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A CONCEPTUAL HYBRID SIMULATION APPROACH FOR ADVANCING SAFETY IN CONNECTED AUTOMATED VEHICLES

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ABSTRACT

Ensuring traffic safety remains a major challenge due to the complexity of traffic environments and the early stage of autonomous vehicle (AV) technology, despite their potential to significantly reduce accidents and enhance road safety. The Artificial Potential Field (APF) approach offers a promising solution by simulating how vehicles adjust their motion, speed, and interactions with surrounding vehicles to maintain safety. This paper aims to introduce a conceptual hybrid simulation using the APF implemented within a multi-agent framework. The objective is to evaluate the suitability of APF model for real-time safety applications across extended time periods and diverse traffic scenarios. This evaluation is conducted through a hybrid simulation approach to identify advantages and limitations compared to existing risk assessment methodologies.

1 INTRODUCTION

Connected and Automated Vehicles (CAVs) represent a transformative shift in transportation, offering the potential for improved sustainability, convenience, safety, and mobility by reducing reliance on human drivers. By automating key driving tasks, these systems aim to eliminate human error—the primary cause of road accidents.

The majority of road collisions in Great Britain involve at least one car: in 2022, most fatalities occurred in collisions involving a car, and this has been consistent throughout the years. It has been reported that the three contributory factors for fatal road collisions in Great Britain in 2022 were: loss of control, driver/rider failing to look properly and driver/rider careless behavior, which are all human errors (Department for Transport 2022). Therefore, with the advent of driverless cars relying on technological innovation to make decisions, accidents should be minimized.

Fully autonomous vehicles (SAE International 2016) are expected to replace human drivers entirely by handling environment perception, risk assessment, decision-making, planning, and vehicle control (Yeong et al. 2021), however, they don't exist at present. Ensuring safety in such systems requires a holistic understanding of the road environment rather than focusing on isolated events—a challenge that current Advanced Driver Assistance Systems (ADAS) still face (Rendon-Velez et al. 2009). Therefore, effective methods for real-time risk assessment and decision-making are essential for accident prevention.

The main safety issues that need to be addressed are: how the technologies that substitute humans can handle uncertainty in the highly dynamic road environment; how all the data gathered from sensors can be handled in real-time; how safety-critical decisions can be made in real time. Most importantly: there is no unified industry standard or framework for autonomous vehicles that can ensure safety. Therefore, how can AVs be assessed on whether they are "safe enough"?

The remainder of the paper will follow this structure: Section 2 covers safety in Autonomous Vehicles from a regulatory point of view, going then into the elements that enable the AV to function, with special focus to threat assessment and state-of-the-art methodologies. Among these, the Artificial Potential Field is explored as a threat assessment methodology, and simulation is also introduced to test its feasibility in realistic scenarios. Section 3 focuses on the hybrid approach to simulation, linking the vehicle model, the traffic model, and the artificial potential field model as a way to evaluate risk, illustrated by a high-level architecture. The simulation is agent-based, which has not yet been used to test this model—the novelty of this approach. Basic scenarios with comparison metrics (based on the EU regulation and literature) are presented, along with useful KPIs to evaluate the effectiveness of the APF compared to other safety metrics. The conclusion and future work are presented in Section 4.

2 BACKGROUND

2.1 Safety in Connected Automated Vehicles

CAVs are a relatively new technology that has not been integrated into the public as of now. As a result, regulations and standards have not kept pace with current developments, and legislation designed for traditional vehicle manufacturing is still being applied to CAVs.

The Society for Automotive Engineering (SAE International 2016) divides autonomous vehicles into five levels. In Levels 0–2 the driver retains responsibility for object detection and response. Safety relies predominantly on passive systems (e.g., airbags, seatbelts) and increasingly on active systems such as ADAS. Examples of ADAS features include adaptive cruise control and lane-keeping assistance, either in the longitudinal or lateral dimension. A notable commercial example is Ford's BlueCruise system (Ford Motor Company UK 2025), approved for hands-free driving in designated "blue zones" in the UK and Germany. While this system enables limited automation, it still requires driver supervision and thus qualifies as Level 2 automation.

