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Joining SUMO and Unreal Engine to Create a Bespoke 360 Degree Narrow Passage Driving Simulator

Peter Youssef[1], Katherine Plant[2], and Ben Waterson[3]

[1] University of Southampton, UK

*Correspondence: Peter Youssef, psy1g16@soton.ac.uk

Abstract. The use of simulators is widespread in driver behavioural research. The ability of driving simulators to achieve the high levels of behavioural fidelity desired by behavioural researchers is argued to be resultant of the physical fidelity of the simulator. Whilst attempts to maximise the physical fidelity of simulators have often been focused on the hardware capabilities of the simulator, the software of the simulator has been argued to be as important. This is because the software of a simulator controls the intelligence and the heterogeneity of the behaviours of the simulated vehicles, as well as the quality of the graphics of the simulation.

Despite the importance of intelligent simulated agents, previous driving simulator studies have tended to simplify the behaviours of simulated vehicles and the scenarios that are presented to participants. This is particularly true of simulator studies investigating the decision-making of drivers at narrow passages, a relatively unregulated but hazardous situation in which two opposing vehicles must negotiate how to safely pass through a road narrowing, in which the interactive nature of the interaction has often been neglected. Following a review of the requirements for a representative narrow passage driving simulator, it is argued that co-simulation, an approach which combines multiple simulator types to create a global simulation, provides the best approach to creating intelligent simulated agents within an immersive environment for narrow passage behavioural research. As such, the development of a simulator for narrow passage behavioural research that combines SUMO and Unreal Engine is described. In particular, the development of a novel narrow passage behavioural model within SUMO that utilises previous behavioural findings is highlighted. To this end, it is argued that this approach facilitates higher levels of behavioural fidelity for narrow passage interaction studies and provides a framework for the investigation of other driver behaviours.

Keywords: SUMO, Unreal Engine, Narrow Passage, Co-Simulation

1. Introduction

The use of driving simulators as a methodology in behavioural research has experienced significant growth in recent decades, since evolving from more rudimentary iterations [1]. This surge in the adoption of simulator studies to investigate driver behaviours may be attributed to the high levels of experimental control allowed by the methodology. Such experimental control ensures a high level of repeatability, surpassing that typical of naturalistic studies, all whilst minimising the level of risk experienced by participants in comparison to on-road studies [2]–[5]. When it is also considered that simulator studies allow researchers to collect vast amounts of quantitative data (e.g., the lateral and longitudinal positioning of vehicles) [2], [3], and that a number of simulator studies have achieved high levels of relative and even absolute validity [6]–[9], the widespread use of driving simulators for behavioural research is, perhaps, intuitive.

Despite the well-documented benefits of utilising simulator studies for behavioural research, concerns persist regarding the representativeness of these studies. This concern is associated with the ability of simulators to replicate the circumstances and motivations experienced by drivers in real-world conditions, as a failure to do so leads to lower levels of behavioural fidelity [2], [3]. For example, whilst simulator studies provide a safe environment for participants to encounter hazardous scenarios, they may inadvertently reduce the consequences discerned by participants that would otherwise be perceived in a real-world setting [10]. This, in turn, could lead to participants performing actions different to what they would do in a natural setting, thereby limiting the study's utility [11].

The representation of consequences in driver decision-making holds particularly significance for research concerning cooperative road interactions. Cooperative road interactions can be defined as situations in which two or more road users interfere with the goals of the other(s) and must work together to resolve this interference [12]. These interactions are characterised by their safety-critical nature [13], [14] and findings that emphasise the importance of the motivation to cooperate held by the interacting vehicles [15]–[17]. These characterisations are especially true of narrow passage interactions, a type of a cooperative interaction that has garnered recent attention from academics. In these scenarios, two or more vehicles travelling in opposite directions converge at a road narrowing and must collaboratively decide who passes through the narrowing first (see Figure 1). Despite the characteristics of narrow passage interactions, questions have arisen as to the representativeness of simulator studies previously conducted [18]. For example, Rettenmaier and Bengler [19] noted a limitation in the external validity of their study as a significant proportion of scenarios presented in their study resulted in collisions, due to the lack of interactivity of the simulated agents, with similar issues also present in the study by Weinreuter et al. [20].

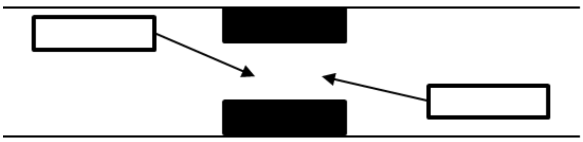

Figure 1. *Schematic of a narrow passage interaction.*

Given the importance of creating representative simulator studies to ensure high levels of behavioural fidelity and validity for behavioural research, this paper seeks to describe the creation of a bespoke narrow passage driving simulator. To this end, a review of the literature is first conducted to set criteria for the creation of a representative narrow passage driving simulator. This review also explores a simulator approach that utilises SUMO to meet the criteria set to create such a driving simulator. Subsequently, the development of a SUMO-based narrow passage driving simulator is described, before the paper concludes by highlighting the simulator's planned application and some preliminary results, and how the framework described in this paper may be employed when investigating other driving behaviours.

2. Literature Review

To establish a set of criteria for the development of a narrow passage driving simulator, it is essential to first understand the aspects that influence the behavioural fidelity of driving simulators, as well as the factors that are necessary to accurately represent narrow passage interactions. Once these criteria are established, a review of approaches to developing a simulator can be made.

2.1 Simulator Behavioural and Physical Fidelity

Academics argue that the capacity of a simulator to achieve high levels of behavioural fidelity is influenced by the physical fidelity of the simulation, with imperfect physical fidelity being associated with diminished behavioural fidelity [21]. This is because the physical fidelity of a simulator system, defined as *"the degree to which the simulator performance characteristics match the actual characteristics of vehicles and roads"* [22, p. 3], is vital to the production of the contextual information presented to participants [23], and therefore important to forming the basis of a participant's understanding of the simulated scenario and the behaviours they subsequently perform [24]. This contextual information includes the replication of the perception of distances, speed and time, as well as the control of the vehicle and its responses to control inputs, that drivers experience during on-road driving [25]–[27].

