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Event-Driven Decision-Making for Autonomous Vehicles in Mixed-Traffic Roundabouts

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ABSTRACT Autonomous vehicle operation in roundabouts remains a challenging task due to continuous traffic flow, limited visibility, and the coexistence of human and automated drivers. Traditional optimization- or learning-based decision frameworks struggle to handle such conditions because they rely on perfect perception, continuous control, or full vehicle connectivity. This paper presents a discrete event system based decision-making framework for autonomous vehicles navigating single-lane roundabouts in mixed traffic. The proposed method models vehicle interactions as event-triggered state transitions, allowing transparent and modular decision logic between offensive and defensive driving behaviors. Simulations demonstrate that the proposed approach achieves collision-free operation and stable flow performance under partial observability, while maintaining interpretability and low computational cost. The results highlight that discrete event reasoning provides a scalable and explainable alternative to existing continuous and data-driven models for autonomous driving in complex urban environments.

INDEX TERMS Autonomous Vehicles, Decision Making, Discrete Event Systems, Mixed Traffic

I. Introduction

The ever growing demand of individual transportation is currently only met by the heavy usage of individual passenger vehicles, resulting in an increasing number of vehicles on the streets [1]. This development is accompanied by the increasing percentage of partial and, in the near future, also fully autonomous vehicles. Although there are already situations where autonomous vehicles and human driven vehicles share the same traffic space without major problems, such as highway driving, the interaction part gets much more relevant, when driving paths of different traffic participants intersect or merge together like at intersections, ramps or roundabouts.

Besides the classical stop- or signalized intersections, roundabouts are becoming a popular alternative for rural and urban areas when it comes to replacing intersections. Although first introduced in 1899 in Görlitz (Germany) the major breakthrough in terms of relevance started in the early 2000s [2]. Since then various different configurations all over the world have been build. For most of the roundabouts the number of entry roads varies between 3 and 5, while typically 1 or 2 lanes form the inner circle. Besides the classical roundabout geometry also more special variants like the turbo-roundabout or the „flower “roundabout exist [3], but those are out of the scope of this work. Even though two lane roundabouts have shown improvements regarding safety and traffic flow in the latest evaluation due to learning effects of the drivers, this work particularly focusses on roundabouts with a single lane circle road and 3 or 4 entry road. This class represents the most prominent roundabouts and also acts as a template for the handling of the remaining classes.

Based on the growing interest of civil engineers and traffic planners about roundabouts, there will be more and more roundabouts at corresponding nodes [4].

As autonomous vehicles become increasingly integrated into everyday traffic, ensuring safe and efficient interactions between human-driven and autonomous vehicles at roundabouts remains a significant challenge. Human drivers rely on implicit communication cues, such as eye contact and hand gestures, to negotiate entry and right-of-way,

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while autonomous vehicles must depend solely on sensor data and algorithmic decision-making. This discrepancy can lead to hesitation, inefficiencies, or even safety risks in mixed traffic scenarios, where human drivers expect the autonomous vehicle to behave as a regular human driven vehicle. Scalability issues emerge as vehicle counts increase in roundabout settings, requiring adaptable and efficient decision-making models like discrete event systems. The successful application of similar models in intersection scenarios, as per previous research [5], indicates their potential for roundabout navigation. Therefore, the development of robust decision-making models tailored to roundabout navigation in mixed traffic conditions is crucial for improving traffic flow and maintaining safety. Addressing these challenges requires a deep understanding of human driving behavior, real-time vehicle coordination strategies, and advanced predictive models to facilitate seamless integration of autonomous vehicles in such environments.

The paper is structured in the following way. First an overview of the most relevant publications is provided. Then, we introduce the proposed model and its decision making process. Section IV describes the simulation framework used to validate the proposed model. The conclusion summarizes the work and provides a brief outlook.

II. Related Work

Research on autonomous vehicle decision-making in roundabouts can be broadly categorized into two major domains: simulation-based investigations and behavioral modeling in mixed traffic, and algorithmic decision and control frameworks for automated vehicles. Together, these strands establish the foundation for developing interpretable and robust decision-making approaches suitable for complex, real-world environments.

With the advent of autonomous systems, simulation environments have become indispensable for studying complex interactions in roundabouts. Leite *et al.* [6] employed the Simulation of Urban Mobility (SUMO) platform to investigate multi-lane roundabouts, demonstrating the benefits of adaptive control on overall efficiency. Nonetheless, their approach assumes homogeneous driver behavior and ideal sensing conditions. Previati and Mastinu [7] extended this line of work by coupling SUMO with a dynamic driving simulator, enabling real human participation in looped simulation. While this provided valuable insights into comfort and driver perception, the approach remains computationally expensive and difficult to generalize across traffic scenarios. Naderi *et al.* [8] proposed a lane-free coordination scheme for automated vehicles at large roundabouts, showing that unconstrained vehicle motion can improve throughput—provided accurate sensing and cooperative control are guaranteed. However, such fully connected or perception-perfect assumptions are rarely attainable in real-world environments. These simulation-based studies thus deliver valuable qualitative insights but fall short of providing decision-making frameworks that operate robustly under uncertainty and partial observability.

A diverse range of control and decision-making strategies has been proposed to handle roundabout navigation, including optimization-based, probabilistic, and learning- or game-theoretic methods. Zhao *et al.* [9] formulated an optimal control problem for connected and automated vehicles (CAVs), and Farkas *et al.* [10] developed a Model Predictive Control (MPC) scheme that optimizes velocity trajectories to minimize travel time while preventing collisions. Although mathematically rigorous, these models require continuous optimization and full state observability, which limits their practical scalability in dense, mixed traffic. To address uncertainty, Bey *et al.* [11] employed a Partially Observable Markov Decision Process (POMDP) framework, enabling robust reasoning about hidden driver intentions. However, POMDP solutions incur high computational cost and are difficult to parameterize for real-time applications. Zhang *et al.* [12], Tian *et al.* [13], and Pruekprasert *et al.* [14] approached interaction modeling through reinforcement learning and game theory, capturing strategic anticipation among multiple agents. While these approaches improve adaptability, they often lack interpretability and are sensitive to training data or payoff assumptions. Hybrid and heuristic approaches have also been explored. Arizala *et al.* [15] integrated fuzzy logic with MPC to handle uncertain interactions, while Antonya *et al.* [16] utilized genetic algorithms to optimize cooperative motion. De Beaucorps *et al.* [17] introduced a human-inspired decision model for unsignalized intersections based on empirical risk assessment. These frameworks offer useful mechanisms for uncertainty handling but typically rely on centralized coordination or scenario-specific calibration, reducing their transferability to unseen configurations.

In contrast to continuous or data-driven approaches, event-discrete decision models describe system behavior as transitions between discrete states triggered by observable events. Weinreuter *et al.* [18] and Leyer *et al.* [5] successfully demonstrated that such discrete event systems can produce interpretable and collision-free decision-making at non-signalized intersections. Their modular structure enables intuitive parameter tuning and intuitive traceability, providing advantages over opaque machine learning or high-complexity optimization schemes. Extending these principles to roundabouts introduces additional challenges—such as overlapping conflict zones, limited visibility, and continuous circulation dynamics—that existing implementations have not yet addressed.