In contrast, Levels 3–5 introduce higher degrees of autonomy, where the system can perform object and event detection, motion control, and in some cases, fallback operations in the event of system boundary exceedance or failure. These capabilities require holistic environmental awareness, supported by both onboard and external sensor data, and Vehicle-to-Everything (V2X) communication. However, despite this technological potential, comprehensive safety validation remains a key challenge.

Traditionally, safety in vehicles is addressed through two key principles: Functional Safety (FS) and Safety of Intended Functionality (SOTIF) (Vyas and Xu 2024), which are formalized into ISO26262 (International Organization for Standardization 2018) and ISO/PAS 21448 (International Organization for Standardization 2022) respectively. FS is concerned with safe operation of systems even in the presence of faults, while SOTIF complements FS by aiming to address potential hazards caused by limitations in the system's intended functionality, especially in ADAS—an example: sensor capability limitations.

Consumer safety in Europe is evaluated by the Euro NCAP (European New Car Assessment Programme n.d) which assesses vehicle safety under the following categories: (i) Adult occupant protection, (ii) Child occupant protection, (iii) Vulnerable Road Users (VRUs), (iv) Safety assist, i.e. effectiveness of lane keeping assist, speed assistance, driver monitoring, etc. While fully autonomous vehicles are not assessed as of now, Euro NCAP does assess ADAS features.

On a legislative front, the EU, with its Regulation EU 2019/2144, has taken a major, foundational step towards a unified industry standard for autonomous vehicle safety (European Parliament and Council 2019). Of interest is Annex IV detailing how Automated Driving Systems (ADS) are evaluated to ensure safe behavior in various scenarios. ADS must be tested to demonstrate safe and predictable behavior in real-world traffic and in critical situations; ensure that they are functioning within their Operational Design Domain (ODD), and that they are equipped with an effective fallback strategy in case of failure / boundary conditions. Tests are divided into three types:

- Simulation (virtual environment) which will be the focus of this paper.
- Track testing (in a controlled physical environment).
- Real world driving on public road testing within the ODD.

The first two are to ensure controlled reproducibility, while the latter is to account for realistic edge cases. Annex IV also outlines scenario types and performance metrics, which are considered in this paper in section 3.3. This regulation serves as the very beginning of a safety assurance framework in CAVs, however, it is not the end. It focuses on minimum safety requirements and details scenarios that the AV must handle safely and predictably, rather than how the outcome should be achieved. Therefore, it is important to explore safety methods that can adhere to scenarios outlined in the EU regulation, and that—even in edge cases—can be traceable, testable, and reproducible.

2.2 Functional Architecture and Threat Assessment Methods

AVs can be seen through both technical and functional lenses. This section focuses on the functional perspective, which identifies the principal modules that enable automated driving behavior.

Multiple functional architectures have been proposed in the literature, each emphasizing different aspects of autonomy. For example: Paden et al. (2016) highlight AVs primarily as decision-making systems, while Badue et al. (2021) present an architecture that focuses mainly on perception and decision-making. Some approaches, such as those by Behere et al. (2015) and Yeong et al. (2021), merge perception with situation analysis into a single module, whereas others maintain a modular separation between them (Dahl et al. 2018; Li et al. 2020). For the purpose of looking at safety in a comprehensive manner, the functional architecture presented in Li et al. (2020) is adopted, with focus on the autonomous driving decision making rather than the ADAS.