Efforts to achieve high levels of physical fidelity have often been focused on the hardware of simulators, with much of the literature focused on the associations between simulator fidelity and haptic feedback [3], as well as the field-of-view (FOV) of the simulator [28]. For example, it is established within the simulator literature that a FOV in the horizontal plane of 50º is an acceptable minimum for vehicle simulators [29]. However, for scenarios in which peripheral information processing is vital, a FOV of at least 180º [30], [31] is essential for maintaining good psychological validity [32]. Such scenarios include those in which braking manoeuvres are prevalent [33] and the navigation of intersections [32].

Whilst a simulator's hardware is crucial to achieving high levels of physical and behavioural fidelity, it is also essential to consider the software of the simulator. The software is argued to be as important to the presentation of realistic scenarios as it controls what is viewed [22], [23]. This extends beyond the visual quality of the simulation and includes the behaviours of the simulated agents. The realism of the behaviours of simulated agents in driving simulators is argued to be assessed against three key criteria [34], [35]:

1. Intelligence: Simulated agents must drive in a way that replicates human drivers.
2. Unpredictability: Simulated agents must represent the heterogeneity of drivers across the population, and random differences in driver decision-making within individuals.
3. Virtual Personalities: Driver types should be included in the simulated population.

Given that it is vital that simulated agents accurately represent the actions of drivers, a deeper understanding of how drivers behave in narrow passage interactions is imperative.

2.2 Narrow Passage Interactions

Perhaps most of interest to narrow passage researchers has been the communication practices of interaction partners at narrow passages. Multiple authors [36], [37] have found that drivers typically communicate via implicit means (i.e., through their vehicle's trajectory). This is despite arguments that explicit communications - those not altering the dynamics or trajectory of a vehicle), such as flashing headlights and hand gestures - are vital for successful narrow passage interactions [38]–[40].

The implicit communications used by drivers include manipulations in the longitudinal movements of the interacting vehicles. In the literature, it is widely agreed that acceleration and the maintenance of speed are perceived as signals that an interaction partner intends to pass through a narrowing first, whilst decelerating and stopping indicate a willingness to give way [18], [38], [40]. Indeed, these alterations in the longitudinal movements of interacting drivers has been found to complement the "first-come, first-served" rule theorised to govern narrow passage interactions [36]. The authors found that vehicles that arrived first at a road narrowing left the narrowing first, often choosing to accelerate or maintain their speed, with the inverse being true of the vehicle arriving second.

Despite these associations, research has indicated that deviations in the lateral positioning of vehicles are vital to understanding a vehicle's intent at a road narrowing [13], [41]. Safer and more efficient narrow passage interactions occur when lateral and longitudinal movements are used in conjunction [13], [19]. Rettenmaier et al. [13], [19] argue that this is because lateral movements allow for more salient communications, due to a greater change in the visual angle of vehicles [42]. Moreover, the importance of lateral movements is argued as these deviations are explicitly part of the manoeuvre that drivers execute [43]. In contrast, when no lateral movement occurs, drivers rely on perceiving the longitudinal movements of their interaction partner and assess changes in their Time-to-Area (TTA_{OV}) [43], [44], a task that is difficult for drivers [45].

In a series of studies, Miller et al. [14], [44] demonstrated that individual differences among drivers influence decision-making during narrow passage interactions. For example, drivers that perceive a higher cost of giving way at a narrow passage were less inclined to do so than those with a lower perceived cost of cooperation [14]. Similarly, individuals with a higher risk-taking propensity were more likely to pass through a road narrowing first at lower TTA_{OV} values than their risk-averse counterparts. This observation was supported and extended upon in a study conducted by Youssef et al. [18], where the likelihood of giving way depended not only on a driver's risk-taking propensity, but also on other dimensions of their driving style, including their level of caution and aggressiveness.

Youssef et al. [18], [46] also showed that the decision-making of drivers at narrow passages was dependent on factors such as the vehicle type being interacted with and the presence of vehicles following the direct interaction partners. Notably, the authors identified the presence of a "convoy" rule during narrow passage interactions, wherein drivers give way not only to their immediate interaction partner but also to the vehicles following them if they chose to give way initially [46]. Pertinently, the study highlighted that drivers perpetually engage in assessment and monitoring actions that address five questions pivotal to the safe navigation of narrow passages. This framework, building upon previous work [47], was argued by the authors as providing a theoretical foundation for mathematical models of narrow passage driver decision-making [46]:

1. Does either interaction partner have priority?
2. What is the intention of the interaction partner?
3. Where can either interaction partner give way?
4. Is the road narrowing wide enough to allow both vehicles to pass through simultaneously if they cooperate to facilitate such an outcome?
5. If vehicles beyond the interaction partners are present, what actions are available to them/ is the 'convoy' rule in effect?

Despite the recent attention given to narrow passage interactions, there is currently no in-depth vehicle trajectory dataset or adequate model known to the authors that effectively captures narrow passage driver decision-making. For instance, while the model proposed by Wenzel et al. [48] incorporates the "first-come, first-served" rule theorised for narrow passage interactions, it overlooks the lateral movements and explicit communications produced by drivers, with similar criticisms applying to other models proposed [20], [49]. This is problematic as achieving high levels of narrow passage behavioural fidelity requires a simulator to accurately represent the behaviours of human drivers. Given the complexity of narrow passage driver decision-making and the need for high simulator fidelity, the following criteria for a narrow passage driving simulator are proposed:

1. Does the driving simulator continually evaluate the considerations proposed in the theoretical framework by Youssef et al. [46]?
2. Does the driving simulator allow for individual differences between simulated agents and within their own decision-making?

3. Does the driving simulator incorporate the ways in which drivers communicate during narrow passage interactions?
4. Does the driving simulator provide a FOV necessary for adequate peripheral information processing?
5. Does the driving simulator provide high-quality graphics?