Overall, existing research provides valuable foundations for understanding traffic interactions, yet significant gaps remain. Simulation-based studies [6]–[8] assume idealized or homogeneous driver behavior; optimization-based approaches [9], [10] depend on continuous and centralized control; probabilistic and learning-based models [11]–[14] struggle with computational tractability and interpretability; and heuristic or fuzzy logic systems [15], [16] require case-specific tuning.

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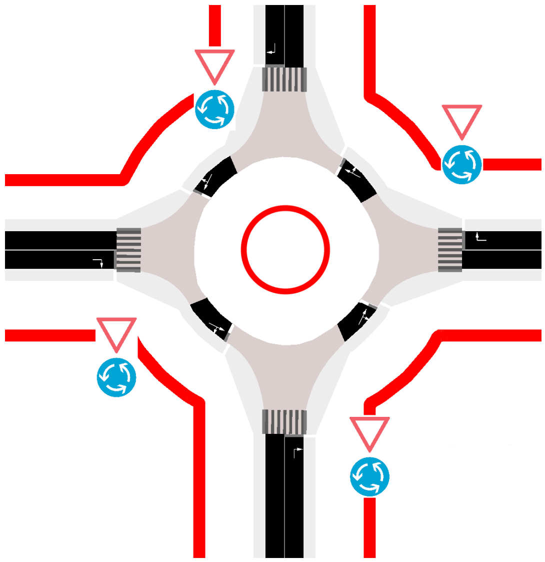

Figure 1: Signage of the roundabout scenarios of this work. Each entry road into the roundabout has to give way to vehicles inside the roundabout. The red lines represent visibility blocking obstacles, resulting in a more realistic partial occlusion of the roundabout.

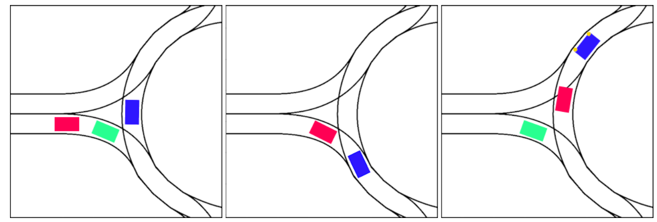

Figure 2: Exemplary situation of interactions with different relations at a roundabout form the perspective of the red vehicle (a) showing leading vehicle (green) and priority vehicle (blue) of the red vehicle; (b) showing blocking vehicle (blue) and (c) showing yielding vehicle (green) while driving on circular road thereby blocking the exit for the blue vehicle

None of these frameworks fully supports decision-making under the combined conditions of partial observability, no communication, and non-homogeneous driver cooperation. The discrete event decision-making approach proposed in this work directly targets these limitations by modeling driving interactions through event-triggered state transitions that naturally accommodate occlusion, indirect communication, and irregular driver behavior. To the authors' knowledge, no existing reference model can operate under these boundary conditions, precluding direct benchmarking.

Building upon these insights, the following section introduces the proposed decision-making framework. It leverages the interpretability of discrete state transitions while maintaining adaptability to the dynamics and partially observable nature of mixed-traffic roundabout scenarios.

III. Discrete Event System

In this section the event-based decision making algorithm is introduced. A Discrete Event System (DES) is a mathematical framework in which the system state evolves through a sequence of discrete events occurring at distinct points in time rather than continuously. This allows complex decision processes to be represented as event-driven transitions between well-defined states, offering transparency and traceability. Based on the classification of relevant vehicles, as well as the computation of used features and events, the decision to drive offensively or defensively is made by the proposed DES. This decision is then translated into a physical behavior based on a modified Intelligent Driver Model (IDM). All the following explanations are based on the assumption of a regular single road roundabout, being defined as: "Roundabouts are circular intersections with specific design and traffic control [...] including yield control of all entering traffic [and] appropriate geometric curvate" [19]. A typical example of a four arm roundabout can be seen in Fig. 1. In order to simplify the scenarios that can occur the assumption is made, that all vehicles follow their center of the lanes, leading to a regular following of the geometric shape of the roundabout. Also a purely vehicle perspective is realized by only considering autonomous vehicles (A-V) and cooperative vehicles (C-Vs) as the only traffic participants in this work. The reasonable driver assumption applies to the C-Vs, with some permitted deviations for the representation of special behavior.

A. Relevant Vehicles

Even though at a roundabout, multiple streets and so also multiple vehicles can be close to the vehicle running the DES algorithm, not all of those vehicles are relevant for the decision making process. Therefore in the following the possible relations and their meaning regarding the decision process will be explained.

- **Priority vehicle (P-V)**: Following the yield control of entering traffic, all vehicles have to give way to vehicles that are passing by on the circular road. If a C-V is approaching the own entry road from another road, it is classified as a P-V and by default has the right of way.
- **Yielding vehicle (Y-V)**: In case the A-V is driving on the circular road, all vehicles trying to enter the circular road have to yield to the A-V, therefore they are labeled as Y-V
- **Leading vehicle (L-V)**: The vehicle driving directly in front of the A-V on the same road is classified as the leading vehicle. It is represented by a custom relation, because it can limit the dynamics of the A-V compared to a free driving situation, however it does not influence the DES model's states.
- **Blocking vehicle (B-V)**: If a vehicle is already occupying the part of the roundabout that the A-V has to pass in order to follow its route the vehicle is classified as a

B-V. A vehicle should only enter an area if the entry or exit is clear; otherwise, it must wait outside to ensure a safe interaction.

Each of the relations can only be assigned once for each vehicle's perspective in the current timestep. Any vehicle which is not assigned any of the aforementioned labels is not considered in the decision making process, drastically reducing the number of constellations to be considered during the modelling phase.

To respect the limited visibility across the center island and the approaching roads, depending on the approaching direction all vehicles that are not visible are either omitted or their presence is expected until proven otherwise. Due to safety considerations the presence of P-Vs and B-Vs is expected until proven otherwise, while for the Y-Vs non visible vehicles are not considered in the decision process.

B. Maps

The maps used in this work consist of different variations of roundabouts. Most common are roundabouts with three and four arms, however also more armed roundabout exists. Based on the German „Instruction sheet for the construction of roundabouts“ [20], roundabouts can be categorized into three main groups:

- Miniature Roundabouts: Mini-roundabouts have a diameter of 13 to 22 meters. Since large trucks or buses cannot navigate around the central island due to their turning radius, they must be designed to be drivable—usually paved and bordered by a low curb or, in some cases, only marked. They are intended to replace existing right-of-way regulations or traffic signals in suitable urban locations.
- Small roundabouts: Small roundabouts have an outer diameter of 26 to 50 meters. The central island is usually not driveable, but they may include a slightly offset, overrun area to accommodate large vehicles with wide turning circles. Small roundabouts are primarily used on the outskirts of towns. According to the guidelines [21] for roundabout design, their size depends on whether they are located within or outside built-up areas. The recommended outer diameter is 26 to 40 meters in urban areas and 35 to 50 meters in rural areas.
- Large roundabouts: Large roundabouts have a diameter of more than 40 meters and are usually multi-lane. They primarily serve to distribute traffic flows over a wide area.

