents, adjust their routes to minimize congestion. Determining agent types and characteristics facilitates the subsequent modelling of detailed behavioural rules tailored to specific scenarios.

Step 3. Rule modelling focuses on representing the behaviour and interaction of agents based on published literature, expert knowledge, and data analysis. Rules typically utilize conditional statements to trigger agent actions in response to stimuli or pursue goals. Agent behaviour and interaction reflect these rules, often influenced by each other and offering feedback to the environment. Balancing the complexity of the model with computational efficiency is crucial, with considerations for employing parallel computing approaches to address computational costs.

Step 4. Model refinement involves verification, calibration, and validation processes to ensure the accuracy and validity of the ABM. Verification ensures the correct implementation of the model, while calibration assesses its fit with empirical data to align with real-world observations. Validation confirms the model's accuracy in representing the ADV system. These processes are essential for demonstrating the reliability and effectiveness of the ABM in assessing the safety of autonomous driving vehicles.

3.4 Preliminary design for a specific use case

Following the above mentioned steps, it is possible to design a preliminary ABM.

In the pre-analysis phase, after delineating the application of the ABM and purpose (a safety assessment for ADVs), the first thing to do is to select the scale of the ABM. This depends on the specific research question, for example, a study of a single intersection might use a smaller scale than a study of an entire city. Another fundamental step in this phase is the choice of the resolution, which refers to the level of detail in the model. A high-resolution model would include more details about the environment, such as lane markings and traffic signals. A lower-resolution model might only include the basic layout of the roads.

After this preliminary phase, it follows the agents definition: in the context of interest, the agents will be the autonomous vehicles, the VRUs and the other vehicles. Each agent will be modeled as an independent decision-maker with its own characteristics that can perceive its surroundings and take actions accordingly.

Then, the ABM requires the so-called rules modelling: the agents' behaviours and interactions are determined. These include rules for following traffic laws, avoiding obstacles, interacting with other agents, following the traffic lights, maintaining a safe distance from other vehicles, and yielding to pedestrians and cyclists. The interaction rules define how the agents interact with each other, with the infrastructure, and with the vulnerable road users. These rules require to be carefully designed to ensure safety and efficiency. Instead, the behavior rules are important as well, but these define how the agents make decisions about their behavior, such as changing lanes, merging into traffic, and stopping at intersections.

Lastly, the model needs to be tuned, passing through a verification, a calibration and a validation. The verification ensures that the ABM is working as intended. This involves checking the model for errors and making sure that the code is functioning correctly. The calibration consists in adjusting the parameters of the ABM to match real-world data, for example the speed of the ADVs in the model might be calibrated to match the average speed of traffic on a particular road. And the validation ensures that the ABM produces realistic results. This involves comparing the output of the model to real-world data. For example, the ABM might be validated by comparing the travel times of simulated vehicles to the travel times of real vehicles.

3.5 An interesting improvement: Markov chains' use

A Markov Chain is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous events. It can be visually described as in the **Figure 2**.

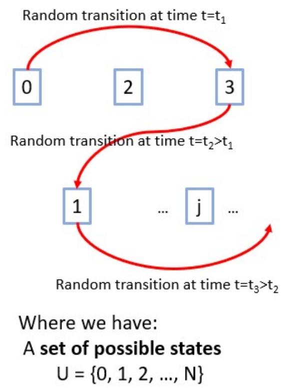

Figure 2 - Markov Chain visual description.

Its basic characteristics are:

1. It describes a system whose states change over time.
   - Discrete-time stochastic process.
2. Changes are governed by a probability distribution.
3. The next state only depends on the current system state.
   - The path to the present state is not relevant.
4. Class of random process useful in different areas.

Since the states are:

- Mutually exclusive, the system must be only in one state at each time.
- Exhaustive, the system must be only in one state at all times.

This can be a suitable way to describe the system considered.

In fact, it could be possible to couple our ABM with the Markov Chain perspective: both describe systems that change over time with discrete states and transitions governed by probabilities. In our context, the states of the agents (ADVs, VRUs, etc.) can be mapped to states in a Markov Chain. For instance, an ADV state could be "stopped at a red light," "changing lanes," or "merging into traffic." Transition probabilities between these states would then be determined by the programmed rules of the ABM. For example, the probability of an ADV changing lanes would depend on the surrounding traffic density as defined in the model's rules. By analysing these Markov Chains, we can gain valuable insights into the long-term behaviour of the ABM. For instance, we could calculate the probability of an ADV encountering a pedestrian after running a yellow light (transitioning from "running yellow light" to "encountering pedestrian"). This approach offers a powerful tool for understanding the emergent properties of the system. But however, it's important to acknowledge the challenges involved: defining a comprehensive set of states and accurate transition probabilities can be complex. Highly dynamic elements or unforeseen events, such as sudden swerving or extreme weather conditions, might require additional considerations or adjustments to the Markov Chain framework.