2.3 Co-Simulation: The Best Approach?

While the "If-Then" rules that are commonly employed to generate scenarios within conventional driving simulators do not facilitate the modelling of the complex decision-making observed during narrow passage interactions, co-simulation provides an alternative approach to driving simulation. Co-simulation approaches integrate different simulator types to create a global simulation [50]. The approach, therefore, seeks to maximise the benefits of each simulation component, while minimising their individual flaws [51]. In the context of driving simulators, co-simulators combine microscopic traffic simulators alongside a visual simulation package. The two simulations are executed in parallel, and utilise comparable road networks, whilst exchanging information perpetually [52]. Co-simulation, therefore, leverages the detailed behavioural modelling from microscopic traffic simulators alongside the graphical qualities of visual simulation packages to achieve high levels of visual and behavioural realism.

The advantages of co-simulation have been demonstrated in various instances [51]–[59]. Olaverri-Monreal et al. [55] coupled the microscopic traffic simulator SUMO [60] with the game development engine Unity, creating a virtual version of part of Vienna that showcased high levels of realism in a computationally efficient manner. Barthauer and Hafner [52] verified their SUMO-SILAB coupling within a small network, whilst Szalai et al. [58] showed that simulated agents in their SUMO-Unity coupling reacted to the behaviours performed by human drivers. The widespread use of SUMO as the microscopic traffic simulator in these couplings may be attributed to its open-source nature and its TraCI protocol facilitating the real-time retrieval of simulation data. The open-source aspect of SUMO can be considered vital, as it allows for the creation of a novel narrow passage model, as exemplified by Liao et al. [59] who integrated their game theory-based model for ramp merging into their co-simulation package. The creation and implementation of a narrow passage model in the driving simulation would, therefore, ensure higher levels of representativeness of human narrow passage behaviours, as set out by the criteria in section 2.2.

However, while Unity has been a popular visual output choice for co-simulation, due to its high-quality graphical outputs and its diverse delivery methods (e.g., VR headsets, TV screens), the game development software Unreal Engine is proposed as an alternative. Unreal Engine, like Unity, provides high quality graphical outputs but also allows for multi-cluster rendering [61]. This feature enables the development of a driving simulator with a 360º FOV, ensuring that the graphical criterion outlined regarding adequate peripheral information processing is also met. As such, the rest of this paper details the development of the SUMO-Unreal Engine narrow passage driving simulator.

3. Narrow Passage SUMO-Unreal Engine Co-Simulation

3.1 Co-simulation Architecture

The overall architecture of the SUMO-Unreal Engine co-simulator is illustrated in Figure 2. As can be seen, the proposed co-simulator transfers information across its three components: SUMO, Unreal Engine (UE4), and a Python Client/Server interface. The subsequent sections detail this process.

3.2 Python Interface

The core module of the co-simulation system is the Python interface that connects and synchronises SUMO and Unreal Engine (UE4). As previously noted, the dedicated TraCI library allows for real-time interactions with SUMO simulations [62], [63]. This functionality, therefore, makes it possible to extract the states of the simulated vehicles (e.g., speed, lateral position, indicator use) and traffic lights (e.g., its signal state) through a series of requests sent from the Python Interface to SUMO, see Table 1. Once the desired data from SUMO has been collated within the Python Interface, the interface immediately transfers this information into UE4 within the same time-step. This maximises the interactivity of the simulation, as it ensures that the data from SUMO is processed and visualised at the same time-step within UE4. The transfer of this data from the Python Interface into UE4 is conducted through a series of TCP and UDP sockets (each socket sends a specific data strand – e.g., vehicle-related data, traffic light data), in which the Python Interface is the server that specific UE4 clients connect to.

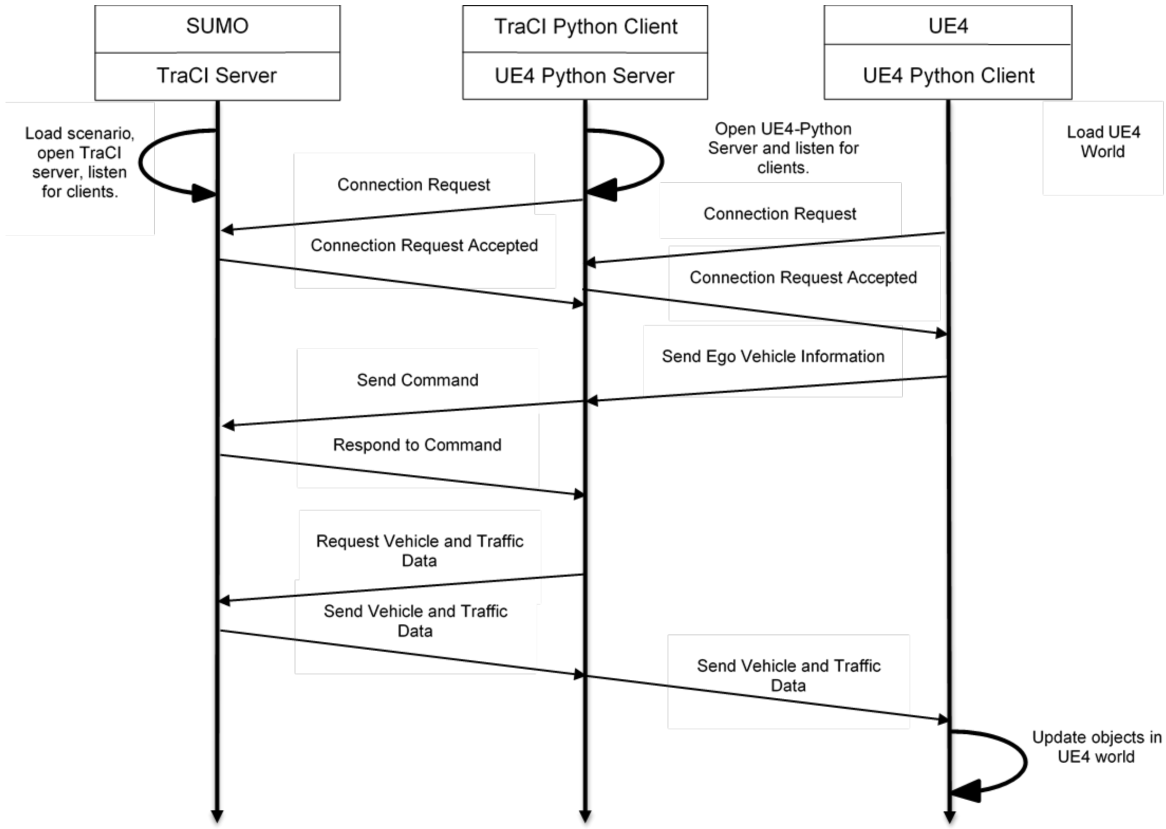

Figure 2. *SUMO-Python-Unreal Engine (UE4) architecture of the developed co-simulator.*