Even though additional special variations like *Turbo* or *Flower* Roundabouts exist [3], these listed categories cover most of the roundabouts present. In the following work we are focused on the small roundabouts with single lane traffic.

The roundabouts consist of single lane circular road with the associated roundabout signage giving the vehicles inside the circular road the right of way. Figure 1 showcases a four armed roundabout with the signage. The approaching vehicles have to give way to the vehicles inside the roundabout.

In contrast to an intersection scenario, where the whole scenario is modeled as a single interaction space, the overall scenario of a roundabout can be split up into the multiple junctions for each entry and exit of the roundabout. Due to the separability of those interactions the decision making model can be separated based on the interactions at those junctions leading into and out of the roundabout. Inside those junctions the decision making model is required, while for the areas in between or outside a regular car following model, like the IDM taking into account the distance to leading vehicle and the maximum velocity, is sufficient.

Inside each junction part of the roundabout multiple driving paths overlap and merge, creating possible collision zones (see Fig. 3). For safety reasons these zones should only be occupied by a single vehicle at a time in order to ensure a safe and collision free passing. Based on those zones the last stopping points (LSPs) can be defined. As the name suggests these are the last positions a vehicle can stop, while not partially blocking any other driving direction, except its own. To integrate those stopping positions into the IDM virtual vehicles are created to force a stop exactly at the last stopping point. The visualization for the entering, passing and leaving maneuvers for the left junction can be seen in Fig. 4.

In order to account for different visibility conditions at roundabouts sight-blocking obstacles, so called visibility blockers (see red lines in Fig. 1), are introduced. Those represent objects like buildings, vegetation or parked vehicles allowing for no line of sight. Additionally reference points were included to distinguish approaches were the visibility allows for a full overview of the upcoming scenario versus scenarios where a total overview is only reached much closer to the roundabout itself. Only if the reference points for the current entry direction are visible an informed decision about the behavior can be made. Those reference points are placed either at the center of the lane of the nearest entrance to the roundabout on the left-hand side, or - if the roundabout is large - at a fixed distance of $d_{\mathrm{ref}} = 25\,\mathrm{m}$ along the line connecting the left-hand entrance and the approaching entrance point.

C. Features

The decision-making model is structured around events that govern state transitions, with these events being determined by features representing the current situation. The superscript notation of a feature specifies the C-V for which it is computed: $(\cdot)^x$, where $x \in \{$a, p, y, b$\}$, corresponding to A-V, P-V, Y-V and B-V, respectively. All vehicles are modeled as rectangular entities with fixed geometric dimensions, specifically a length of $l_{\mathrm{v}} = 4.4\,\mathrm{m}$ and a width of $w_{\mathrm{v}} = 1.8\,\mathrm{m}$. Distances are measured along the lane center of the driving path rather than using Euclidean metrics. To ensure accuracy, all relevant features are recalculated at each time step. For clarity, the time index is omitted throughout the text.

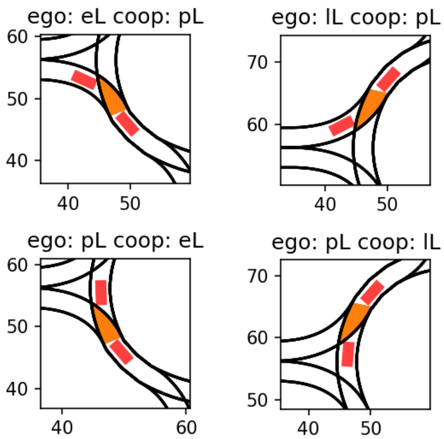

Figure 3: All relevant collision zones (orange areas) related to the left hand side entry/exit junction and the respective entry and exit positions for the different passing modes. Independent of the overall driving pattern only the current entering (e), passing (p) or leaving (l) at this Left junction (L) is considered. Those collision zones can also be computed for the remaining entries and exits of the roundabout.

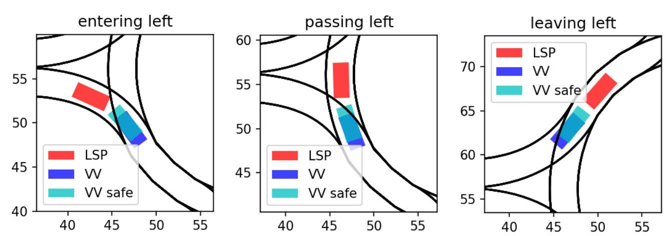

Figure 4: The last stopping points for the left entry/exit junction. Based on the collision zones information and the geometric shape of the vehicle the last stopping points' vehicle position (red) can be computed. In order to force the vehicle to stop at this point exactly a virtual vehicles (blue) in combination with the IDM is used. The virtual vehicle with safety distance (cyan) of $d_{\text{safe}} = 1\,\text{m}$ also includes an additional safety distance before the real stopping point and the latest possible stopping point.

The core features used in the algorithm are the distance to the beginning $d^x_{\text{s,b}}$ and the end of the scenario $d^x_{\text{s,e}}$. They describe the position of the vehicle with respect to the entry intersection into the roundabout or the leaving intersection respectively, allowing to determine, whether the vehicle is still before, inside or after the roundabout at any given timestep.

The collision zones, created by overlapping driving paths of the vehicle x and its C-V x_c, may only be occupied by one vehicle at a time. They are therefore important aspects for the algorithm, and thus the distance to the collision zone is defined for the beginning $d_x^{c,x_c,b}$ and the end $d_x^{c,x_c,e}$ of the collision zone. Besides the spatial distance, the temporal distance is also calculated by assuming a constant velocity for vehicle x, based on the current speed:

$$t^x_{\text{c},x_\text{c},\cdot} = \frac{d^x_{\text{c},x_\text{c},\cdot}}{v^x} \tag{1}$$

The *distance to stop* d^x_{b} describes the distance required to stop completely given the velocity v^x and acceleration a^x:

$$d^x_{\text{b}}\left(v^x, a^x\right) = \begin{cases} -\frac{(v^x)^2}{2a^x}, & a^x < 0\,\text{m}\,\text{s}^{-2} \\ 0\,\text{m}, & a^x = 0\,\text{m}\,\text{s}^{-2} \wedge v^x = 0\,\text{m}\,\text{s}^{-1} \\ \infty, & \text{otherwise} \end{cases} \tag{2}$$

Values chosen for the different braking methods are a comfort deceleration $a_{\text{comf}} = -2.5\,\text{m}\,\text{s}^{-2}$ for the regular cases, hard deceleration $a_{\text{hard}} = -4.5\,\text{m}\,\text{s}^{-2}$ and an emergency deceleration to prevent collision with $a_{\text{em}} = -7.5\,\text{m}\,\text{s}^{-2}$.