Key functional elements presented in the architecture are:

1. Perception: gathers data from onboard sensors (including RADAR, LiDAR, cameras, and Real-Time Kinematic (RTK) positioning systems). This information is fused to be analyzed by the next module.
2. Situation Analysis: Integrates the outputs from the perception module and assesses the elements around the vehicle (such as other road users, obstacles, and traffic conditions) to inform the decision-making process.
3. Decision and Planning: Includes path planning, obstacle avoidance, trajectory optimization, and action prediction.
4. Vehicle Control: performs physical functions and actions (e.g. steering, braking, accelerating, etc.) based on information provided by the previous module.

Threat assessment (TA) is part of the “situation analysis” component and this element is arguably one of the most important tasks in an AV, bridging perception and decision making by continuously evaluating the environment and potential risks posed by dynamic and static elements in it. This is what arguably distinguishes an ADAS in traditional vehicles from autonomous driving in autonomous ones, the latter needing holistic processing and understanding of the environment rather than focusing on single aspects, as explained in Section 1. There are many TA techniques, with different classifications. Strictly speaking, TA methods refer to how risk is evaluated to inform decision-making, while surrogate safety measures (SSM) (Wang et al. 2021) “quantify safety benefits of CAV based on simulation results”, which will be presented when discussing performance metrics in the following sections.

Dahl et al. (2018) include methodologies for both threat assessment and decision making of ADAS and automated driving. A summary of their categorization follows. (1) Single-Behavior (Time/Acceleration/Distance Domain): driven by threat metrics based on single future behaviors of the different traffic participants. (2) Optimization: solving optimization problems by minimizing a cost function constrained by dynamical models, inputs and boundaries on states. Applications include Model Predictive Control-based methods to assess threat level for forward collision warning (based on thresholds), optimal braking, etc. (3) Formal: started to gain popularity in recent years as it is capable of handling: safety, task sequentiality and restrictiveness arguments. It is very popular in control theory, while it has limited applications in threat assessment due to the contextual and probabilistic nature of threats. (4) Probabilistic: involves assigning probabilities to different events on the road and, given some assumptions or uncertainties, calculate how likely the chance of collision is in the future. (5) Machine Learning: data driven method. In automated driving, it is used for end-to-end learning i.e. mimic a driver's behavior given a training data set.

Li et al. (2020) classify them similarly. (1) Time and Kinematic-Based metrics are the same as Dahl et al. (2018) Single Behavior Threat metrics, which look at threats from a time or acceleration or distance perspective. (2) Statistics-Based metrics describe threat using either probability methods or machine learning ones. (3) Potential field-based metrics: field perspective of risk, which will be described in the following section in more depth. (5) Unexpected driving behavior-based metrics: evaluate the driving risk based on unusual driving behaviors and traffic conflicts (e.g. running red light).

From these two surveys, advantages and limitations of threat assessment methodologies can be summarized as such: methodologies that look at threat from a single perspective tend to be very simple to run and are effective for certain scenarios only. Statistical/ Probabilistic methods are ideal for road uncertainty modelling; however, they are very computationally expensive, making them infeasible for real-time applications. Machine learning's black box problem makes algorithms difficult to validate from a legislative perspective. Potential field-based methods can describe risk related to non-collision entities; however, calibration is very difficult and there are insufficient on-road tests.

2.3 The Artificial Potential Field (APF) Model

The Artificial Potential Field model has been widely used in Robotics, especially in path planning applications. In Dahl et al.'s (2018) classification, it falls under the optimization approaches because risk is determined by computing a potential function to guide movement while avoiding the obstacles. Meanwhile, in Li et al.'s (2020) classification, it is part of the potential field-based metrics. The advantages to using this method are its potential for efficient real-time computation and flexible modelling for dynamic scenarios, which would address issues associated with more complex but accurate TA methods.

The base idea behind this model is that the target destination has an attractive force and the obstacles along the path have a repulsive force (Szczepanski et al. 2022). This, however, is not enough to describe the highly dynamic environment of a road: in robotics, the potential function is based on relative distance (Hongyu et al. 2018) while on the road there are other parameters that need to be considered, such as velocity, acceleration, road conditions, etc. Hence, there have been many studies looking into developing a model that could encapsulate all these factors, as APF has great potential to model the dynamic nature of the road while allowing for real-time computation due to risk being the result of a potential function.