Other than allowing for the retrieval of information from the SUMO simulation, TraCI also allows for commands to be sent into SUMO, which enables the addition and manipulation of vehicles within the simulation. This is particularly valuable, as the function allows for the integration of the actions performed by participants within the visualised UE4 world (i.e., the "Ego Vehicle") into the SUMO network, thus allowing the simulated agents in SUMO to see and interact with the Ego Vehicle according to their driver behaviour models. As such, a UE4-Python socket is employed to send data related to the Ego Vehicle, see Table 1, into the Python Interface at every time-step, with this information subsequently forwarded into SUMO at the same rate.

The Python Interface is also responsible for outputting data at each time-step into a readable format for post-processing by researchers and ensuring that the UE4 and SUMO remain synchronised throughout run-time. The interface synchronises the simulations by specifying and matching the time-steps of the two packages (in the current simulator this occurs at 0.02s intervals) and controlling the iteration rate at which time-steps are iterated through. This is accomplished because UE4 and SUMO can iterate at rates faster than specified by the interface, but they only proceed to the next time-step when prompted by the interface. This command is issued after all the requisite information has been transferred across the interface and the resulting processes have been completed in UE4/SUMO. As part of simulator testing, the synchronization of SUMO and UE4 was confirmed by the alignment of the locations of the vehicles in both programs, as well as the signal states of the vehicles, see Figure 3.

Table 1. *Data sent across the Python Interface at each time-step.*

Ego Vehicle	Simulated SUMO Vehicles	Traffic Lights
Vehicle ID x-y Coordinates Speed Acceleration Angle Indicator use Headlight use Brake light use	Vehicle ID Vehicle Type Vehicle Dimensions (Length, Width) x-y Coordinates Longitudinal Lane Position Lateral Lane Position Speed Acceleration Angle Indicator use Headlight use Brake light use	Traffic Light ID Junction Type Traffic Light State Pedestrian Light State x-y Coordinates Angle

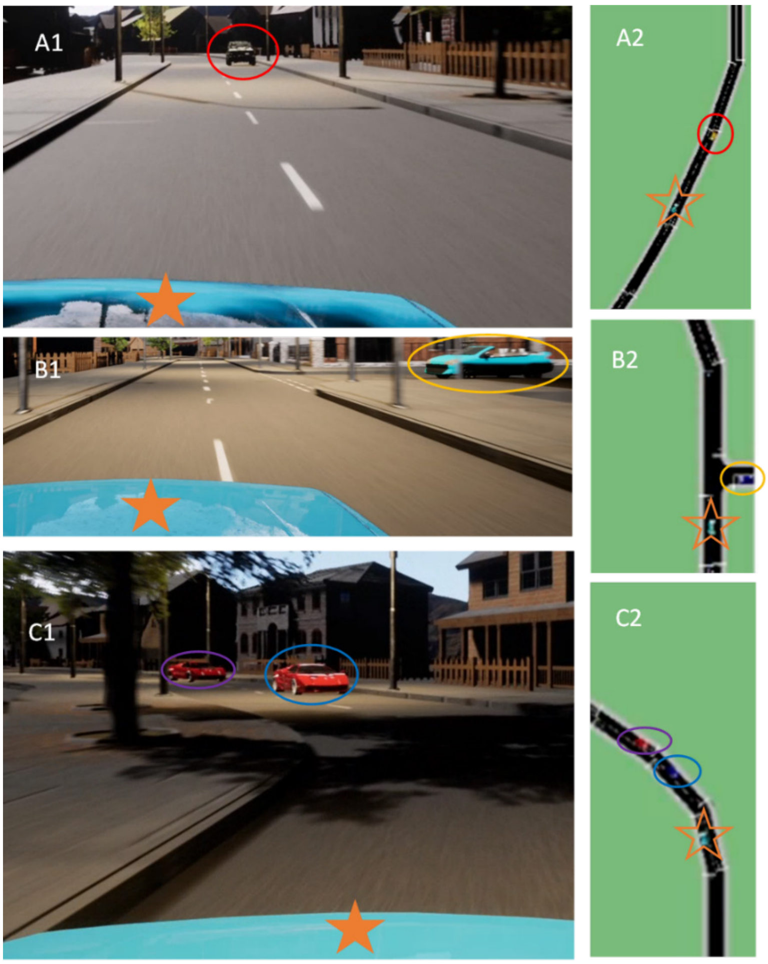

Figure 3. *View of three situations in Unreal Engine (left) and SUMO (right). The Ego Vehicle in both simulations is indicated with the star.*

3.3 Unreal Engine Visualisation and Control

The visualisation and control interface that participants interact with is developed within UE4 and comprises of three main components: the replication of simulated vehicles and traffic lights within UE4, the Ego Vehicle driven by participants, and the replication and visualisation of the SUMO road network.

3.3.1 Simulated Vehicles and Traffic Lights

The vehicle data received by UE4 is represented by a single array consisting of arrays for each vehicle in the SUMO network for the given time-step. To ensure the proper assignment of vehicle data from SUMO to the corresponding vehicle object in UE4, an ID matching system is employed, in which it is checked whether an ID from SUMO has been previously allotted in UE4. If the data stream received from SUMO contains an ID that has not been allocated to an object within UE4, the unique SUMO ID is assigned to a previously unassigned UE4 vehicle object. Conversely, if a SUMO vehicle ID is already present in UE4, the corresponding vehicle object in UE4 is allocated the vehicle data array from SUMO. This data is then assigned to the congruent variable within the vehicle object, from which the state of the vehicle object is dynamically altered according to the developed code. This developed code controls all aspects of the vehicle object, including its signal state of the vehicle object, speed, and lateral positioning.