The *free distance behind the B-V* d^{b}_{f} describes the length of free street behind the B-V that can be used by the A-V if it were to pass the junction area:

$$d^{\text{b}}_{\text{f}} = d^{\text{b}}_{\text{i}} - l_{\text{v}} + d^{\text{b}}_{\text{b}}\left(v^{\text{b}}, a_{\text{e}}\right), \tag{3}$$

where d^{b}_{i} is the current distance from the intersection end to the B-V. To enable the A-V to follow the B-V sooner, the distance the B-V will travel in any case even if it stops with an emergency deceleration is accounted for. The final feature is the *distance to the last stopping point* d^x_{l}.

D. Events

By using those features different base events (see Tab. 1) and events (see Tab. 2) can be defined. While the base events are checks for different feature combinations, the events result from a logical combination of the base events. For easy understand whether a C-V allows the A-V to drive, a simplified traffic light analogy is used. The A-V can only drive offensive if all traffic relations have a green light assigned; otherwise a deceleration or even stopping is inducted.

To get a green light from the P-V relation $e_{1,\text{p}}$ one of three base events have to be true: Either the P-V relation does not exist (e_{b1}) or a sufficiently large gap in time and space between the A-V's exit and the P-V's entry of the common collision zones exists (e_{b2}). Additionally the special behavior of a P-V is considered by e_{b3}, allowing the A-V to drive first against the P-V if it has been waiting longer than a given time threshold waiving its right of way.

In order to be cleared to drive first against the Y-V one of the following four conditions has to be met:

- The A-V exits the common collision zone before the Y-V does enter the same zone (e_{b4}).
- The A-V can still stop before the LSP by applying a hard deceleration a_{h} plus a safety distance d_0 while the Y-V is braking and moving with a velocity lower than the slow velocity v_{sl} and can still come to a stop before the common collision zone by applying the current deceleration for the current velocity (e_{b5}).

- The distance to the LSP of the A-V is bigger than twice the distance required to come to a complete stop by applying the comfort deceleration a_{comf} ($e_{\mathrm{b}7}$).
- While still breaking the Y-V's velocity is below the standing threshold velocity v_{s} and it has not yet reached the beginning of the common collision zone ($e_{\mathrm{b}6}$).

For the B-V only two base events can lead to a green light: Either no B-V exists ($e_{\mathrm{b}8}$) or the existing B-V has preceded far enough, such that enough space for the A-V behind the B-V is free in order to enter into the area fully ($e_{\mathrm{b}9}$).

The remaining two events are purely related to the A-V itself. For the handling of the transition between different zones the event e_2 is introduced. The final event e_3 represent, if an emergency braking maneuver is still possible in order to come to a stop before the upcoming LSP.

E. Decision Model

The custom defined zones are visualized in Figure 5. For each vehicle those zones' definitions are applied in order to divide the decision process. The zones are defined based on the distance to the beginning of the scenario $d^{\mathrm{a}}_{\mathrm{s,b}}$ and the distance to the exit of the scenario $d^{\mathrm{a}}_{\mathrm{s,e}}$. In zones 1 and 5 only a single, neutral state s_{10} and s_{50} exist, due to the free driving only limited by a potential leading vehicle, maximum speed and the own vehicles' dynamics. For zones 2, 3 and 4 offensive (s_{21}, s_{31}, s_{41}) and defensive (s_{22}, s_{32}, s_{42}) states exist. In this context the offensive states represent an offensive driving based on the current observation, because the relevant vehicles are associated with a green traffic light, allowing the A-V to pass first. When those observations change, a transition to a new state is possible only if all required events occur to initiate the change. Otherwise, the vehicle remains in its current state.

During the approaching and entering of the roundabout the relevant relations for the decision are the priority vehicle (P-V) and the blocking vehicle (B-V). Only if both give a green light $e_{1,\mathrm{p}} \wedge e_{1,\mathrm{b}}$ the vehicle can get into an offensive state. While for the transition between states 1, 2 and 3 the decision is only made at the entering of a new zone e_2, inside of zone 3 the driving behavior can be changed in each timestep. Only for the change between the entering of the roundabout via s_{31} and the waiting to enter state s_{32} also an emergency stop before the LSPs has to be possible e_3 in order to still change the behavior.

While inside the roundabout only yielding vehicles (Y-V) and blocking vehicles (B-V) can exist. Again both have to allow the A-V to drive in order to get into an offensive state s_{41} to drive through the roundabout and leave it by transitioning into zone 5.

Even though the relation to the leading vehicle is not present in the decision making model as displayed in Fig. 6 the presence of those vehicles is reflected in the behavior generation of the vehicle (see F). In contrast to ambiguous scenarios like non-signalized intersections the driving order is always determined for roundabouts by this decision making model.

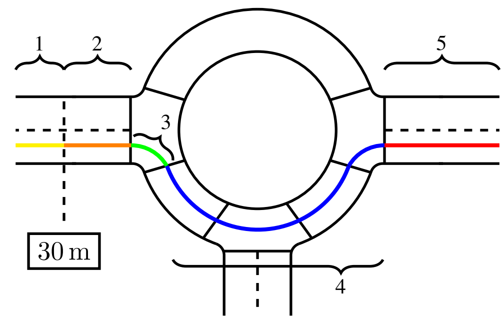

Figure 5: Zones of roundabout for a straight passing entering from the left side. Passing through the roundabout is split into five zones. $30\,\mathrm{m}$ before the entry point the vehicle changes from the first (yellow), free driving zone into the second zone (orange). With the entry into the junction area the vehicles transitions into zone 3 (green) turning into the circular lane. While on the circular lane the vehicles remains in zone 4 (blue) and leaves the roundabout while getting back into the free driving zone 5 (red).

F. Behavior Generation

For each of the eight states an associated target velocity is defined (see Table 3). The A-V tries to reach this desired speed v_{t} while being also limited by a potential leading vehicle (L-V). In order to compute the required acceleration values to reach the desired speed while respecting the leading vehicle, the car following model *Intelligent Driver Model* (IDM) is used. It is originally developed as a car-following model for highway scenarios, but has already been used for longitudinal control in different cases [22], [23] and is a suitable fit for this task due to its guaranteed collision-free motion and anticipatory deceleration toward predefined stopping points along the trajectory.

$$a = a_{\max}\left(1 - \left(\frac{v^{\mathrm{a}}}{v_{\mathrm{t}}}\right)^4 - \left(\frac{d^*}{\Delta d}\right)^2\right) \tag{4}$$

$$\text{with } d^* = d_{\min} + v^{\mathrm{a}} t_{\min} + \frac{v^{\mathrm{a}}\Delta v}{2\sqrt{a_{\max} a_{\mathrm{b}}}}. \tag{5}$$

The determination of the acceleration is based on the Equation 4, giving us a connection between the maximum possible acceleration $a_{\max} = 2.5\,\mathrm{m\,s^{-2}}$, the ratio between the current speed of the A-V v^{a} and the desired speed v_t as well as the target gap d^* and the current gap to the leading vehicle Δd. The target gap represents the desired gap of two vehicles being defined by a minimum headway in distance $d_{\min} = 1.5\,\mathrm{m}$ and time $t_{\min} = 1.2\,\mathrm{s}$, while also considering the breaking acceleration and the velocity gap to the leading vehicle (see Equation 5).

