D2.8 Analysis of simulation results and identification of future safety-critical traffic interactions

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Document history

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0.1	28/02/2022	Antonio Mesones (IDI)	Basic template draft. Sent out for distribution to partners
0.2	24/03/2022	All Authors	Integrated all T2.5 partners input
0.3	5/4/2022	Antonio Mesones (IDI)	Finished first draft to review.
0.4	25/04/2022	Antonio Mesones (IDI)	Final draft for review.
0.5	27/04/2022	Antonio Mesones (IDI)	Frozen draft for final review.
0.6	18/05/2022	Antonio Mesones (IDI)	Changes due to final review.
1.0	27/05/2022	Antonio Mesones (IDI)	Final version

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Executive summary

The SAFE-UP project aims to proactively address the novel safety challenges of the future mobility systems through the development of tools and innovative safety methods that lead to improvements in road transport safety.

Future mobility systems will rely on partially and fully automated vehicles to reduce traffic collisions and casualties by removing causal factors like driver distraction, fatigue, or infractions and by reacting autonomously to emergency situations. On the other hand, they may introduce new collision risk factors or risky behaviours when interacting with other traffic participants.

SAFE-UP's Work Package 2 has identified existing critical scenarios in Task 2.1, developed new safety metrics in Task 2.2, new agent models for several kinds of road agents in Task 2.3, and integrated all models and metrics into a new traffic simulation environment in Task 2.4. The aim of Task 2.5 is to analyse (and iterate) these simulations to find future critical scenarios.

To this end Task 2.5 will run the simulations as designed and analyse the results, performing comparative analysis, and provide a deliverable, D2.8, where the simulation execution and preliminary results will be presented. And an update, D2.13, where the outcome of the analysis will be elaborated.

This deliverable is divided as follows: Section 2 will present the simulation environment. Section 2.1 presents the experiment design plan, while the workflow of the traffic simulation tool based on Aimsun Next is described in Section 2.2.

Section 3 covers the analysis of preliminary simulation results. Section 3.1 presents the analysis approach developed by TNO, which focuses on car to car interactions using driver profiling. Section 3.2 will elaborate on IKA analysis, focused on pedestrian and bicycle critical situations. Section 3.3 provides an overview of the car to car interaction analysis performed by TUD, based on their probabilistic driving risk field approach. Section 3.4 describes how UNI analyses PTW critical scenarios. Section 3.5 will elaborate on IDIADA analysis, baseline critical situation analysis.

Finally, section 4 provides a brief conclusion of the preliminary results.

This deliverable presents our initial simulation analysis plans. This work will continue through 2023, and the final results of our work will be presented on the final version of this document "D2.13 Analysis of simulation results and identification of future safety-critical traffic".

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List of abbreviations

Abbreviation	Meaning
AD	Autonomous Driver
AV	Autonomous Vehicle
CI	Crash Index
CIF	Criticality Index Function
CPI	Crash Potential Index
CPM	Crash Propensity Metric
D	Deliverable
DRAC	Deceleration Rate to Avoid Crash
DSS	Difference of Space distance and Stopping distance
H	Headway
HD	Human Driver
KRI	Key Risk Indicator
MADR	Maximum Available Deceleration Rate
MaxD	Maximum deceleration
ML	Machine Learning
MTTC	Modified Time-to-Collision
NDD	Naturalistic driving data
PET	Post-Encroachment Time
PICUD	Potential Index for Collision with Urgent Deceleration
PSD	Proportion of Stopping Distance
PTW	Powered Two-Wheelers
RBR	Required Braking Rate
SMoS	Surrogate Measures of Safety
SotA	State-of-the-Art
T	Task
TET	Time Exposed Time-to-Collision
TIDSS	Time Integrated DSS
TIT	Time Integrated Time-to-Collision
TTA	Time-to-Accident
TTC	Time-To-Collision
TTCD	Time-to-Collision with Disturbance
UD	Unsafe Density
VRU	Vulnerable road user
WP	Work Package
SV	Stimulus Vehicle
RV	Response Vehicle

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1. Introduction

1.1 The EU Project SAFE-UP

The SAFE-UP project aims to proactively address the novel safety challenges of the future road mobility environment by developing tools and innovative safety methods, leading to improvements in road transport safety.

Future mobility systems are expected to make use of vehicles with full or partial automation of the driving task, the so-called SAE L3/4/5 vehicles (SAE, 2018). By supporting (or even replacing human) drivers during the driving task, such vehicles may help improve road safety by removing some of the known sources of collisions (e.g., driver distraction) or by taking control during critical situations (e.g., automated emergency braking). On the other hand, automated vehicles may introduce new collision risk factors (e.g., increased distraction during transition of control) or induce new risky behaviours in other traffic participants (Hamilton, 2019).

The true impact of vehicle automation technologies on road safety will become apparent in the decades to come, as it depends on social and market trends that are difficult to forecast (like technological developments in sensors for automated vehicles, market penetration and acceptance of automation technologies, etc.).

Through the work in Work Package (WP) 2, SAFE-UP will further advance the understanding of the future impact of vehicle automation technologies by leveraging newly developed behavioural traffic simulation tools. These tools, developed by SAFE-UP's partners in Tasks (T) 2.3 and 2.4, will allow one to simulate specific road networks with a variable proportion of vehicles equipped with automation technologies. By analysing the simulation results in T2.5, one will be able to determine whether these technologies induce changes (positive or negative) in surrogate indicators of traffic safety.

1.2 Objective of this Deliverable

This deliverable presents the work done in the first months of Task 2.5. The main topics are:

- The simulation experiment design (developed in two WP2 Simulation Workshops)
- The experiment execution workflow.
- The preliminary analysis of simulation results performed by each Task 2.5 partner.

It is important to remark this deliverable constitutes the initial version of WP2's contribution to this topic. A second and final version of this deliverable, D2.13 (expected in March 2023), will include the final work products of the T2.5.

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1.3 Deliverable Organization

The rest of the deliverable is organized as follows:

Section 2 presents the simulation environment. Section 2.1 presents the experiment design plan, while the workflow of the traffic simulation tool based on Aimsun Next is described in Section 2.2.

Section 3 covers the analysis of preliminary simulation results. Section 3.1 presents the analysis approach developed by TNO, which focuses on car to car interactions using driver profiling. Section 3.2 will elaborate on IKA analysis, focused on pedestrian and bicycle critical situations. Section 3.3 provides an overview of the car to car interaction analysis performed by TUD, based on their probabilistic driving risk field approach. Section 3.4 describes how UNI analyses PTW critical scenarios. Section 3.5 will elaborate on IDIADA analysis, baseline critical situation analysis.

Finally, section 4 provides a brief conclusion of the preliminary results.

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2. Future Traffic Simulation

One of the goals of WP2 is to develop a micro-simulation-based approach to assess the impact of automated driving technologies on safety. Our approach is based on differential analysis. That is, we first create a baseline simulation of a "typical" (urban) environment populated with a typical mix of traffic participants (e.g., human driven vehicles, pedestrians, powered two-wheelers, cyclists, etc.). Such baseline simulation produces over time a number of traffic interactions that can then be classified as non-safety-critical or safety-critical according to a different safety indicators. After the baseline simulations are established, they are repeated with only one difference: a number of human driven vehicles are replaced by automated vehicles (AVs). In this way, we theorize that any changes in the statistics of safety indicators can be attributed to the presence of AVs.

In order to implement this approach, a number of elements from different tasks in WP2 need to correctly combined. First the new simulation models developed in Task 2.3 need to be integrated in a single simulation environment. This has been done in Task 2.4, which has also developed an appropriate road network that contains most of the important safety-critical situations identified in Task 2.1 (Deliverable 2.6). The simulation results will be analysed with a number of safety metrics, which were developed in Task 2.2.

Task 2.5 will make of these combined assets to run and analyse interactively multiple simulation experiments. The rest of this section elaborates in the following topics:

- Section 2.1 provides details and a rationale for our initial experiment design.
- Section 2.2 describes the workflow of the Aimsun Next platform, which will be the operational tool used through Task 2.5.

2.1 Experiment design

As mentioned above, the goal here to "Identify safety-critical scenarios for future mobility systems that mix Vulnerable Road Users (VRU), automated and manually driven vehicles" by performing a differential analysis on traffic micro-simulation results.

Two types of simulation experiments were identified during the first SAFE-UP Simulation Workshop in October 2021: Experiments containing complete road network layouts, allowing several types of driving scenarios and interactions to arise and experiments containing only single driving scenarios, allowing us to focus on specific kinds of critical situations.

The latter is very similar to virtual testing and will be performed in some capacity in WP3. Here, given the goals of WP2 and Task 2.5, we will focus mostly on the former type of experiment. As a shorthand, we call this experiment "Alpha".