A similar ID matching process precedes the assignment of SUMO information to object variables for traffic light objects. In this case, the traffic light state from SUMO dictates the state of the traffic light in UE4, which is subsequently implemented and visualised in UE.

3.3.2 Ego Vehicle

The Ego Vehicle leverages UE4's PhysX physics system to simulate physical interactions between the vehicle and the virtual world, which includes damping, steering and friction effects to the vehicle. In addition to the physics system, several functions were implemented to enhance the realism of the vehicle model, providing a more accurate representation of the stimuli and actions available to drivers. The extended functionality encompassed the use of the vehicle's horn, indicators, and headlights, complete with the appropriate audial and/or visual outputs. Furthermore, a more representative gear system was integrated, accompanied by the implementation of RPM-related vehicle engine sounds and an externally linked dashboard. To facilitate and optimise the realism of user input, Unreal Engine's RawInput plugin was employed to compatibility with a steering wheel and pedal system. This ensures that the controls of the simulator closely resembles those used by drivers in their own vehicles.

3.3.3 Simulator Environment and nDisplay

To ensure compatibility between the SUMO and UE4 simulations, it is mandatory to replicate the road network in SUMO in the UE4 environment. This was accomplished using the "SUMO2Unreal" XML plugin [64], which outlines the SUMO road network in UE4, by converting the x-y coordinates of the SUMO road network to the UE4 coordinate system. This then facilitated the creation of a procedurally generated road network within UE4 by replacing the traces implemented by the plugin, with road and pavement surfaces of the required dimensions and high levels of realism. To enhance the fidelity of the UE4 environment, additional elements such as buildings, road signs and street furniture were incorporated. These assets were sourced from the Unreal Engine Marketplace or developed using Blender. Furthermore, a pedestrian system was implemented in the UE4 environment, which allowed for dynamic control of pedestrian objects during simulation runtime.

To fulfil the requirement of achieving a FOV that allows for adequate peripheral information processing, the simulator employs UE4's nDisplay multi-cluster system to create a 360º immersive environment, see Figure 4. This implementation involved the use of cluster events and actor replication components that ensure visual consistency between the different nodes of the system. Since objects cannot be spawned across different nodes when using nDisplay, pre-loaded vehicle, pedestrian and traffic light “banks” were created. These hidden banks allowed for the “spawning” of these objects via instantaneous teleportation when needed as specified by SUMO.

Figure 4. *Example of view provided in the simulator.*

4. Development of SUMO Narrow Passage Vehicle Behaviours

Whilst the preceding sections have focused on the transfer of information across the co-simulator modules and its visualisation, as per the simulator fidelity criteria set, it is crucial that the behaviours exhibited by the simulated agents are representative of human driver behaviours. Therefore, the subsequent sections detail and justify the behavioural models implemented/created to represent narrow passage behaviours.

4.1 Car-Following Model

The car-following model implemented in the co-simulator is the Extended Intelligent Driver Model (EIDM) [65]. The EIDM seeks to improve on the Intelligent Driver Model (IDM) car-following model [66] by more accurately representing human perception and reaction times, jerk limits and the drive off behaviours of vehicles. Evidence for these improvements were shown in a comparison between real-world data and the produced accelerations, headways and speeds of vehicles using different car-following models [65]. Considering the stop-start nature inherent in narrow passage environments, the enhancements made to the EIDM render it a suitable choice to simulate human driver car-following behaviours within the driving simulator.

4.2 Lane Changing Model

The second key model utilised is SUMO’s SL2015 lane changing model [67] and its associated sub-lane model [68]. Whilst driving in narrow passage environments does not require vehicles to change lanes in the manner typically modelled by lane-changing models, the sub-lane model divides lanes into smaller “sub-lanes.” In the context of narrow passages, this quality is valuable as it allows vehicles to overtake parked vehicles that form a road narrowing, contingent upon safety checks. The sub-lane model, therefore, ensures a more realistic depiction of the lateral positions adopted by drivers during narrow passage interactions within the co-simulator.

4.3 Narrow Passage Model

The behaviours of drivers at narrow passages are modelled as having three iterative stages: *Situation Recognition*, *Decision-Making* and *Navigation*. This structure mirrors the perpetual and cyclical nature of perception-based decision-making, as suggested by theories of cognition [24], and is affected by the individual characteristics of the simulated agents, as indicated in the literature [14], [18], [44]. The rest of this section provides insights into each stage of the model.

4.3.1 Driving Style Assignment

The simulation incorporates driver heterogeneity by randomly assigning each agent a driving style class (Anxious, Careful, Aggressive, High-Velocity/Reactive) upon loading into the simulation. These classes represent the driving styles found to affect driving behaviours at narrow passages [18] and dictates the behavioural parameters of the agents. Within each class, further variations of driver profiles are implemented, in which the vehicle type of the agent is accounted for in the assignment of driving style variables (e.g., HGVs have different acceleration capabilities to non-HGVs).

The behavioural SUMO parameters dictated by the driving style of the agents include the maximum speed, acceleration, and deceleration values, as well as the minimum acceptable lateral and longitudinal gaps. For example, agents with aggressive driving styles exhibit higher degrees of acceleration, accept smaller gaps and travel at greater speeds in narrow passage environments than those with more careful profiles, aligning with broader findings in the driving style literature [69], [70]. Additionally, the driving style influences planning horizon of agents, determining the distance they look ahead to perceive information. This mirrors previously proposed perception mechanisms [71], where a longer planning horizon indicates a more proactive approach to information gathering [72], and therefore impacts the decisions and behaviours exhibited by simulated agents. The maximum planning horizon value is set at 7 seconds down the road, and is based on empirical evidence that indicates that this is the point that drivers begin to react to road obstacles [19]. Conversely, the minimum planning horizon is set at 50m, reflecting the distance at which drivers engage with one another at a road narrowing [73], [74].