In 2011, Ni (2011) applied the concept of a physical field onto the road and studied the forces acting on the vehicles (see Figure 1). The general case was further defined into a car following model: the Longitudinal Control Model. Wang et al. (2015) further refined the concept by introducing influencing factors i.e. vehicle's virtual mass (given by its actual mass, speed, vehicle type), road conditions (adhesion coefficient, slope, curvature, visibility) and driver, then categorizing the fields based on the type of object on the road—with the influence of these fields being calculated separately. Li et al. (2020; 2020a) and Jia et al. (2022) included two other parameters to road field calculation: vehicle acceleration, and steering angle. These are important because the field model can now be considered dynamic and therefore allows for the estimation of driving risk under different motions. There are only a couple of methods used for validating the proposed APF models, but they are very limited in scenario testing when simulated or—in case of on-the-road validation—might lack external validity due to the nature of current CAV testing.

Li et al. (2020) and Jia et al. (2022) define the driving risk potential field in a simple road environment as made up of three equations:

1. Lane potential field U_L.
2. Road Boundary potential field U_B.
3. Adjacent Vehicles Potential field U_V.

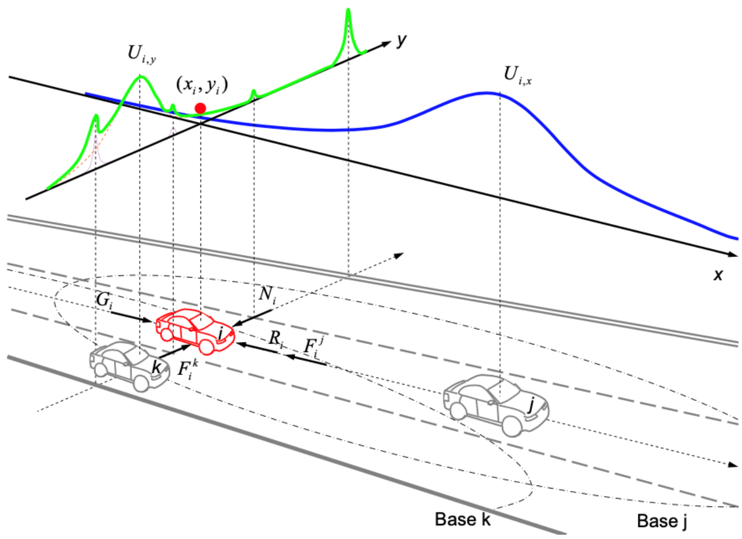

Figure 1: View of the artificial potential field on the road, from Ni (2011).

The total driving risk potential field U_T is given by:

$$|U_T| = \omega_L|U_L| + \omega_B|U_B| + \omega_V|U_V| \tag{1}$$

Where ω indicates the weight of the respective equation in the context. For example, the lane marking field in a car-following scenario will have a certain weight that will keep a car driving within the lanes, whereas in a lane-changing scenario, the weight will be much lower since one of the lanes will need to be crossed

The Lane marking potential Field U_L is represented using a quasi-Gaussian function. When considering lanes, different markings have different weights, i.e. double white lines along a carriageway indicate a different permitted driving behavior compared to a white broken line.

$$U_L = \sum_{i=1}^{N-1} A_l e^{\left(-\frac{(x-x_i)^2}{2\delta^2}\right)} \cdot \frac{x-x_i}{|x-x_i|} \tag{2}$$

Where:

- A_l is the intensity coefficient for lane marking. E.g. if the broken white line is set as A_1 and the double white line is set as A_2, then based on importance, $A_2 \gg A_1$.
- δ represents the velocity at which the potential field increases or decreases as the vehicle approaches.