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An Alpha experiment contains the following elements:

i. A road network containing enough elements (road furniture, traffic participants, etc.) to reproduce several driving scenarios and interactions of interest.

ii. Sufficient number of traffic participants to re-create traffic properties of interest (e.g., vehicle densities, speed distributions, congestion levels, etc.).

iii. Calibrated models for each type of road participant (human driving cars, AVs, vulnerable road users, etc.) from the perspective of driving safety (i.e., typical inter-vehicle following distances, reaction times for drivers and pedestrians, etc.).

iv. A test matrix indicating the specific changes in independent variables that are hypothesized to create detectable changes in safety indicator statistics.

v. Analysis toolchain to process simulation outputs to test the hypotheses.

It is not clear at this point whether significant changes in safety indicators are detectable when replacing human-driven vehicle by AVs, whether those changes are positive or negative, or whether new types of critical situations arise when AVs interact with other road users. These are all open questions T2.5 hopes to explore.

It is also important to remark that although our approach is based on statistical analysis, it will be correct only qualitatively[1]. For our analysis to also be quantitatively correct, the simulation experiment described above should contain a digital twin of a real road network. However, to create such a twin, the following four concurrent data sources on the same location are needed:

- A digital map of the desired location under study in right OpenDRIVE format (needed for point (i) above)
- Traffic-level data (e.g., from induction coils on tarmacs) on vehicle density, average travel time per location, speed distributions, etc. (needed to calibrate traffic-level properties in point (ii) above)
- Naturalistic driving data describing the driving behaviour of road users at the desired location (needed to calibrate the simulation models in point (iii) above).
- Accident-level data, needed to relate the statistics of safety indicators as measured in the NDD and traffic level data to accident occurrence and type.

[1] That is, if our experiments show a 10% reduction on rear-end collisions due to the presence of AVs, this should be interpreted as an indication that AVs could reduce the number of rear-end collisions in practice, albeit most-likely by a different percentage.

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To the best of our knowledge, no such concurrent data is currently available or will become available during the rest of the project, so our analysis can only indicate the validity of our hypotheses but cannot yield numerically correct results.

During the first Simulation Workshop, the team agreed to implement steps (i)-(v) listed above will be implemented as follows:

- The road network will be Town 7 (see Figure 1). It is already in the right format and contains urban and peri-urban roads, which allows us to recreate the most important, known safety-critical scenarios identified in Task 2.1 (it cannot recreate highway critical scenarios, but these will be explored in WP4).
- Traffic parameters will be adjusted to represent two types of traffic scenarios: low congestion moments of the day (i.e., outside rush-hour) and rush hours. The parameters for such moments will be adjusted by AIM drawing on their long experience on setting up such simulations.
- Each model-owner partner (TNO, IDI, UNI, IKA) will calibrate their models separately. See Deliverables 2.9-2.11 for details on the model calibration.
- The experimental test metric will become available in the coming months. The parameters of interest include the number of vehicles of each type; the penetration rate of AVs; the distribution of driver, rider, pedestrian, and cyclist characteristics (e.g., attentiveness, fatigue); etc.
- The toolchain varies per type of analysis and per partner. Each of these will be described in Section 3.

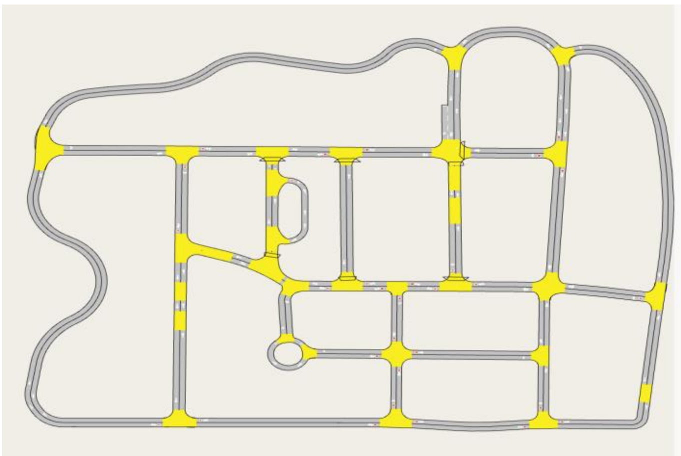

Figure 1: Layout of Town 7

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2.2 Experiment execution

2.2.1 Workflow

The simulation environment, described in Deliverable 2.7 is summarized in Figure 2, where the Aimsun Next platform is running in a Windows 10 computer, the Human driver and PTW models are implemented as a dynamic library, while the cycling and pedestrians models run in a UBUNTU 20 computer and the AVs model runs in a UBUNTU 18 computer. The bikes, pedestrians and AVs models interface the Aimsun Next platform using the TCP/IP communication through External Agent Interface (EAI).

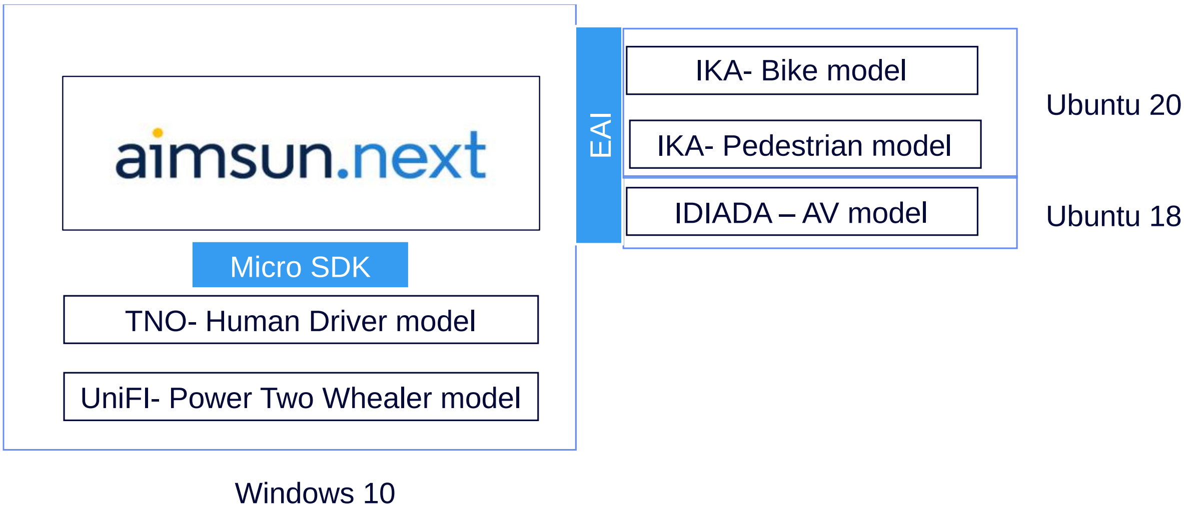

Figure 2: Simulation environment schema

Considering the current schema, the workflow of an experiment execution is described by the following steps (see Figure 3):

1. Definition of the Scenario simulation
2. Simulation Run
3. Collect Traffic Simulation outputs
4. Analyse Simulation outputs

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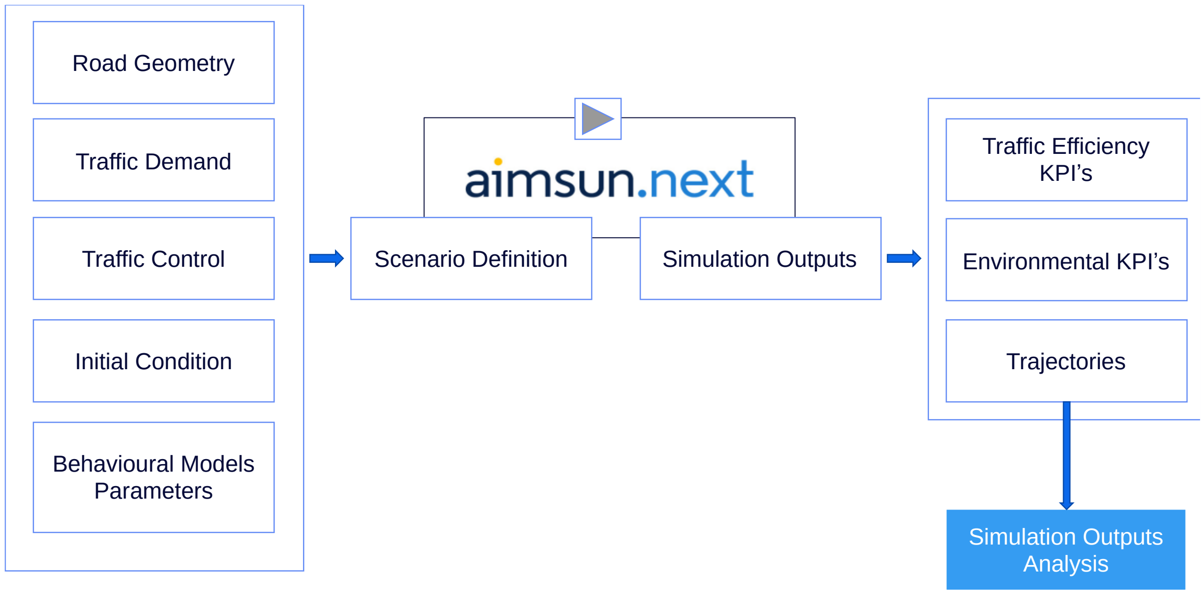

Figure 3: Experiment workflow

2.2.1.1 Scenario definition

The required elements of a scenario in order to run an experiment are:

I. Road Network: Also known as Road Geometry. The simulation framework requires all behavioural models have the same view of the infrastructure, having a common digital map. This common digital map selected is OpenDrive format. OpenDrive is an open format specification to describe a road network's logic. Its objective is to standardize the logical road description to facilitate the data exchange between different driving simulators and traffic simulators.