If no leading vehicle exist the distance Δd is set to infinity and the A-V only cares about the desired speed v_{t}. For the

Table 1: Base events (BE) for the DES based on the computed features.

BE	Condition
e_{b1}	P-V does not exist
e_{b2}	$t^{\mathrm{a}}_{\mathrm{c,p,e}} + \Delta t^{\mathrm{p}} < t^{\mathrm{p}}_{\mathrm{c,p,b}} \wedge d^{\mathrm{a}}_{\mathrm{c,p,e}} + \Delta d^{\mathrm{p}} < d^{\mathrm{p}}_{\mathrm{c,p,b}}$
e_{b3}	$t^{\mathrm{p}}_{\mathrm{w}} > t_{\mathrm{y}}$
e_{b4}	$t^{\mathrm{a}}_{\mathrm{c,y,e}} < t^{\mathrm{y}}_{\mathrm{c,y,b}}$
e_{b5}	$d^{\mathrm{a}}_{\mathrm{l}} > d^{\mathrm{a}}_{\mathrm{b}}(v_{\mathrm{a}}, a_{\mathrm{h}}) + d_0 \wedge v^{\mathrm{y}} < v_{\mathrm{sl}}$
	$\wedge\, a^{\mathrm{y}} < 0\,\mathrm{m\,s^{-2}} \wedge d^{\mathrm{y}}_{\mathrm{c,y,b}} > d^{\mathrm{y}}_{\mathrm{b}}(v^{\mathrm{y}}, a^{\mathrm{y}})$
e_{b6}	$v^{\mathrm{y}} < v_{\mathrm{s}} \wedge a_{\mathrm{y}} \leq 0\,\mathrm{m\,s^{-2}} \wedge d^{\mathrm{y}}_{\mathrm{c,y,b}} > 0\,\mathrm{m}$
e_{b7}	$d^{\mathrm{a}}_{\mathrm{l}} > 2 \cdot d^{\mathrm{a}}_{\mathrm{b}}(v_{\mathrm{a}}, a_{\mathrm{comf}})$
e_{b8}	no B-V detected
e_{b9}	$d^{\mathrm{b}}_{\mathrm{f}} > l_{\mathrm{v}} + d_{\mathrm{min}}$
e_{b10}	$d^{\mathrm{a}}_{\mathrm{l}} > d^{\mathrm{a}}_{\mathrm{b}}(v^{\mathrm{a}}, a_{\mathrm{e}})$

Table 2: Events for DES based on logic combinations of BEs.

Definition	Description
$e_{1,\mathrm{p}} = e_{\mathrm{b1}} \vee e_{\mathrm{b2}} \vee e_{\mathrm{b3}}$	P-V: green light
$e_{1,\mathrm{y}} = e_{\mathrm{b4}} \vee e_{\mathrm{b5}} \vee e_{\mathrm{b6}} \vee e_{\mathrm{b7}}$	Y-V: green light
$e_{1,\mathrm{b}} = e_{\mathrm{b8}} \vee e_{\mathrm{b9}}$	B-V: green light
e_2	entered new zone
$e_3 = e_{\mathrm{b10}}$	emergency stop possible

defensive states in zone 3 and 4 the A-V is supposed to stop at the aforementioned LSP the latest in order to not block the other vehicles form passing through the roundabout. In case no leading vehicle is limiting the A-V behavior a virtual vehicle is inserted in order to make the A-V come to a stop at the LSP plus a safety margin of $1\,\mathrm{m}$. To make the simulation results more realistic the braking effects allowed by the IDM model are, in contrast to the original publication [24], also limited by a maximum of the emergency deceleration of $-7.5\,\mathrm{m\,s^{-2}}$ in order to prevent collisions, for regular deceleration the maximum is set to $-2.5\,\mathrm{m\,s^{-2}}$.

IV. Simulation

In order to run simulations with different configurations to test the behavior of the model, first a short overview of the used simulation framework is provided. Then a brief introduction of the simulation of the C-V behavior is given. Finally the different evaluation metrics for a comparison are introduced.

Table 3: desired speeds in $\mathrm{m\,s^{-1}}$ for each state. The initial speed v_0 can vary depending on the starting configuration, which is randomly chosen between $4\,\mathrm{m\,s^{-1}}$ and $8.3\,\mathrm{m\,s^{-1}}$.

state	s_{10}	s_{21}	s_{22}	s_{31}	s_{32}	s_{4X}	s_{50}
desired speed	v_0	4.5	3.0	3.5	2.0	4.5	8.33

A. Simulation Framework

The simulations are implemented in the simulation framework SUMO [25]. SUMO provides a rich environment for microscopic traffic simulation of various road configurations like highways, intersections and roundabouts. Due to the original purpose of SUMO for the traffic flow simulation some interaction however do not represent a realistic interaction with different vehicles, especially in cases where the vehicle routes overlap like in intersections and roundabouts. To tackle this limitations the provided ”Traffic Control Interface” (TraCI) is used to get information of the current simulation step from SUMO in order to process those in a custom python decision making algorithm. The resulting acceleration for the next time steps is then feed back into the simulation and the next time step is computed. This continues until all vehicles have reached there target positions or a maximum simulation duration is met.

The maps used for those simulation were created by the utilizing the graphical map creation tool *Netedit* provided by the SUMO package. This allows to manually tune different parameters like the junction shapes and the default driving paths inside the junctions as well as the dimensions of the map.

Table 4: Overview of road intersection geometries with variations in arm count, outer diameter, junction size, and shape. Arm count refers to the number of connecting roads. Outer diameter defines the overall width of the intersection. Junction size indicates the arc radius at corners, affecting turn dynamics and lane geometry. Shape describes the layout type: Plus has four arms forming a symmetric cross; T has three arms with one perpendicular to the main road; Y has three arms diverging at 120-degree angles.