Road Boundary Potential Field U_B follows a quasi-inverse square law behavior. This is because road boundaries cannot be crossed, therefore extending to infinity as the vehicle approaches them.

$$U_B = \sum_{r=1}^{2} \frac{1}{2}\lambda\left(\frac{1}{|x^r|}\right)^2 \cdot \frac{x^r}{|x^r|} \tag{3}$$

Where:

- r is the road boundary line. $r = 1$ denotes the left boundary line while $r = 2$ is the right one.
- x^r is the distance from the vehicle to the road boundary in the x-axis direction.
- λ is the gain parameter of position.

An adjacent vehicle's potential field U_V models how two vehicles B and A interact with each other. Jia et al. (2022) use a function of Lennard-Jones 6-12 potential, while Li et al. (2020) use Yukawa's potential, applied in (4) to illustrate the potential field of vehicle A.

$$U_V^A = M_A \eta \frac{e^{-\beta_1 a_A}}{|k'_x|} \cdot \frac{k'_x}{|k'_x|} \tag{4}$$

Where:

- M_A is the virtual mass of vehicle A, expressed as a function of actual mass of the vehicle along with its velocity.
- η is a coefficient scaling field strength.
- β_1 and a_A are parameters quantifying sensitivity to acceleration and velocity.
- k'_x is the pseudo-distance introduced to describe changes to potential safety risk as the vehicle approaches from different angles.

The potential field intensity, i.e. how strong the repulsive force is and by proxy how risky the situation is - described by (5), where A is the ego vehicle (leading) and B is the following vehicle:

$$F_{AB} = m_B \cdot e^{\beta_2 v_B} \cdot \left|U_V^A\right| \tag{5}$$

Where:

- m_B is mass of vehicle B.
- β_2 is an undetermined coefficient.
- v_B is the velocity of vehicle B.

2.4 Traffic and Agent-Based Simulation

Simulation is one of the approaches for testing AVs. Real-world trials are difficult and expensive to set up, and the technology is not advanced enough to test higher automation (level 4 or 5) in a realistic traffic context.

Traffic simulation covered in the literature (Ni 2015) is generally divided into: (1) microtraffic models, focusing on individual vehicle interactions and capture the motion and interaction among vehicles—will be the focus of this paper (2) macrotraffic models, emphasizing the collective and average behavior of vehicles, looking at: flow, speed, density and how they vary dynamically over time and space. (3) mesotraffic models, combining both micro and macrotraffic models.

In terms of the simulation's theoretical framework, a discrete-time, agent-based model (ABS) seems to be the most suitable to simulate the APF scenario for the following reasons (based on Grimm and Railsback 2011): (i) Each vehicle is different from one another in the environment and can therefore act as an agent (unique). (ii) Each vehicle interacts with its neighboring vehicles to "create" its APF (interacting locally). (iii) Autonomous vehicles act independently of each other i.e. each has their own destination (autonomous).

Jing et al. (2020) conducted a review of simulations in the AV field, and according to their findings, ABS is mainly used to predict the impact of CAV penetration in the market and on the road, followed by simulation for system understanding, and management / decision support. Simulation is not popular for hypothesis testing. The service area is usually fixed, unless the aim is to look at results from different service areas. There have been many experiments carried out to test the APF, but they were limited to simple scenarios. ABS, on the other hand, has the potential to uncover issues in a realistic implementation of APF on the road, and to this end, there has been very limited work involving the APF and agent-based simulation in the AV context, adding to the theoretical base of agent-based simulation.