   The OpenDrive map is imported into the Aimsun Next platform, using its internal tool. As result, the simulation environment has these two representations of the digital map which are consistent between them, and each behavioural model takes as input one representation or another.

   The synthetic network example from CARLA, Town 7, was selected for testing, and is shown in the Figure 1.

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II. Traffic demand: The definition of the demand consists of the following elements:

- Define Vehicle Types and classes:
    - The minimum vehicle types required to be defined are cars, bikes, motorbikes and pedestrians. These vehicle types could be extended if the simulation needs to be compatible with fleet compositions describing certain traffic conditions.
    - The vehicle classes are required to define the inputs to the External Agent Interface. In this example each vehicle type has its own vehicle class.

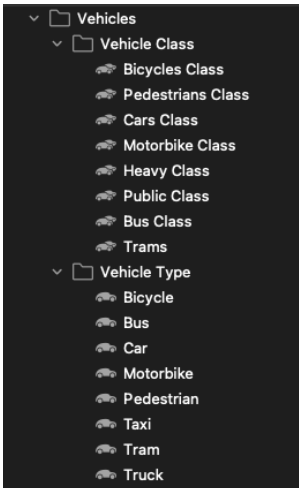

Figure 4: Vehicle Type and Class definition

- Define Origins and Destinations:
    - The generation of the vehicles or pedestrians are associated to an origin centroid connected to the road network. Once the vehicle is in the network, the route followed by the vehicle is computed with a Route Choice model, available in Aimsun Next.
    - The attraction of the vehicle or pedestrians are associated to a destination centroid connected to the road network.

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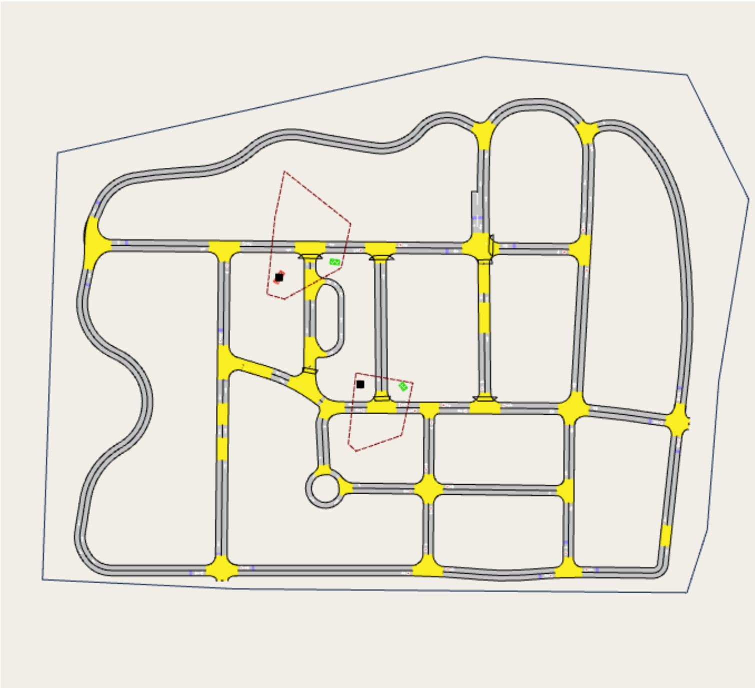

Figure 5: Origins and Destination Centroids for pedestrians.

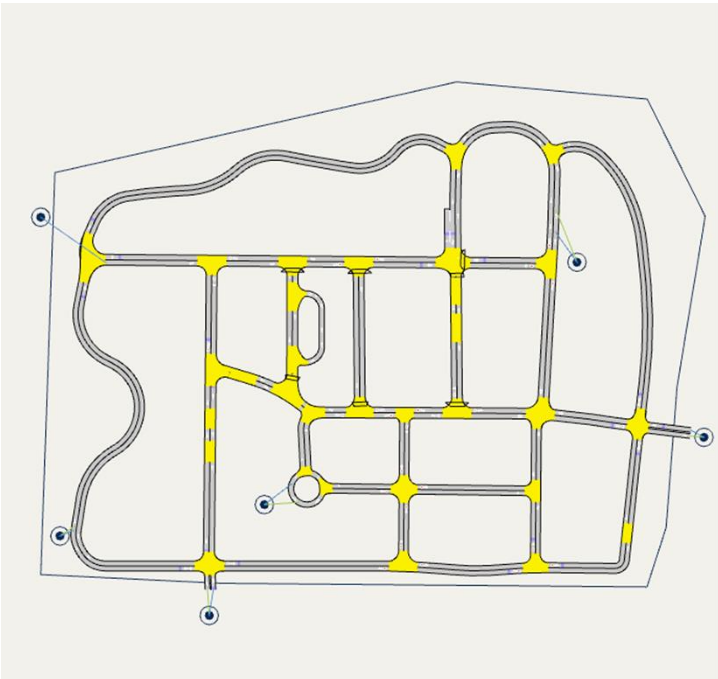

Figure 6: Origin and Destination definition for vehicles.

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- Define Traffic Demand
    - The Traffic demand defines per time interval and per each vehicle type, the number of trips between each origin and each destination (termed the OD matrix).