The main expected output of Markov Chain strategy applied to ABM is a better understanding of the relationship between microscopic and macroscopic dynamical properties **(Banisch et al., 2013)**.

For practical purposes, this is the most relevant information because the chains describe the evolution of the system before external perturbations take place and possibly throw it into a new setting: a well-posed mathematical basis for these models may help the understanding of many observed properties.

Coupling the micro-description from ABM with the macro-description from the Markov Chain will provide information about the transition from the interaction of individual actors to the complex macroscopic behaviours observed in social systems.

4.Key findings

Based on the literature review and on the proposed methodology using ABM, one of the expected key findings of this research is an improved safety assessment for autonomous driving vehicles. This will allow to assess how ADVs perform in various scenarios, potentially leading to recommendations for improved safety measures. The ABM will be also able to predict pedestrian trajectories around ADVs. This information can be used to understand how pedestrians react to these vehicles and how to design them and the surrounding infrastructure to enhance safety for pedestrians. Considered that ABM can handle many ADVs with varying capabilities, this will allow to analyse their behaviour in complex traffic situations. Additionally, the model can be designed to simulate realistic scenarios to assess the performance of these vehicles in real-world environments. Moreover, the model can simulate the behaviour of human drivers and pedestrians in scenarios with a mix of conventional and autonomous vehicles: this can provide insights into how ADVs can operate safely in mixed traffic environments. Finally, the ABM framework can handle the inherent uncertainties and complexities involved in simulating interactions between multiple autonomous vehicles and other agents in the traffic environment. This ensures the reliability and scalability of your simulations.

By incorporating Markov Chains into this ABM analysis, it is expected to gain a deeper understanding of the long-term behaviour of the system. Specifically, having defined states for the agents (ADVs, VRUs, etc.), it could be possible to calculate the probabilities of transition between these states based on the programmed rules of the ABM. For example, the probability of an ADV encountering a pedestrian after running a yellow light. Furthermore, analysing the Markov Chains, it is expected to gain insights into the emergent properties of the ABM system, which arise from the interactions of individual agents.

In general, our findings indicate that integrating agent-based modelling into safety assessments for autonomous vehicles enhances the predictive capabilities and robustness of these evaluations. This integration allows for more dynamic and realistic simulations of various traffic scenarios, which traditional methods fail to capture. The implications of this research are profound, suggesting that adopting agent-based modelling could lead to safer deployment of fully autonomous vehicles by providing more accurate risk assessments and facilitating the development of better safety protocols.

5.Conclusions and future directions

In conclusion, the ABM is designed to analyse interactions between ADVs, pedestrians, and conventional vehicles, while also predicting pedestrian trajectories around these vehicles. This will provide valuable insights into how ADVs perform in real-world scenarios with mixed traffic and complex situations. Enriching ABM through a Markovian lens opens avenues for connecting microscopic agent models to macroscopic observables, facilitating a nuanced understanding of model dynamics. It allows for the study of collective variable dynamics and provides insight into how macro dynamics emerge from micro dynamics, especially during transient periods.

The utilization of a Markov chain proves particularly valuable in this context, illustrating how an agent-based model can be mathematically described. Although the entire dynamics of the ABM are encapsulated within the Markov chain, extracting insights directly from this representation can be challenging due to the vast dimensionality of the configuration space and its corresponding Markov transition matrix.

Looking ahead at the next steps of this research, this will consist in the final design of the ABM framework following the four-step process. Additionally, it will be developed a comprehensive set of states and accurate transition probabilities for the Markov Chain analysis. Later on, it will be developed a functional prototype to validate our proposed agent-based modelling approach. Obviously, this prototype will be tested extensively, to analyse the results and appreciate the significant improvement in safety assessment accuracy compared to traditional methods (if present).

By addressing these aspects and exploring methods to handle unforeseen events within this framework, the future research aims to leverage the combined power of ABM and Markov Chains to calculate specific probabilities relevant to safety assessments. Ultimately, these future developments aspire to provide a deeper understanding of the connection between microscopic agent behaviours and macroscopic system dynamics in the context of autonomous vehicles navigating complex traffic environments.

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