3 PROPOSED APPROACH

3.1 Hybrid Simulation Architecture

From an architecture standpoint, Pereira and Rossetti (2012) conceptualized an integrated architecture for AV simulation that incorporates both the robotic and traffic simulation aspect of a CAV. Schoener (2018) also outlines a similar architecture for AV simulation, with key components identified being consistent across AV simulation studies, such as Zhao et al. (2022) and Yilmaz-Niewerth et al. (2024). These components are: (i) the road model, where all the simulation traffic participants will drive, which will either involve a predefined map from CARLA (Dosovitskiy et al. 2017) or will be implemented through OpenStreetMap; (ii) the traffic model, which will be implemented in SUMO Eclipse (Lopez et al. 2018), and (iii) the sensor and vehicle models, which will be both implemented in CARLA. The implementation will be a hybrid one because it will use different simulators, coordinating both SUMO and CARLA to run concurrently to deploy the APF. The main components of the proposed hybrid simulation architecture and their functions are shown in Figure 2. In terms of synchronization, we investigate different approaches such as co-simulation as well as distributed simulation with High Level Architecture (HLA) (IEEE 2010).

The reason why two simulators are needed (making it a hybrid simulation) is because: while CARLA provides more detailed information regarding lane information, agent states, position and velocity, it cannot handle traffic flow management due to rendering and physics constraints. SUMO, on the other hand, can model realistic traffic patterns and scenarios with many agents, as well as providing control over traffic light logic, routing and lane-changing behavior—which is otherwise hard-coded in CARLA. Therefore, the aim is to use CARLA to create detailed simulations of the ego vehicle, running concurrently with SUMO.

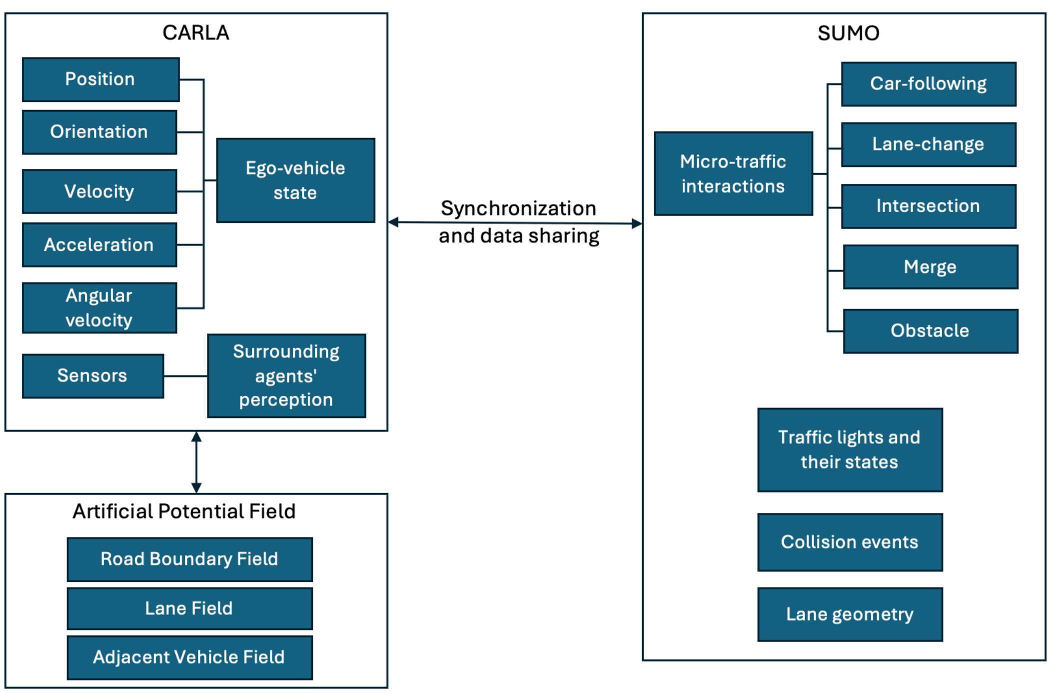

Figure 2: Hybrid Simulation Architecture.

The APF model can be embedded into CARLA (or in a separate Python wrapper) and then, using the information that CARLA gathers from the ego sensors, it can compute the risk function for the ego regarding the road boundary, lanes and other vehicles around it. As this is a conceptual framework, the initial focus will be on TA for the ego vehicle, rather than decision-making—which can be implemented in future experiments.