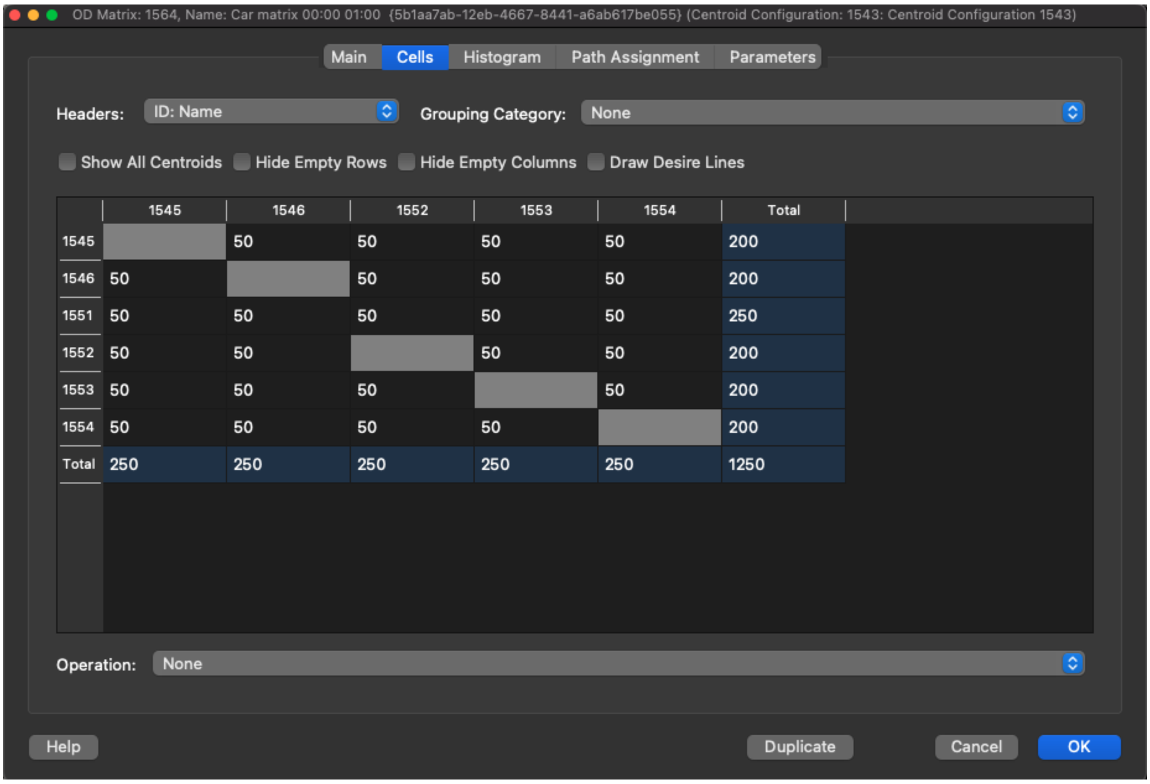

Figure 7: Example of OD matrix for cars

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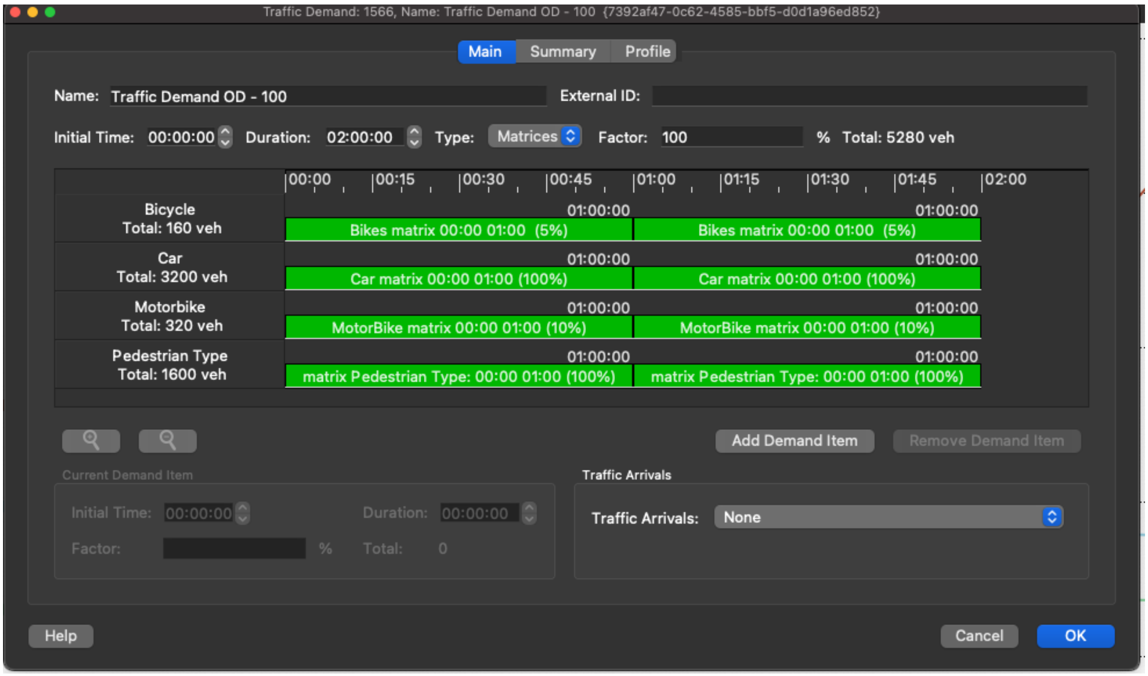

Figure 8: Example of the traffic demand.

All scenarios are based on a base traffic demand with a set of factors (for bikes and motorbikes) to represent an average fleet composition. The number of trips defined for Town 07 are defined as:

- “Car” (Human Driver): 3200 vehicles – 1600v/h
- “Motorbike” (PWT): 320 vehicles – 160 v/h (Factor 10% respect to “Car”)
- “Bike”: 160 vehicles – 80 v/h (Factor 5% respect to “Car”)
- “Pedestrians”: 1600 agents – 800 agents/h

Considering the base traffic demand there are 3 scenarios available, considering different traffic densities (Figure 9 depicts the density of each traffic scenario over the time):

- DynamicScenario 50 – Base demand applying a 50% factor to the base demand, representing low density.
- DynamicScenario 100 – Base demand applying a 100% factor to the base demand, representing moderate density.
- DynamicScenario 150 – Base demand applying a 150% factor to the base demand, representing high density.

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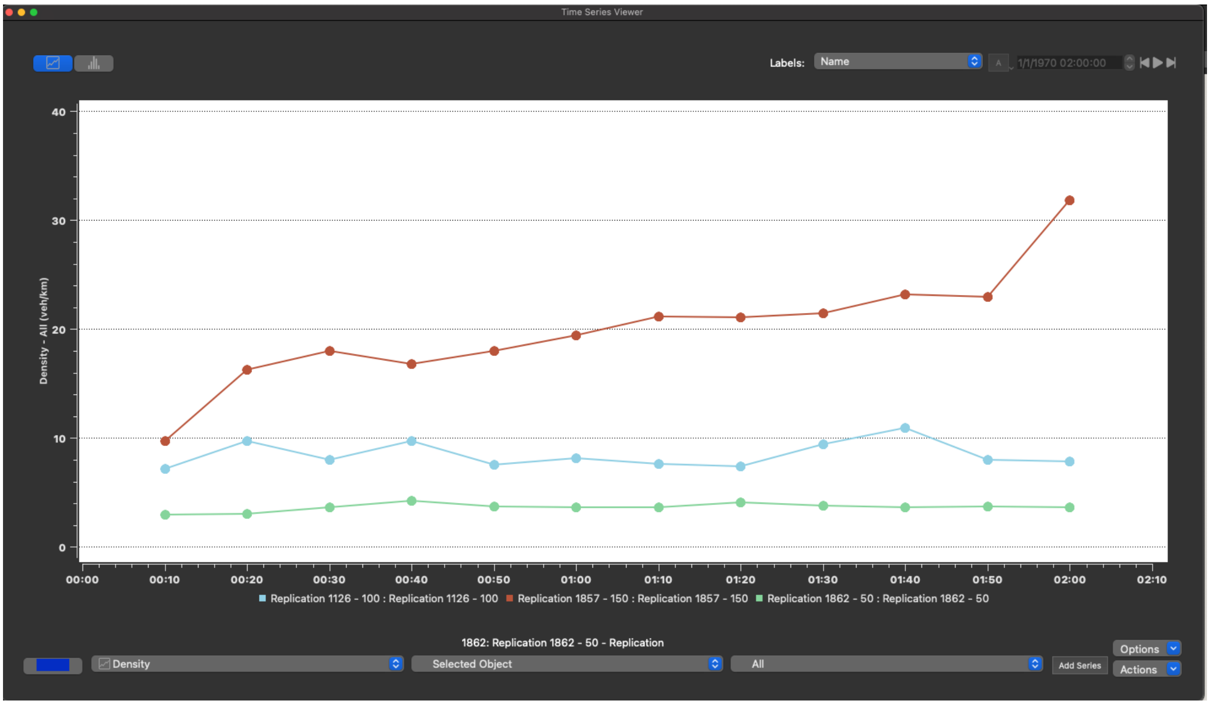

Figure 9: Density of the defined Traffic demand scenarios

III. Traffic Control: The OpenDrive map contains information defining the traffic lights. This definition must be complemented with the green time sequence.

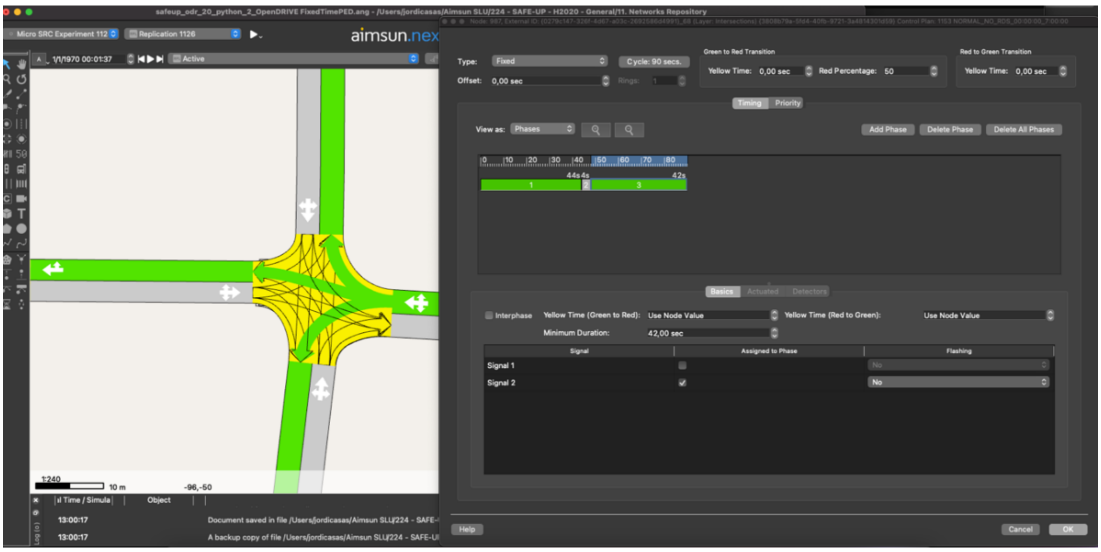

Figure 10: Example of Traffic signal control plan

IV. Behavioural model parameters: The behavioural model parameters should be included as part of the Experiment type object defined in the Aimsun Next data

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model. In each experiment it is possible to define the values. With these values being used during the simulation for each behavioural model.