4.3.2 Situation Recognition

Mirroring the findings made in narrow passage behavioural research [46], the simulated agents perpetually scan the road environment for information relevant to their narrow passage decision-making. This includes the location and dimensions of parked vehicles, the location and size of gaps that could be used to give way in and the location, speed and signal states of vehicles approaching the road narrowing.

Whilst SUMO typically does not allow for the perception of multiple vehicles travelling in the opposite direction, the narrow passage model utilises the programme's ability to set opposing lane pairs in the network. By coupling opposing lanes, the simulated agents can retrieve the same information about their opposing lane that is available to them in their own lane. This includes the dimensions of the opposing lane, as well as the IDs of the vehicles currently on the opposing lane, which subsequently allows for the retrieval of a range of data including the location and speed data of these vehicles. This information enables the model to decipher where vehicles are parked (i.e., are they are stationary and specified as being a parked vehicle), locate gaps to give way in, and determine the location, signal state and speed of potential interaction vehicle partners. The monitoring of these elements is limited by the planning horizon of the vehicle, in that vehicles only within the perceptual limits of the ego vehicle are perceived. For the purpose of simplicity, the planning horizon of vehicles does not vary according to any visibility constraints that may exist (e.g., road geometry). While this may result in vehicles performing narrow passage actions earlier than human drivers would, the early perception of narrow passage information is considered desirable as it limits the potential for collisions.

4.3.3 Decision-Making

Once simulated agents perceive an approaching road narrowing, thus signalling the possibility of a narrow passage interaction, the decision-making portion of the model is activated. Simulated agents evaluate the information perceived every 0.5 seconds according to the narrow passage decision-making framework proposed by Youssef et al. [46].

Initially the model seeks to define right-of-way at the narrowing by evaluating whether the “first-come, first-served” [36], [46], [47] rule is applicable. This is determined by calculating the Time-to-Area (TTA), see Equation 1, for the two lead interaction partners. The evaluation involves assessing if either interaction partner can safely navigate through and exit the narrow passage before the opposing vehicle reaches the road narrowing, while considering the longitudinal gap requirements of the simulated agent. If a vehicle is assessed as being significantly closer to the narrowing or if there is no interaction partner present, the “first-come, first-served” rule is enforced, and the agent will seek to pass through the narrowing first.

$$\text{If } u \neq 0: TTA_{vehicle} = s/u$$

$$\text{Else: } TTA_{vehicle} = (2*s)/(u+v) \quad (1)$$

where:

s = distance to the narrow passage

u = current speed

v = desired narrow passage speed of vehicle

If the “first-come, first-served” rule is not in effect, the model proceeds to evaluate the three possible outcomes of narrow passage interactions, as per Youssef et al. [46]: the ego vehicle gives way and the opposing vehicle passes through first (and vice versa) or the vehicles pass through the narrowing simultaneously. This assessment considers three aspects [46]: determining right-of-way, evaluating the feasibility of narrow passage outcomes, and understanding the communicated intention of the interaction partners.

Right-of-way is assessed by the location of the narrowing obstacles and whether the “convoy” rule is in effect [46]. The representation of the “convoy” rule involves the simulated agents determining if they are in a car-following mode and whether their leader has passed through the narrowing. If confirmed, the agent follows its leader as the “convoy” rule is in effect, providing the opposing vehicle continues to give way. Conversely, if a vehicle has already given way and assesses that it can not safely pass through the narrowing before the following interaction partner arrives, the vehicle will continue to give way.

The model determines the feasibility of giving way by comparing the length of possible give way gaps to the length of the relevant interaction partner, while accounting for the assessing vehicle’s minimum acceptable longitudinal gap. Additionally, simulated agents assess the location of the give way gaps to determine whether it is plausible for the relevant interaction partner to give way in the gap based on the relative locations of the interaction partners to the gap. If the simulated agent assesses that there are no suitable gaps available to an interaction partner, the model acknowledges that the situational outcome in which that vehicle gives way is not possible. Similarly, the evaluation of whether both vehicles can pass through the narrowing simultaneously requires the model to evaluate the width of the narrow passage, in conjunction to the width of the interaction partners and the minimum lateral gap that the agent is willing tolerate.

Finally, the intention communicated by the involved interaction partners is considered by the model according to the meanings of the different explicit and implicit communications as proposed in the literature [13], [18], [36].

The above assessments are integrated within a rule-based decision-making structure to decide which action the simulated agent should take, and how it should communicate that intent. For example, if the ego vehicle assesses it has right-of-way according to the location of road narrowing obstacle, but it is also acknowledged that their interaction partner does not have a suitable gap to give way in and that the ego vehicle does, the ego vehicle will choose to give way, as per Youssef et al. [46]. Similarly, if a vehicle assesses that they do not have priority at a narrow passage, but their interaction partner is signalling that they intend to give way, they will choose to pass through the narrowing.

While primarily deterministic, due to the lack of quantitative data needed for other model types and the need to prevent collisions, the model fulfils the unpredictability and virtual personality criteria required of high-fidelity simulators. As previously noted, differing driver types are randomly assigned to the simulated agents, which affects the parameters that are used to assess the information perceived (e.g., minimum lateral gap). Moreover, stochasticity is introduced when agents select their actions from the options they have deemed to be viable, using probabilities derived from an on-road data set [46]. For example, if an agent determines the narrow passage is wide enough for the interaction partners to simultaneously pass through, the agent stochastically determines if this is its desired outcome using the observed percentage occurrence of how often vehicles simultaneously pass through a narrowing. Additionally, the actions executed by agents to represent their decision are stochastically chosen using the same methodology (e.g., should the vehicle accelerate or maintain their speed when passing through first).

To maintain consistent behaviour during interactions, a memory array is incorporated in the model. The array stores information about the previous states of the interaction, including the actions taken by both interaction partners and the assessment made by the agent. This ensures that previous actions are considered in subsequent time-steps. Furthermore, if no discernible changes in the circumstances of the interaction occur from the past time-steps, the model reproduces the previous decision.

4.3.4 Navigation

Using the outputs of the decision-making portion of the model, the model proceeds to enact the chosen action by altering the speed, lateral position, and signal state of the vehicle via TraCI commands. As per the cyclical nature of this model, and indeed of cognition, the actions of the interaction partners serve as the inputs for the next perception-action iteration of the model.