3.2 Data and Scenarios

The minimum set of traffic scenarios that need to be considered by an AV (European Commission 2022) are as follows: lane change; turning and crossing by the fully automated vehicle—either crossing or merging; emergency maneuvers e.g. collision avoidance; motorway entry and exit; passing a toll station; operation on other road types (than motorways).

Each of the scenarios will have its own parameters and expected outcomes (an example of this is illustrated in Table 1). The safety indicators or the SSM (Wang et al. 2021), are selected based on their usage frequency in the literature, with the time to collision (TTC) metric being the most popular one, while the other indicators are outlined in the Commission Implementing Regulation (European Commission 2022) for the given scenarios. A brief description is provided below.

- TTC: time it would take to collide with a leading vehicle or an object in the ego vehicle's lane if both continue at their current speed.
- TTC_{dyn}: minimum safe TTC required when merging into traffic that has right of way.
- TTC_{int}: TTC considering a path with an oncoming privileged vehicle.
- $TTC_{cut\text{-}in}$: TTC after a vehicle cuts into the ego vehicle lane. It is used to determine if a collision can still be avoided.
- PET: time difference between when the ego vehicle occupies a location and when the trailing vehicle arrives at the same location (Morando et al. 2018).

Both APF and SSM detect risk when the values being measures exceed certain thresholds (e.g. for TTC is typically set to 1.5s), but as Dai et al. (2023) noted in their paper, it is usually at the discretion of the analyst. This, along with additional SSM comparisons—such as time exposed time to collision (TET), time-integrated time to collision (TIT), or other acceleration-based metrics—as well as the exploration of other scenarios, are intended for future investigation.

3.3 KPIs for Performance Analysis

The EU Implementing Regulation 2022/1426 (European Commission 2022) outlines the performance metrics on which ADS are evaluated during each scenario. These have been included in Table 2.

One approach to compare APF with SSM metrics could be normalizing their outputs, i.e. having certain thresholds, and based on whether the output exceeds the threshold (1—risk) or doesn't (0—no risk) then a binary classification of risk is created. This approach could be evaluated as follows:

Detection time and accuracy of perception in this case could be interpreted as:

- Detection time - How early does the APF model predict a dangerous situation compared to the SSM? This can be calculated by subtracting the time at which the APF detects a risk with the time the SSM exceeds the safety threshold:

  $$Detection\ Lead\ time\ =\ APF\ detection\ time\ -\ SSM\ detection\ time$$

  A positive value means the APF detects risk earlier compared to the SSM of choice.
- Accuracy: Does APF correctly or wrongly detect a risk? For APF, it could mean having true positives or false positives, which are common performance metrics for ML model predictions (Flach 2019).

Table 1: Base scenarios for APF comparison (from the EU Implementing Regulation 2022/1426).