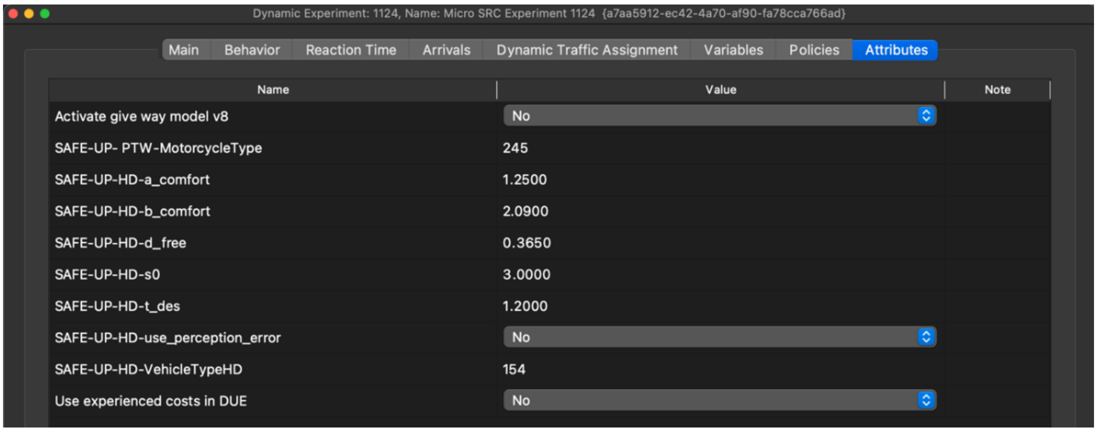

Figure 11: Behavioural model parameters defined in one experiment.

The parameters of the Human Driver and PWT behavioural models are described in Table 1 and Table 2.

Table 1: Human Driver model parameters

Unique Name	**External Name**	**Type**	**Default value**	**Comment**
GKExperiment:vehicleTypeHD	SAFE-UP-HD-VehicleTypeHD	int	154	The Human driver model is applied only to vehicles with this Vehicle Type ID
GKExperiment:a_comfort	SAFE-UP-HD-a comfort	double	1.25m/s^2	Comfortable Acceleration. Range [0,4]
GKExperiment:b_comfort	SAFE-UP-HD-b_comfort	double	2.09m/s^2	Comfortable Deceleration Range [0,4]
GKExperiment:t_des	SAFE-UP-HD-t_des	double	1.2s	Desired Time Gap Range [0.8,2]
GKExperiment:s0	SAFE-UP-HD-s0	double	3m	Standstill distance
GKExperiment:d_free	SAFE-UP-HD-d_free	double	0.365	Desired threshold for free lane change.
GKExperiment:use_perception_error	SAFE-UP-HD-use_perception_error	boolean	No	Turn on or off perception error in driver estimation of speed.

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Table 2: Powered Two-wheeler model parameters

Unique Name	**External Name**	**Type**	**Default value**	**Comment**
GKExperiment:MotorcycleType	SAFE-UP-PTW-MotorcycleType	int	245	The PTW model is applied only to vehicles with this Vehicle Type ID

V. Initial Conditions: The Initial conditions determine whether the simulation starts with an empty network or with the presence of different vehicles with specific locations and speeds, previously stored as a result of a simulation. The following figure depicts how to define it in Aimsun Next at the level of Experiment.

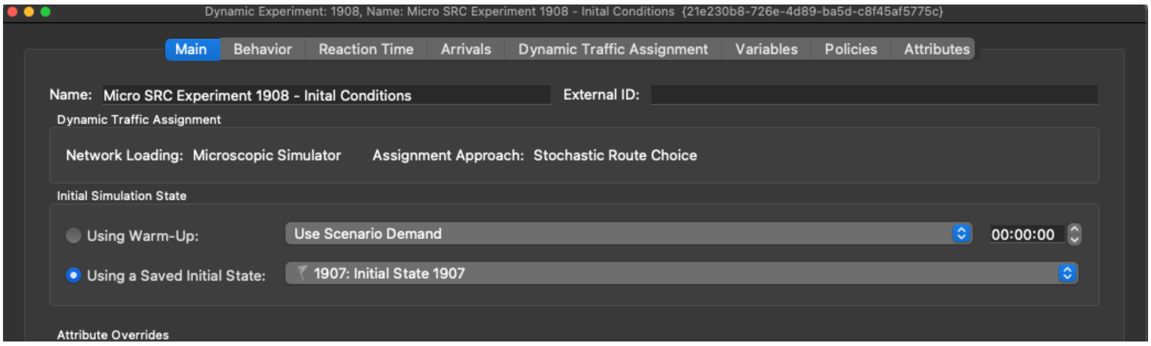

Figure 12: Definition of the Initial Conditions at Aimsun Next

Considering all elements required to setup a scenario, and the combination of different traffic densities profiles and the initial conditions, the Town 07 model contains 6 different experiments: Traffic Demand high, moderate and low combined with an empty network or with an initial state.

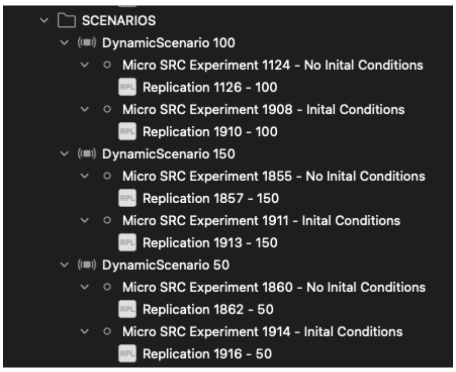

Figure 13: Experiments defined in Aimsun Next

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2.2.1.2 Simulation Run

The process of running one experiment is summarised as:

I. Activate all behavioural models: The activation is comprised of two steps:

- Activate integrated behavioural models using MicroSDK (Human Driver and PWT models). The activation is undertaken by selecting the tab folder “Behaviour” at Experiment object and setting “Activate External Behavioural Model”.

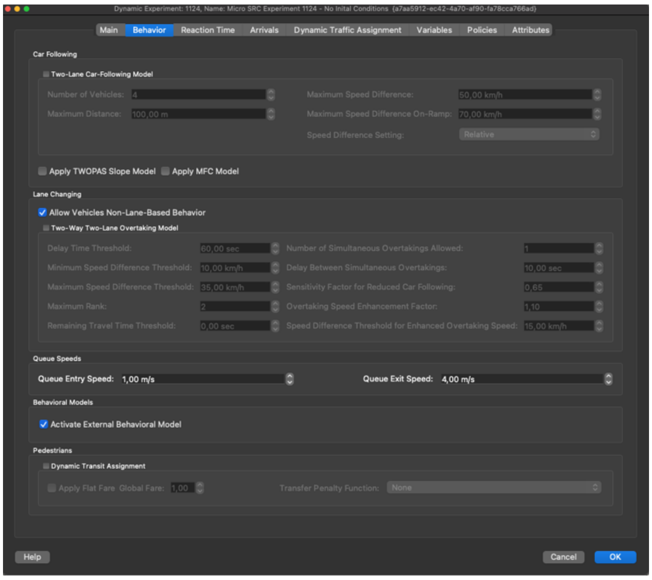

Figure 14: Activate External Behavioural model

- Activate behavioural models integrated using External Agent Interface (Pedestrian, Bike and AVs models). The activation is undertaken by selecting the tab folder “Aimsun Next APIs” at Scenario object and setting “External Agent Extension” (see Figure 15). The definition of the External Agent interface requires the configuration of its properties. The configuration options are (see Figure 16):

  - Initial Communications Timeout(s): Set a time in seconds for which Aimsun Next will wait for the external controller to connect. After this timeout, the simulation will start without communication.
  - Message Timeout(s): Set a time in seconds for which the Protocol Buffer Interface will wait for a response. After this timeout, the communication will be closed.
  - Server Port: Select or enter the number of the server port.