In addition to enacting the outputs of the decision-making portion of the model within SUMO, the outputs of the decision-making portion of the model related to the explicit and implicit communications of the vehicle (see Table 1) are sent to Unreal Engine. Using these outputs, the simulated agents within Unreal Engine are dynamically altered for participants to interact with.

5. Example Results

After extensive testing of the simulator to ensure its fidelity in replicating narrow passage behaviours, which spanned several months and involved multiple pilot testing, participants were invited to take part in a simulator study. This study consisted of two drives: a 15-minute session in an open world “neighbourhood”, where participants had full autonomy over their route and encountered various narrow passages; and a second drive in which participants completed 20 predefined narrow passage scenarios. These drives followed a 30-minute study briefing, which included a 10-minute test-drive in the simulator alongside pre-study questionnaires. Some example results from 5 participants are presented below.

5.1 Human-Agent Interaction

Figure 5 presents the longitudinal (solid) and lateral (dashed) movements of a participant (red) and a simulated agent (blue) as they approach a road narrowing (black). As can be seen, the Ego Vehicle passes through the narrowing first, speeding up and moving centrally as they do so, in line with expectations from the literature. More interestingly, Figure 5 demonstrates interactivity, and therefore intelligence, from the simulated agent. As the Ego Vehicle signals its intention to proceed first, the simulated agent reciprocates by decreasing its speed (evidenced by the reduction in longitudinal position rate of change). This is accompanied with the simulated agent pulling in, aligning with the literature, before the simulated agent proceeds to move centrally once it has assessed that the Ego Vehicle has navigated the narrowing. Figure 5, therefore, exemplifies a key criterion for a representative narrow passage simulator: simulated agents react in real-time to participant behaviours, in a way that replicates the human drivers.

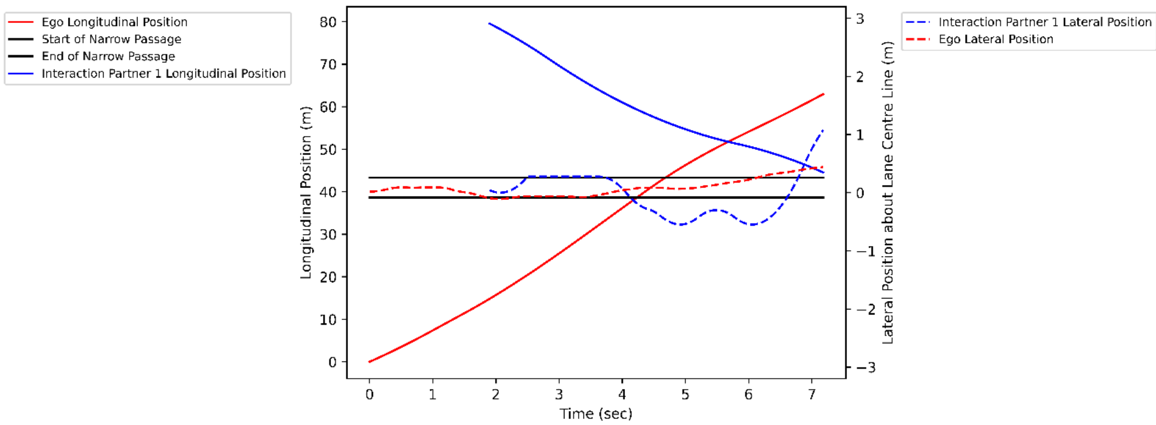

Figure 5. *A graph showing how the longitudinal and lateral positions of a participant and their simulated interaction partner changes as they approach a road narrowing.*

5.2 Multiple Vehicle Interaction

In Figure 6, an interaction between a participant and multiple interaction partners is displayed. The lead simulated interaction partner (blue) reacts to the participant pulling in and stopping, by speeding up and moving centrally, after initially beginning to slow down. The second simulated agent (green) then follows its leader as the participant continues to give way, thereby enacting the theorised narrow passage “convoy” rule. This, again, highlights the ability of the simulator to respond dynamically to human participants, in a way that is representative of human driving behaviours. However, Figure 6 also reveals variations in the behaviours of the two simulated vehicles, as evidenced by the differences in their longitudinal and lateral traces. The differences are, therefore, indicative of differing decision-making, and are perhaps due to the simulated vehicles having different behavioural stimuli and differences in the driver profiles throughout the simulated population.

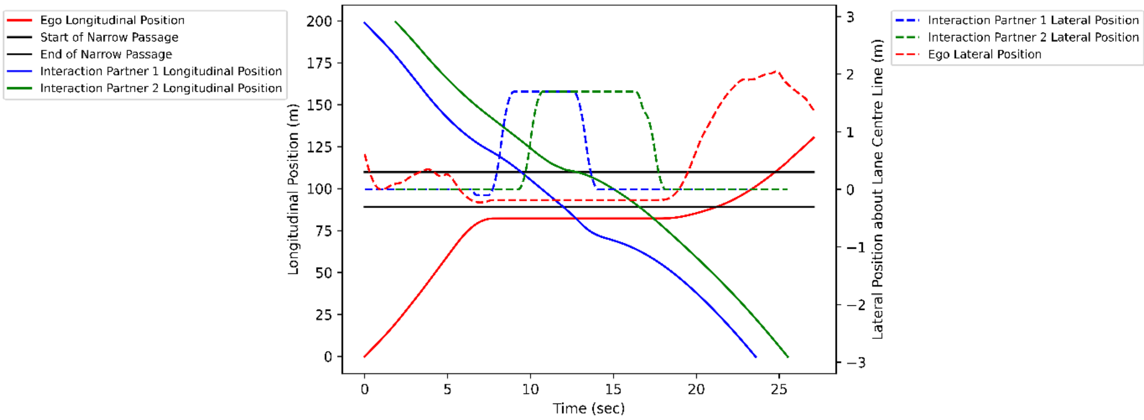

Figure 6. *A graph showing the longitudinal and lateral positions of a participant as they interact with multiple interaction partners.*

5.3 Time-To-Area and Driver Decision-Making

Figure 7 illustrates the average speed of the 5 participants across predefined narrow passage interactions, categorized by interaction asymmetry (i.e., the TTA difference between the interaction partners – negative values indicate that the participant is closer). Consistent with previous results [44], participants were more likely to pass through first at higher speeds for greater narrow passage asymmetries, when the asymmetry of the interaction lent itself to being defined by the "first-come, first-served" narrow passage rule. This not only underscores previous narrow passage behavioural findings but also attests to the simulator's high fidelity in providing the necessary contextual stimuli for such behavioural nuances.