Map Name	Arm Count	Outer Diameter	Junction Size	Shape
r_{000}	4	$50\,\mathrm{m}$	5	Plus
r_{001}	4	$40\,\mathrm{m}$	5	Plus
r_{002}	4	$30\,\mathrm{m}$	5	Plus
r_{003}	4	$30\,\mathrm{m}$	3	Plus
r_{004}	4	$30\,\mathrm{m}$	1	Plus
r_{005}	4	$30\,\mathrm{m}$	7	Plus
r_{006}	3	$50\,\mathrm{m}$	5	T
r_{007}	3	$40\,\mathrm{m}$	5	T
r_{008}	3	$30\,\mathrm{m}$	5	T
r_{009}	3	$40\,\mathrm{m}$	5	Y

B. Cooperation Vehicle Decision Making Model

Similar to the proposed decision model in III-E the decisions made by the C-V are also depending on a discrete event

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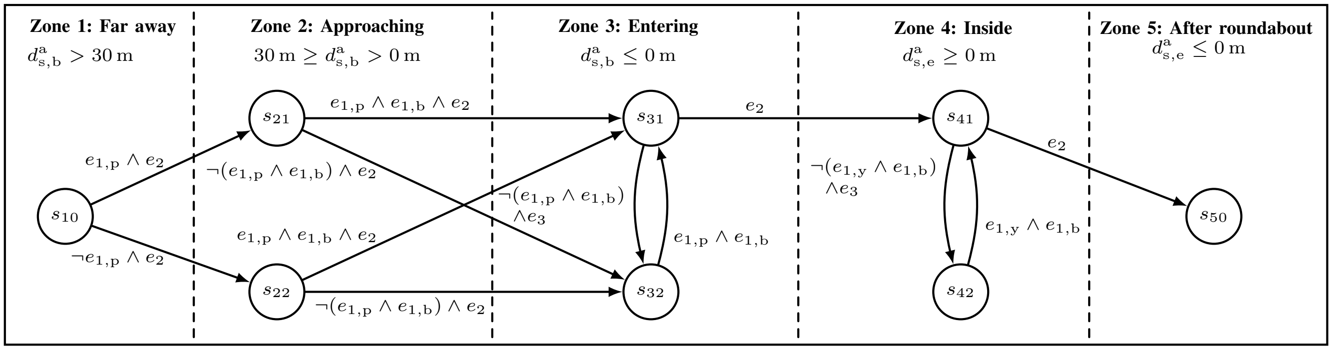

Figure 6: Discrete Event decision-making model for autonomous vehicles at roundabouts. The zone of the vehicle depends on the current distance to the begin $d^{\mathrm{a}}_{\mathrm{s,b}}$ and end $d^{\mathrm{a}}_{\mathrm{s,e}}$ of scenario. If no events for a state transition occur, the vehicle remains in its current state. The events are introduced in Table 2.

system. In contrast to the main model some interaction events are modified in order to create special behavior of those vehicles that deviates form the regular traffic rules in both offensive and defensive manner. Those special behaviors are only applied against A-Vs.

The general concept of the decision model is the same; based on computed features, base events are deducted. By logical combination of those the events for the C-Vs are formed, which are then used to transition between different states of the decision model. While the possible states and transition conditions are the same as for the A-V (see Fig. 6), the base events and their combinations differs.

To get a green light for the P-V relation, either the P-V does not exist ($\neg e_{\mathrm{c,b0}}$), or the vehicles can pass before the P-V. There is either a regular passing before the P-V, while it is not yet inside the intersection ($\neg e_{\mathrm{c,b0}}$), with no special behavior applied ($\neg e_{\mathrm{c,b4}}$), and a sufficiently large time and space gap to pass ahead ($\neg e_{\mathrm{c,b3}}$); or a special behavior, where the P-V is still not inside the intersection ($\neg e_{\mathrm{c,b4}}$), but special behavior is applied ($e_{\mathrm{c,b3}}$), allowing even for a small or negative time and space gap relative to the P-V($e_{\mathrm{c,b1}}$).

For the B-V the same two conditions exist as for the A-V model, either the B-V simply does not exist ($e_{\mathrm{c,b5}}$) or the gap behind the B-V is sufficiently large enough for the A-V to enter the common collision zone ($e_{\mathrm{c,b6}}$).

In order to get a green light for the Y-V, one of the following four conditions has to be meet:

- The Y-V does not exist ($\neg e_{\mathrm{c,b7}}$)
- Y-V is not inside the intersection ($\neg e_{\mathrm{c,b12}}$), special behavior is not applied ($\neg e_{\mathrm{c,b8}}$) and no regular yield to the Y-V ($\neg e_{\mathrm{c,b10}}$)
- Y-V is not inside the intersection ($\neg e_{\mathrm{c,b12}}$), special behavior is not applied ($\neg e_{\mathrm{c,b8}}$) and Y-V is waiting before the collision zone ($e_{\mathrm{c,b11}}$)
- Y-V is not inside the intersection ($\neg e_{\mathrm{c,b12}}$), special behavior is applied ($\neg e_{\mathrm{c,b8}}$) and no yield with waiting time is happening ($e_{\mathrm{c,b9}}$)

Table 5: Base events for C-V algorithm

BE	Condition
$e_{\mathrm{c,b0}}$	P-V does not exist
$e_{\mathrm{c,b1}}$	Offensive flag is set AND P-V vehicle is A-V
$e_{\mathrm{c,b2}}$	Yield to P-V regular
$e_{\mathrm{c,b3}}$	Yield to P-V offensive behavior
$e_{\mathrm{c,b4}}$	P-V inside intersection
$e_{\mathrm{c,b5}}$	B-V does not exist
$e_{\mathrm{c,b6}}$	Enough space behind B-V
$e_{\mathrm{c,b7}}$	Y-V exists
$e_{\mathrm{c,b8}}$	Offensive behavior against A-V
$e_{\mathrm{c,b9}}$	Yield to Y-V with wait time
$e_{\mathrm{c,b10}}$	Yield to Y-V regular
$e_{\mathrm{c,b11}}$	Y-V is waiting
$e_{\mathrm{c,b12}}$	Y-V inside the intersection
$e_{\mathrm{c,b13}}$	Emergency stop possible

Besides the relation specific events, the two general events for a zone change ($e_{\mathrm{c,2}}$) and the possibility of an emergency stop ($e_{\mathrm{c,3}}$) exist.

By utilizing this slightly modified version of the decision making algorithm for the C-V's the untypical behavior, representing the human driven vehicles, can easily be integrated and the response behavior of the algorithm can be investigated.