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- Synchronous Communication: Tick this box to synchronize the clocks of Aimsun Next and the external software. This is the recommended setting. (Note: When this box is unticked, asynchronous communication occurs. This means there is no clock synchronization and Aimsun Next does not wait for the external agent to advance the time. You can use this option to check what happens if for any reason the external software cannot run at least as fast as real time. We recommend that this test is run just before deployment on real vehicles. However, synchronous communication should cover 90% of pre-deployment tests.)
- Number of Connections Expected: Aimsun Next can connect to multiple clients. Set the number of clients that will be expected for this simulation. The server will stop waiting for new connections if this value is reached.
- Requires Expected Number of Connections: Tick this box if the simulation should be aborted in case that the number of established connections is lower than the expected connections.
- Record Input Messages: This box activates the storage of the messages Aimsun Next receives from external software during simulation. The file will be stored as replicationID_connectionID_replay.eai.
- Record Output Messages: This box activates the storage of the messages Aimsun Next sends to external software during simulation. The file will be stored as replicationID_connectionID_replay_out.eai.
- Detailed Vehicle Trajectory: Tick this box to apply visual smoothing to the position of vehicles as they change lanes in the main view of the Aimsun Next UI.
- External Agent Type To Vehicle/Pedestrian Type: Select one of the five vehicle types, or the Pedestrians option, for each external agent type available. (Note: None of the behaviour parameters or dynamic routing parameters defined for the selected option, which are normally used by Aimsun Next, are relevant in determining the actions of the externally controlled vehicle.)
- Vehicle Class To External Agent Type: Select which vehicle class will represent each external agent type. If no classes are selected, AGENT_NOT_DEFINED will be used as the default external agent type. If a simulated vehicle belongs to more than one vehicle class with defined external agent type translation, a lower type value will have priority.

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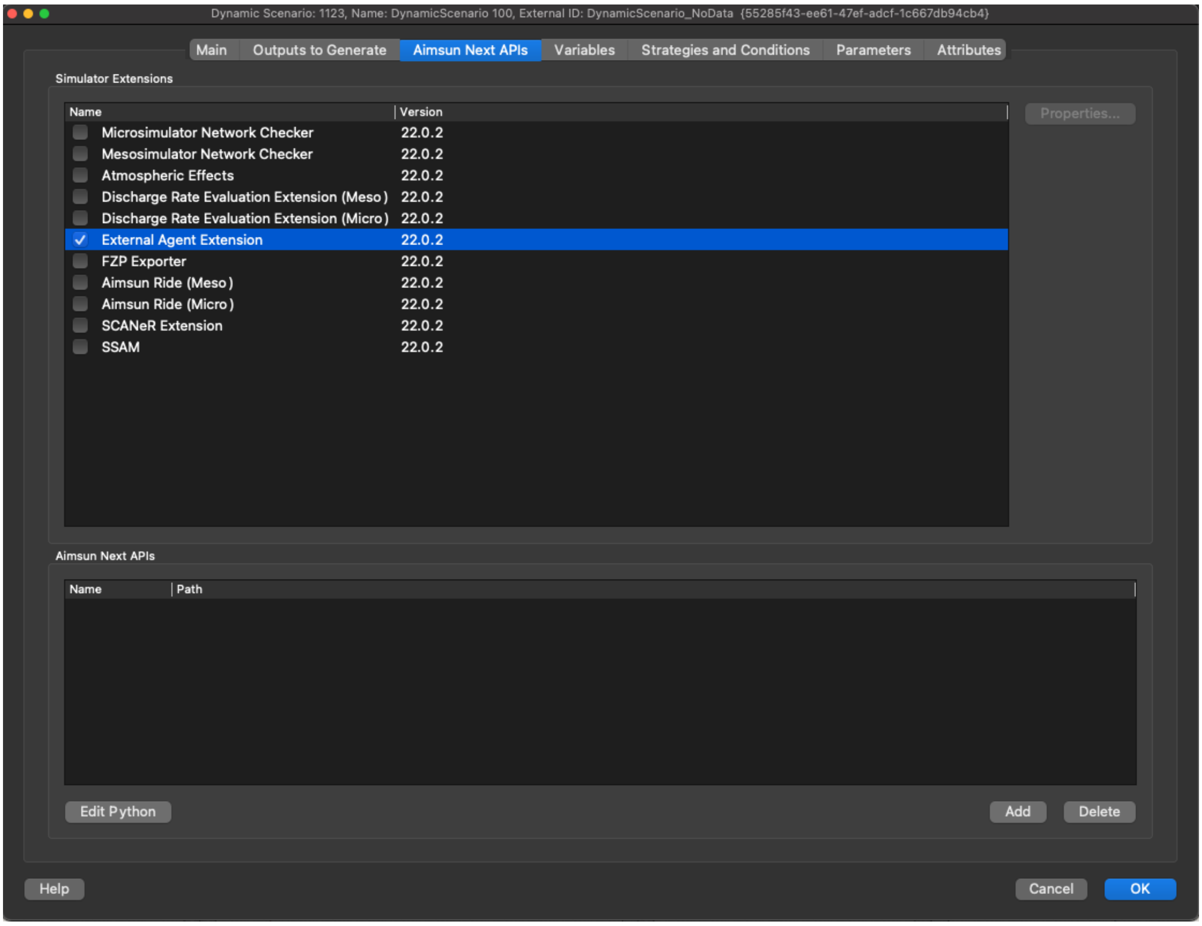

Figure 15: Activation of External Agent Interface

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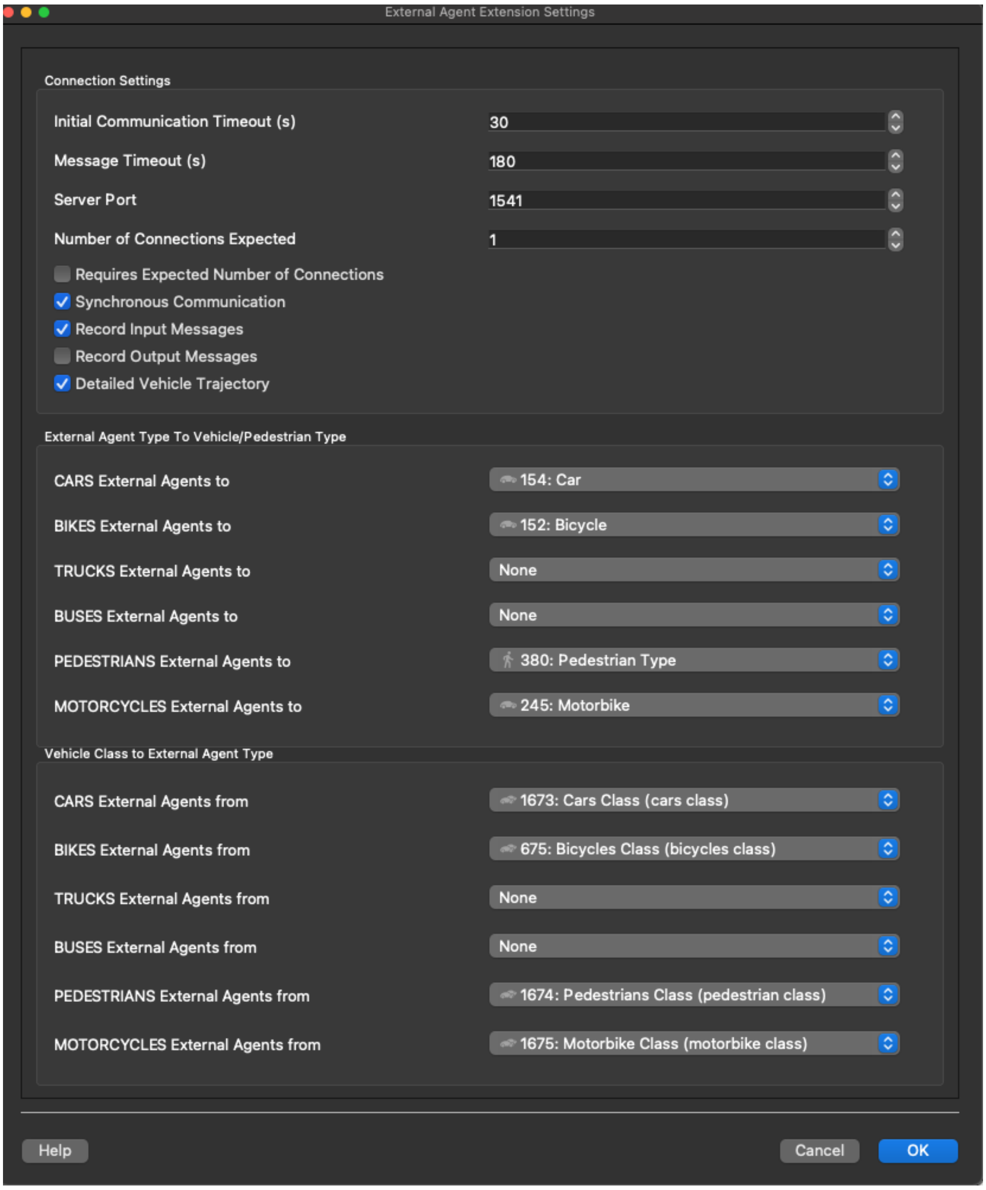

Figure 16: Configuration option of the External Agent Interface

II. Start behavioural model process integrated using External Agent Interface: AV, Bike and pedestrian models. They will wait until the connection with Aimsun Next is established.