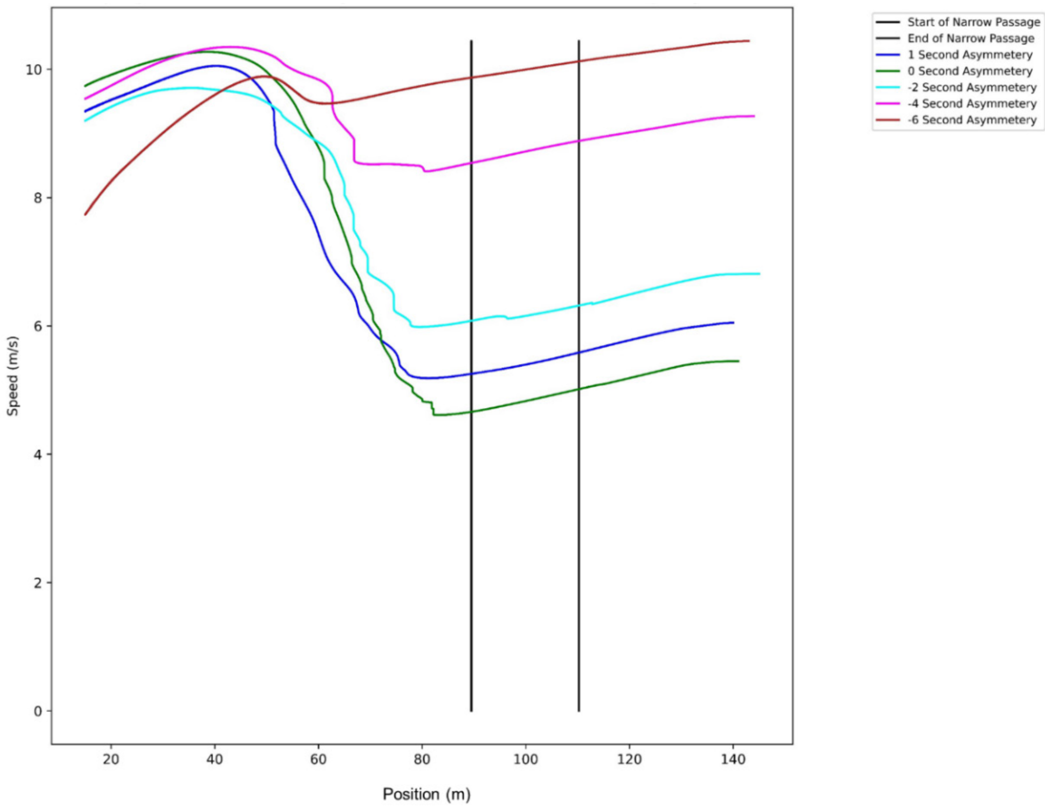

Figure 7. *The average speed of participants as they approach the narrowing for different narrow passage asymmetries.*

6. Conclusion and Future Work

The fidelity of simulators is crucial for ensuring that findings from simulator studies accurately reflect real-world behaviours. While much research has focused on enhancing simulator fidelity through hardware advancements, recent attention has turned to the software of driving simulators. This has led to recent couplings of game development engines with microscopic traffic simulations that seek to maximise the visual and behavioural realism.

Addressing concerns regarding the representativeness of simulated agent behaviours in narrow passage studies, a co-simulation approach has been adopted. This approach followed a review of literature on narrow passage behaviours and simulator fidelity, which guided the establishment of criteria for a high-fidelity narrow passage simulator. Consequently, a bespoke 360º narrow passage simulator has been developed, leveraging the immersive qualities of Unreal Engine and the modelling capabilities of SUMO. In particular, the creation of a novel narrow passage model that follows a theoretical behavioural framework for narrow passage decision-making has been described. Preliminary results conducted using the developed narrow passage simulator study are argued to indicate that these fidelity criteria have been met. Notably, previous findings have been reproduced and evidence indicates that the simulated agents display dynamic, intelligent, and representative behaviours during interactions with participants. Given these preliminary findings from the developed narrow passage simulator, further data collection will be continued.

While the primary focus of this work lies in narrow passage behavioural research, it is worth acknowledging the broader potential and challenges of the approach to behavioural research. For example, whilst the in-house development of a co-simulator offers a cost-effective means of conducting simulator studies, when compared to conventional driving simulator software, researchers must consider whether the added benefit of higher simulator fidelity is worth the increased complexity of developing a novel behavioural model. Furthermore, it is important to note that the ability to employ this co-simulation approach for other traffic scenarios is limited by the theoretical foundations a researcher has of that traffic scenario. Without a fundamental understanding of the behaviour that it is to be investigated, the development of a behavioural model that is representative enough, such that participants will behave in a way that replicates their on-road behaviours, is unlikely to be achieved, thereby negating the benefits of the approach. In cases in which researchers have a satisfactory theoretical foundation of the behaviours they which to investigate, the integration of SUMO and its capacity to create novel behavioural models allows researchers to explicitly integrate behavioural research and modelling. This synergy is critical as both research streams are complementary, such that if the outputs of one phase of research serves as the input to the next, the outputs of both phases can be maximised. As such, the adaptability allowed by this methodology allows researchers to continuously improve their simulator fidelity and therefore the behavioural fidelity of their studies.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author, PY. The data are not publicly available due to containing information that could compromise participant privacy.

Author contributions

PY: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing; KP: Supervision; BW: Conceptualization, Methodology, Writing – review & editing, Supervision.

Competing interests

The authors declare that they have no competing interests.

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