C. Evaluation Metrics

The overall used metrics can be grouped into safety, utility and comfort metrics. While safety metrics take into consideration the avoidance of collisions or occurrence of dangerous situations due to short distances between vehicles, utility metrics reflect the difference to the ideal reaching of the target position. A qualitative measure of the driving comfort is measured by the comfort metrics. These three metrics sometimes work in opposite directions, which is why a pure optimization according to one of the metrics does not lead to any reasonable configurations, e.g. an excessive waiting

Table 6: Events for CV-algorithm

Definition	Description
$e_{\mathrm{c},1,\mathrm{p}} = \neg e_{\mathrm{c,b0}} \vee (\neg e_{\mathrm{c,b4}} \wedge \neg e_{\mathrm{c,b3}} \wedge e_{\mathrm{c,b2}}) \vee (\neg e_{\mathrm{c,b4}} \wedge e_{\mathrm{c,b3}} \wedge e_{\mathrm{c,b1}})$	P-V green light
$e_{\mathrm{c},1,\mathrm{b}} = e_{\mathrm{c,b5}} \vee e_{\mathrm{c,b6}}$	B-V green light
$e_{\mathrm{c},1,\mathrm{y}} = \neg e_{\mathrm{c,b7}} \vee (\neg e_{\mathrm{c,b12}} \wedge \neg e_{\mathrm{c,b8}} \wedge \neg e_{\mathrm{c,b10}}) \vee (\neg e_{\mathrm{c,b12}} \wedge \neg e_{\mathrm{c,b8}} \wedge e_{\mathrm{c,b11}}) \vee (\neg e_{\mathrm{c,b12}} \wedge e_{\mathrm{c,b8}} \wedge \neg e_{\mathrm{c,b9}})$	Y-V green light
$e_{\mathrm{c},2}$	Zone changed
$e_{\mathrm{c},3} = e_{\mathrm{c,b13}}$	Emergency stop possible

in front of the entry of the roundabout would optimize the safety score but does not consider the reaching of the target position in a reasonable time and manner. Metrics used in this work are mainly based on Kreutz et al. [26], [27].

a: Safety

To quantify the safety of the decision model, the Post-Encroachment Time (PET) is employed. PET is a well-established metric commonly used for assessing safety in side-swipe crash scenarios at intersections and roundabouts. It measures the time interval between the leaving of a common collision zone by one vehicle and the entry of the same collision zone by the next vehicle. A PET value of zero represents simultaneous entry and exit of collision zones between two vehicles, indicating potentially critical situations, although not necessarily collisions. Higher PET values correspond to larger time gaps between vehicles, resulting in safer interactions. When multiple vehicles are considered, the interaction with the smallest PET is used to account for the most critical situation, allowing for a model-independent comparison across scenarios. The choice of PET for this work is motivated by its widespread use in roundabout and intersection safety analysis, as well as its computational simplicity and interpretability.

b: Utility

The utility is defined as $\mathrm{U} = \frac{\langle v \rangle}{v^*}$, where $\langle v \rangle$ represents the actual average speed of the vehicle, and v^* denotes the desired speed profile set by the desired speed values of Table 3. In cases where the vehicles cannot reach the desired speed or need a longer period to accelerate to the desired speed the utility score can be below 1. For scenarios where the vehicles can pass freely this values can also be above 1 due to the delayed decay of the velocity due to the limited deceleration of the vehicle and the only asymptotic approach of the set target velocity based on the IDM. Despite the deceleration imposed by roundabout geometry, the metric, which quantifies a vehicle's deviation from its ideal energy-optimal condition, serves as a meaningful, dimensionless measure of efficiency, as it consistently employs the same reference baseline for comparison, thereby allowing for the evaluation of different scenarios.

Additionally the time to pass the scenario is used to quantify the utility of the decision model. The time to pass measures the time span from $40\,\mathrm{m}$ before to $10\,\mathrm{m}$ after the scenario. Even though this result value depends heavily on the selected desired speeds and simulated scenarios, it is suitable for comparing different scenarios with each other.

c: Comfort

In order to quantify the comfort for passengers, jerk is a suitable metric [29] or as described in Kreutz et al. the variance of the lateral acceleration can be used [26]. Therefore the comfort score is defined as $\mathrm{VAR}_a = \langle (a - \langle a \rangle)^2 \rangle$ where a represents the longitudinal acceleration and $\langle \cdot \rangle$ denotes time-averaged mean, resulting in a numeric representation of the comfort. The lower the comfort score, the lower the variance in acceleration and thereby the lower the jerk, resulting in a more comfortable driving experience.

It should be noted that no reference implementation or comparative benchmarking was performed in this study. To the authors' knowledge, no existing decision-making framework currently addresses the specific boundary conditions defined here — particularly the combination of mixed-traffic interaction, special behavior and limited perception. Consequently, the proposed approach is evaluated in isolation, emphasizing interpretability, robustness, and methodological consistency rather than direct quantitative comparison.

V. Results

In order to analyze the influence of individual parameters, systemic variations of these were simulated and evaluated. Based on the roundabout geometry different influencing factors can be observed and evaluated based on the results displayed in Figure 7. By considering only a single A-V vehicle with 7 C-Vs the three main takeaways are:

1) The decreasing outer diameter for the four arm roundabouts between r_{000}, r_{001} and r_{002} from $50\,\mathrm{m}$ to $30\,\mathrm{m}$ does also significantly reduce the time to pass, while a comparable distribution is maintained. The same applies to the three-arm roundabouts with matching shapes r_{006} to r_{008}, further supporting the expected behavior
2) For the variation of the junction size r_{003} - r_{005}: A smaller junction does reduce the time to pass but the effects are marginal compared to the influence of the outer diameter. Despite being described by only one parameter, the junction size in the simulation has two relevant variables: The beginning of the junction from the entry road and the beginning from the circular road inside the roundabout. Due to the usage of collision zones and LSPs for the decision model the starting position on the circular road does not play a vital role for the time to pass. However the changing starting

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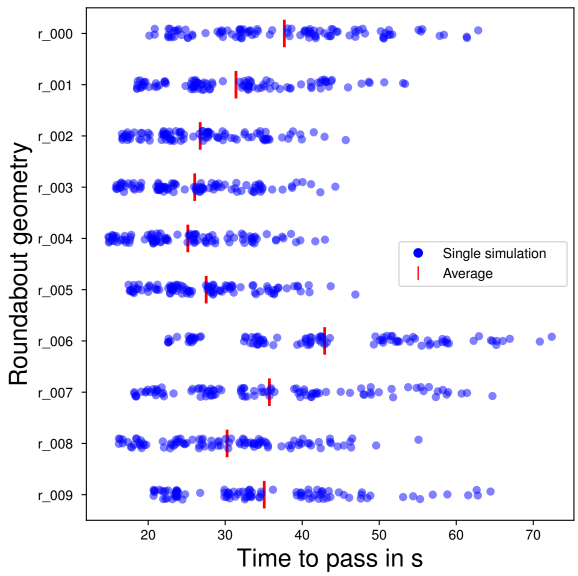

Figure 7: Scatter Plot of the A-V time to pass for the different roundabout geometry shapes of a total of 100 runs and the respective average per geometry, while interacting with a total of 7 C-Vs. The jitter in each row is only for visualization purposes.

position from the entry road does change when the vehicle enters zone 3 and get an updated desired speed for this zone, directly reflecting in the time to pass value for the overall maneuver.