III. Start Aimsun Next Replication. The behavioural models integrated using microSDK with be initialised (Human Driver and PWT models) and Aimsun Next platform will establish connection with all behavioural models that work through the External Agent Interface.

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2.2.1.3 Traffic Simulation Outputs

Simulation outputs of related to traffic efficiency, such as Travel Time, Average Speed, Delay Time, etc, are necessary to generate outputs related to safety. The safety measures are computed using trajectories of all the agents and the Aimsun Next platform generates them either: tables in the database that contains all simulation outputs or generating a TRJ file, format used by SSAM (https://highways.dot.gov/research/safety/ssam/surrogate-safety-assessment-model-overview) to compute the surrogate safety measures, or FZP file, format used for ·D animation.

2.2.1.3.1 Trajectories Tables in the simulation outputs database

From the Dynamic Scenario/Output/Individual Vehicles Tab it is possible to define the outputs for individual simulated vehicles. As these kinds of statistics are not dependant on any object, only vehicles themselves, they are only available in the database.

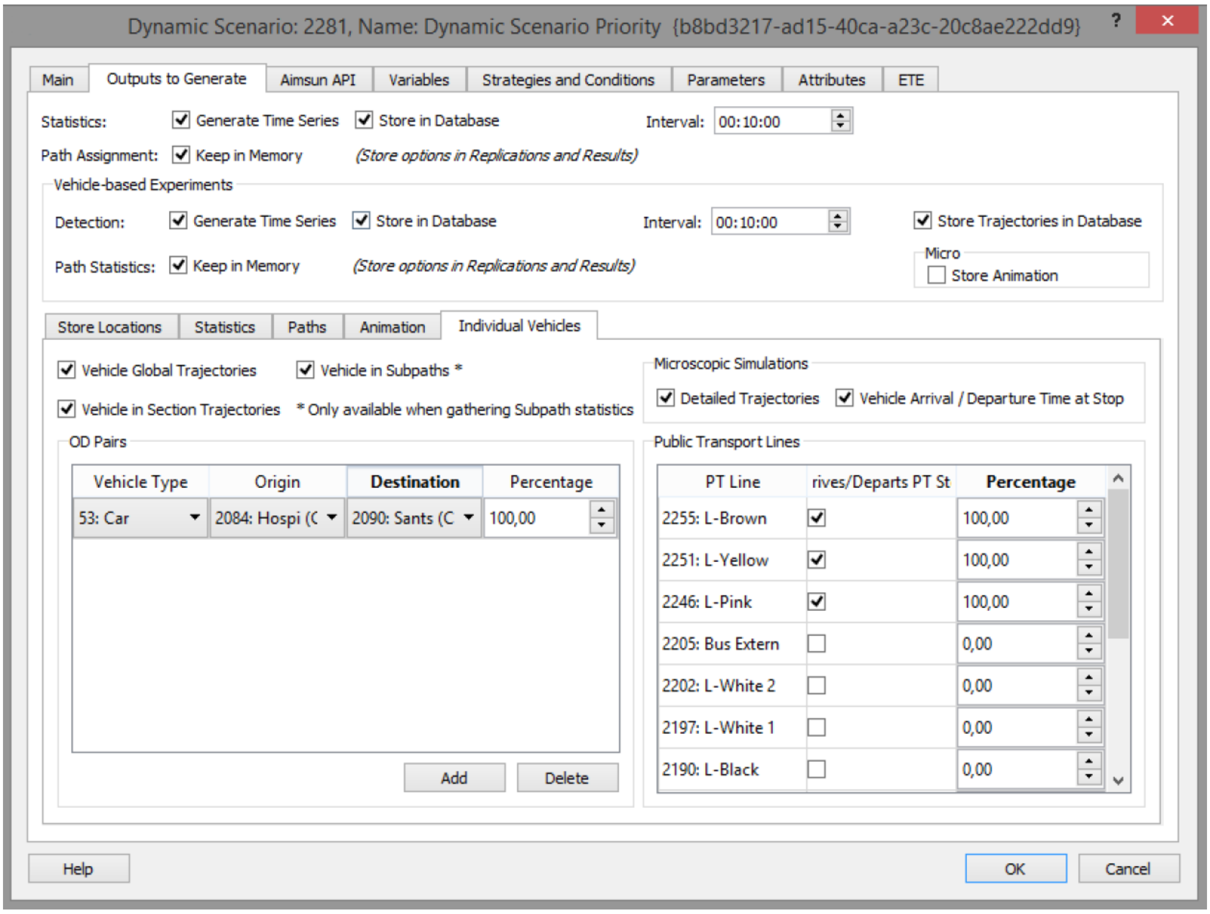

Figure 17: Setting the trajectories as simulation output in Aimsun Next

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The description of the tables that contain trajectory information are:

- **Global Trajectories**

These statistics provide general information about the vehicles that have exited the network. The database table is MIVEHTRAJECTORY for microscopic simulations and MEVEHTRAJECTORY for mesoscopic simulations.

- **Generation Time**: time when vehicle is generated.
- **Entrance Time**: time when the vehicle enters the network.
- **Exit Time:** time when the vehicle leaves the network.
- **Travel Time:** can be calculated using the exit time minus the entrance time.
- **Delay Time:** delay time in seconds.
- **Distance Travelled:** total vehicle's distance travelled in meters.
- **Expected Travel Time**: travel time expected from a previous run, in seconds. This expected travel time is coming from the input APA file, zero in case of no input APA file.
- **Path type:** vehicle's path type:
  - 0: Route Choice
  - 1: Path from APA
  - 2: OD route
  - 3: Public transport line
  - 4: Lost vehicle with random path
- **Speed:** speed in m/s. Only in meso.

- **Section Trajectories**

These statistics provide information of vehicles at each section in its path. The tables are MIVEHSECTTRAJECTORY (microscopic simulation) and MEVEHSECTTRAJECTORY (mesoscopic simulation).

- **Exit Time:** time when the vehicle exits the section.
- **Travel Time:** time that the vehicle takes to go through the section.
- **Delay Time:** delay time in the section.

- **Detailed Trajectories**

These statistics provide information of each vehicle each simulation step. It is only available in microscopic simulations. The table is MIVEHDETAILEDTRAJECTORY.

- Lane: section lane index where the vehicle is located.
- xCoord: global x coordinate.
- yCoord: global y coordinate.

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- Stationary Time: simulation stationary time.
- Speed: speed in km/h or mph depending on network units.
- Distance Travelled: distance travelled by the vehicle in metres.
- Acceleration: vehicle acceleration in m/s^2.

Global and Section Trajectories are available in Microscopic and Mesoscopic simulations. Detailed (simulation step) and Vehicle Arrival/Departure Time at Stop are only available in Microscopic Simulations. An example of the detailed trajectories is as follows:

Table: MIVEHDETAILEDTRAJECTO

	did	oid	ent	sectionId	laneIndex	xCoord	yCoord	stationaryTime	speed	travelledDistance	acceleration
1	1209	178	1	932	1	426234.72	4581180.03	208.621	49.47	2.46	0.0
2	1209	178	2	932	1	426244.96	4581184.03	208.8	49.47	13.46	0.0
3	1209	178	3	932	1	426255.2	4581188.03	209.6	49.47	24.45	0.0
4	1209	178	4	932	1	426265.44	4581192.03	210.4	49.47	35.44	0.0
5	1209	178	5	932	1	426275.68	4581196.04	211.2	49.47	46.44	0.0
6	1209	178	6	932	1	426285.92	4581200.04	212.0	49.47	57.43	0.0
7	1209	178	7	932	1	426296.16	4581204.04	212.8	49.47	68.43	0.0
8	1209	178	8	932	1	426306.4	4581208.04	213.6	49.47	79.42	0.0
9	1209	178	9	932	1	426316.64	4581212.04	214.4	49.47	90.41	0.0
10	1209	178	10	932	1	426326.64	4581215.95	215.2	47.12	101.15	-0.82
11	1209	178	11	932	1	426335.26	4581219.32	216.0	36.18	110.4	-3.8
12	1209	178	12	932	1	426341.66	4581221.82	216.8	25.72	117.28	-3.63
13	1209	178	13	932	1	426345.99	4581223.51	217.6	16.04	121.92	-3.36
14	1209	178	14	932	1	426348.45	4581224.48	218.4	7.8	124.57	-2.86
15	1209	178	15	932	1	426349.49	4581224.88	219.2	2.22	125.69	-1.94
16	1209	178	16	932	1	426349.74	4581224.98	220.0	0.19	125.95	-0.7
17	1209	178	17	932	1	426349.76	4581224.99	220.8	0.0	125.98	-0.07
18	1209	178	18	932	1	426349.76	4581224.99	221.6	0.0	125.98	0.0
19	1209	178	19	932	1	426349.76	4581224.99	222.4	0.0	125.98	0.0
20	1209	178	20	932	1	426349.76	4581224.99	223.2	0.0	125.98	0.0

1 - 21 of 263339 Go to: 1

Figure 18: Example of detailed trajectories table

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2.2.1.3.2 Trajectories file TRJ

In Aimsun Next, we can set up the generation of the TRJ file compatible with SSAM. The dialog for defining this output is shown in the following figure.