<table>
<tr><th>Base Scenarios</th><th>Safety indicator</th><th>Equation</th><th>Data needed for SSM</th><th>Data needed for APF</th></tr>
<tr><td>Car following</td><td>TTC</td><td>$\frac{distance}{relative\ speed}$</td><td>• Ego speed
• Leading vehicle speed
• Distance between the two vehicles</td><td rowspan="4">• Ego mass
• Following vehicle mass
• Ego velocity
• Following vehicle velocity
• Ego acceleration
• Following vehicle acceleration
• Distance between ego and following vehicle</td></tr>
<tr><td>Merge into privileged traffic</td><td>TTC_{dyn}</td><td>$\frac{\mathrm{v_e} + \mathrm{v_a}}{2\beta} + \rho$</td><td>• Ego speed $\mathrm{v_e}$
• Approaching vehicle speed $\mathrm{v_a}$
• Maximum accepted deceleration β (3 m/s^2)
• Reaction time ρ (1.5s)</td></tr>
<tr><td>Turn across oncoming traffic</td><td>TTC_{int}</td><td>$\frac{\mathrm{v_c}}{2\beta} + \rho$</td><td>• Conflicting traffic speed $\mathrm{v_c}$
• Conflicting traffic deceleration β
• Conflicting traffic reaction time ρ</td></tr>
<tr><td>Obstacle ahead, e.g.: lane intrusion (vehicle cut-in)</td><td>$\mathrm{TTC}_{cut\text{-}in}$</td><td>$\frac{\mathrm{v_{rel}}}{2\beta} + \rho + \frac{1}{2}\tau$</td><td>• Relative speed between ego and obstacle $\mathrm{v_{rel}}$
• Maximum deceleration β (6m/s^2)
• Time to reach maximum deceleration τ (0.3s)
• Time to initiate ego emergency braking ρ (0.1s)</td></tr>
<tr><td>Lane change (from Allen et al. 1978)</td><td>PET</td><td>$t_2 - t_1$</td><td>• Time t_1 for ego to depart conflict point
• Time t_2 for following vehicle to reach conflict point</td><td>• Ego spatial position coordinates
• Angle (ego to certain point)
• Ego acceleration (maximum: 4.001)
• Ego velocity
• Turning angle
• Ego length
• Following vehicle length
• Distance between ego center and potential field edge (backwards)
• Distance between following vehicle center and potential field edge (forwards)</td></tr>
</table>

- Consistency across repeated scenarios: how often is it accurate?

Table 2: KPIs for normalized risk.

EU performance metric	KPI
Detection time and accuracy of perception	Detection Lead Time (s) True Positive False positive
Decision-making appropriateness and timing	Not applicable
Control behavior including smoothness and safety	Not applicable
Responsiveness to dynamic elements such as vehicles / VRUs	Detection Lead Time (s)
Consistency across repeated trials	True Positive Rate (%) True Negative Rate (%)

- Responsiveness to dynamic elements: this can be interpreted as either how well the vehicle 'acts' based on changes to the environment, which is outside the scope of the initial scenario testing, or how early does it detect changes to the environment (which is linked to detection time).

Another way of comparing the APF model and SSMs is by plotting their risk indicators over the simulation time (for APF it will be field force over time; for SSMs, since the selected ones so far are time based, they could be plotted as a function of velocity over time—inversing them) and compare through a graphical inspection at which points the gradients increase and at which points they decrease (detection time); if they do detect them in the same scenario (accuracy); how often for repeated scenarios the gradients match. This is usually how studies described in section 2.3 carry out their evaluation.

4 CONCLUSIONS AND FUTURE WORK

This paper proposed a hybrid simulation framework for evaluating the APF method as a real-time threat assessment model for CAVs. By combining SUMO for traffic flow modeling and CARLA for detailed vehicle dynamics, APF for threat assessment, a conceptual hybrid simulation architecture was presented. The use of agent-based simulation to test APF in realistic traffic scenarios represents a novel contribution, offering a more thorough assessment for effectiveness.

Although the approach is conceptual, the framework aligns with EU regulations for scenario-based testing and lays out a validation strategy using surrogate safety metrics and performance indicators. This work is meant for simulation-based evaluation of whether APF can meet real-world safety requirements.

Future work will focus on implementing the hybrid simulation environment and synchronizing SUMO and CARLA using a co-simulation interface. The APF model will be embedded in the ego vehicle logic and tested across regulatory scenarios. We anticipate to face scale limitations due to time and hardware constraints. Further limitation analysis will be conducted in future work.

Key directions include: (1) Comparing APF outputs with standard surrogate safety metrics (e.g., TTC, PET), (2) Running sensitivity analyses on APF parameters and scenario variables. (3) Testing scalability under denser traffic. (4) Incorporating uncertainty and noisy sensor data. (5) Expanding KPIs to cover decision quality and response timing. (6) Exploring adaptive APF parameter tuning through learning-based approaches.

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