3) In a direct comparison between r_{007} and r_{009} the influence of the shape of a three arm roundabout can be examined. Due to the symmetric shape of r_{009} the distribution of the time to pass almost ideally matches the three possible driving patterns available here, representing the first exit, second exit and return to entry arm for each of the three entry arms plus some special cases with higher time to pass. In contrast the distribution of r_{007} clearly shows a fourth peak, around $40\,\mathrm{s}$. This observation is further supported by the time to pass splitted by driving patterns, shown in Fig. 8. Even though the plot shows the result for the default four arm map r_{000} it highlights the formation of the four possible main peaks in the occurrence of time to pass values for a random initialization. The three peaks with the smaller time to pass values are dominant in contrast to the fourth peak.

While the aforementioned results only cover scenarios where a fixed number of vehicles and just a single A-V are interacting, Table 7 displays the average time to pass for different combinations of total vehicles (A-Vs + C-Vs) and just A-Vs. Depending on how the table is read, two points can be concluded:

- In a row, for a fixed number of A-Vs, an increase in the total number of vehicles does always increase the average passing time for the considered vehicle by a consistent increment while also increasing the standard deviation.
- For a fixed number of total vehicles an increase of the proportion of A-V, by allowing for more than just a single A-V, does influence the corresponding passing time, however no linear relationship can be observed. While some increments reduce the passing time (e.g. transition from 2 to 4 A-V at a total of 8 vehicles), while also lowering the respective standard deviation, further increases will reverse this tendency. The reason for the relationship is the special behavior interaction between C-Vs and only A-Vs and the overall more defensive decision model for the A-Vs. In each case the magnitude of the variations is smaller compared to the changes in the number of total vehicles.

In order to gain a comprehensive picture of the behaviour, the interactions were evaluated according to the remaining metrics presented in section IV-C in addition to the time to pass.

Therefore five different configurations with an increasing number of A-Vs at a total of 8 vehicles have been investigated. The results are visualized as a histogram in Figure 9. An increasing ratio of A-Vs does result in a concentration of lower comfort scores, while only marginally affecting the utility score. In contrast the concentration of the low safety score for lower numbers of A-Vs is shifted to even lower scores for a medium number of A-Vs. This is caused by the higher interaction rate of special behavior C-Vs against A-Vs. For the case of only A-Vs the safety score is improved again, resulting in the best configuration regarding the safety aspects.

Table 7: Time to pass the roundabout in seconds for a fixed A-V, interacting with a different number of vehicles and different ratios of A-Vs for 100 fixed, but random configurations. In brackets the corresponding standard deviation is provided. The missing entries represent combinations that cannot be realized.

A-V \ Total	2	4	6	8
1	31.72 (7.00)	32.68 (7.95)	36.09 (8.25)	37.68 (10.70)
2	31.64 (7.14)	32.71 (7.96)	36.21 (8.40)	37.74 (10.54)
4	-	32.98 (8.08)	35.97 (8.23)	37.12 (9.90)
6	-	-	35.61 (7.84)	37.49 (10.35)
8	-	-	-	37.13 (10.05)

VI. Conclusion

This work presented an event-driven decision-making framework for autonomous vehicles operating in mixed-traffic roundabout scenarios. The study demonstrated that vehicle decision processes can be effectively modeled as discrete events, enabling a transparent, interpretable, and parameter-

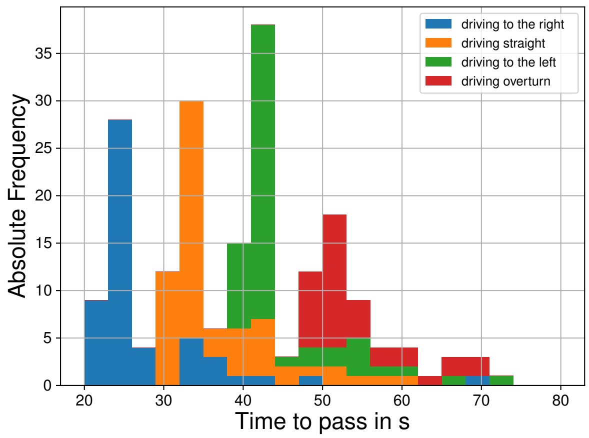

Figure 8: Time to pass for different driving patterns of the A-V in 200 scenarios with 7 vehicles at a symmetric four arm roundabout. Depending on the driving pattern a shift toward longer passing times is observed, matching the expected outcome. The driving pattern only depends on the relative, not absolute, exit direction: Whether the vehicle for instance exits to its right side by using the first exit or returns to the entry point again by overturning.

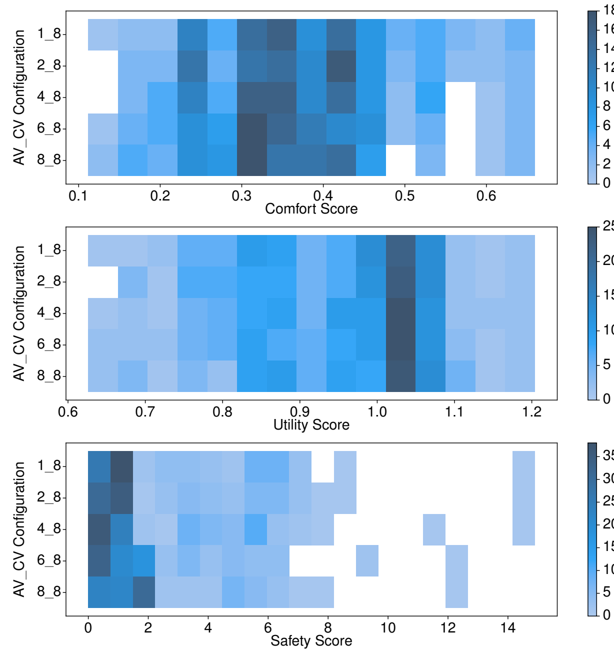

Figure 9: Comparison of different rations of autonomous vehicles in a fixed scenario with a total of 8 vehicles. The evaluation is based on the safety, utility and comfort score introduced in IV-C. Darker bins representing a higher number of samples within the respective boundaries.

izable representation of autonomous behavior in complex traffic environments.

Simulation results demonstrated that the proposed approach enables safe, efficient, and comfortable navigation within roundabouts under mixed-traffic conditions. Across all tested configurations, the model maintained collision-free performance and generated smooth vehicle trajectories with low acceleration variance, indicating high passenger comfort. The analysis further showed that roundabout geometry, particularly the outer diameter, influences traversal time, while junction size and shape have only minor effects. Moreover, increasing the proportion of autonomous vehicles led to improvements in safety and comfort metrics, confirming the robustness and adaptability of the proposed decision-making framework across varying traffic densities and compositions.

While the current study captures key interaction dynamics, the surrounding traffic agents are based on simulated interaction models, which may not perfectly reproduce real human driving behavior. Future work will therefore focus on extending the proposed framework to broader traffic contexts, including pedestrians, cyclists, and more diverse interaction patterns, as well as integrating real-world traffic data to further validate and refine the model's realism and applicability. Additionally, future work could explore the incorporation of additional duration-based metrics, such as the Time Exposed Time-to-collision (TET) and Time Integral of Time-to-collision (TIT), to provide a more comprehensive safety assessment.

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