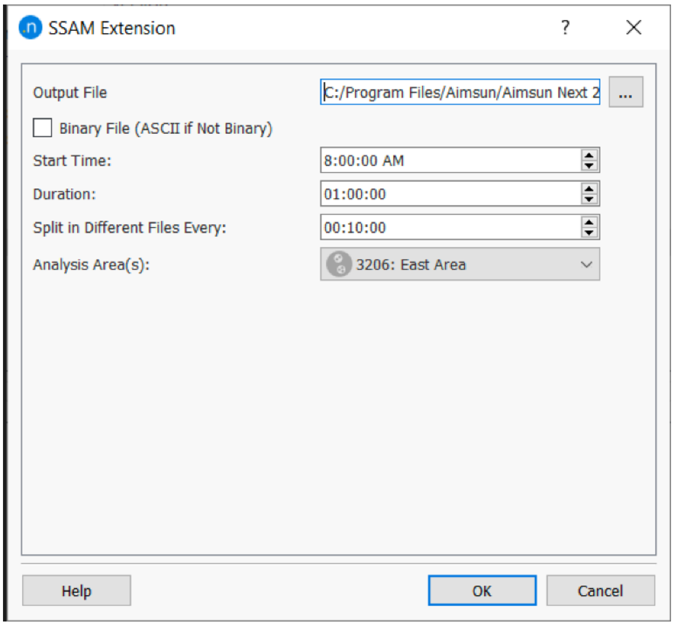

Figure 19: Setting the TRJ file generation as simulation output

This allows the definition of the output file name, the start time, the duration and the different areas to be analysed, setting a grouping object. If the selected grouping contains sections, trajectories of vehicles are included for those in any included sections and connected nodes. If the selected grouping contains nodes, trajectories of vehicles are included for those in nodes and any sections that enter or exit any of the nodes in the grouping. Trajectory files will be split by the included groups.

Once we have the TRJ files, then we can postprocess them using SSAM, and its outputs are a csv file with all surrogate safety measures and a csv file with a summary.

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2.2.1.3.3 Trajectories file FZP

The generated FZP file consists of two parts: the header and the data. The data is organized as a semicolon-separated table.

The parameters exported to the file are:

- VehNr: Vehicle ID
- LVeh: ID of the next vehicle downstream
- Type: Vehicle Type ID
- VehTypeName: Vehicle Type Name
- Length: Length [m]
- t: Simulation Time [s]
- a: Acceleration [m/s^2] during the simulation step
- v: Speed [m/s] at the end of the simulation step
- DesLn: Desired Lane (by Direction decision)
- Grad: Gradient [%] of the current link
- WorldX: World coordinate x (vehicle front end at the end of the simulation step)
- WorldY: World coordinate y (vehicle front end at the end of the simulation step)
- WorldZ: World coordinate z (vehicle front end at the end of the simulation step)
- RWorldX: World coordinate x (vehicle rear end at the end of the time step)
- RWorldY: World coordinate y (vehicle rear end at the end of the time step)
- RWorldZ: World coordinate z (vehicle rear end at the end of the time step)
- x: Distance from the start position (of the current section or turn the vehicle is in) to the front part of the vehicle, in meters, at the end of the simulation step
- y: Lateral position relative to middle of the lane (0.5) at the end of the simulation step

2.2.1.4 Events Detection analysis

The designed prototype of Event Detections will be implemented in Aimsun Next to complement the simulation Analysis.

The Event Detection plugin in Aimsun Next evaluates vehicle trajectory and behaviour using user-specified parameters. The plugin makes automated checks at every simulation step for the duration of the simulation.

The Event Detection Log captures unusual vehicle behaviour, collisions, and near-collision events so that these can be replayed or analysed after the simulation has finished running.

The log can be accessed through the UI or via a text file that is written at the end of the simulation.

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An example of a UI-based detection log is given in Figure 20.

Aimsun Auto Playback Log (t)

Show All

Repeated	Message	Aimsun Time	AV Time	Target	Extra
0	Collision.	08:00:16.800	08:00:16.800	3325	9, 1, 3325, 1
0	Collision.	08:00:27.200	08:00:27.200	3325	17, 1, 3325, 1
0	Collision.	08:00:30.400	08:00:30.400	3325	22, 1, 3325, 1
0	Collision.	08:00:38.400	08:00:38.400	3325	27, 1, 3325, 1
0	Collision.	08:00:44.800	08:00:44.800	3315	9, 1, 3315, 1
0	Collision.	08:00:56.000	08:00:56.000	24	25, 1, 24, 1
0	Collision.	08:01:41.600	08:01:41.600	75	82, 1, 75, 1
0	Collision.	08:01:48.000	08:01:48.000	30	44, 1, 30, 1
0	Collision.	08:01:54.400	08:01:54.400	80	80, 1, 85, 1
0	Collision.	08:02:12.800	08:02:12.800	60	69, 1, 60, 1
0	Collision.	08:02:13.600	08:02:13.600	60	69, 1, 60, 1
0	Collision.	08:02:14.400	08:02:14.400	60	69, 1, 60, 1
0	Collision.	08:02:15.200	08:02:15.200	60	69, 1, 60, 1
0	Collision.	08:02:16.000	08:02:16.000	60	69, 1, 60, 1
0	Collision.	08:02:16.800	08:02:16.800	60	69, 1, 60, 1
0	Collision.	08:02:17.600	08:02:17.600	60	69, 1, 60, 1

Figure 20: Events Detection UI-based detection Log

Repeated – The number of simulation steps over which the event occurs.

Message – What type of event has occurred?

Aimsun Time – According to the Aimsun Next clock, the time elapsed since the start of the simulation.

AV time – According to the software controlling the Autonomous Vehicle (AV), the time elapsed since the start of the simulation.

Target – The vehicle responsible for the event.

Extra –

1. Vehicle 1 ID
2. Vehicle type of vehicle 1
3. Vehicle 2 ID

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4. Vehicle type of vehicle 2

where vehicles 1 and 2 are the vehicles involved in the event and the vehicle type is defined, numerically, as follows:

1 = car, 2 =bike, 3 = truck, 4 = bus, 5 = pedestrian, 6 = motorbike.

When a collision is detected, the responsible agent is identified according to the following logic:

- If the collision is between a pedestrian and another type of vehicle, and the vehicle was stopped, then the pedestrian is responsible; otherwise, the vehicle is responsible.
- If the angle between the vehicles' headings is greater than 30°, the vehicle on the left is responsible.
- If the collision is head on, the first vehicle considered in the simulation step is responsible; otherwise, the rear vehicle is responsible.

An example of the text file log with explanations of columns is given below.

```
INFO,Collision.,4,4/1/15/1,900,900,692997.55,5338908.71
INFO,Collision.,4,4/1/15/1,1000,1000,692996.36,5338909.53
INFO,Collision.,4,4/1/15/1,1100,1100,692995.16,5338910.34
INFO,Collision.,4,4/1/19/1,1100,1100,692995.16,5338910.34
INFO,Collision.,4,4/1/24/1,1100,1100,692995.16,5338910.34
INFO,Collision.,15,19/1/15/1,1100,1100,693006.40,5338900.76
INFO,Collision.,4,4/1/15/1,1200,1200,692993.97,5338911.15
INFO,Collision.,4,4/1/19/1,1200,1200,692993.97,5338911.15
INFO,Collision.,4,4/1/24/1,1200,1200,692993.97,5338911.15
INFO,Collision.,15,19/1/15/1,1200,1200,693006.40,5338900.76
INFO,Collision.,15,19/1/15/1,1300,1300,693006.40,5338900.76
INFO,Collision.,15,19/1/15/1,1400,1400,693006.40,5338900.76
INFO,Collision.,15,19/1/15/1,1500,1500,693006.40,5338900.76
INFO,Collision.,15,19/1/15/1,1600,1600,693006.40,5338900.76
INFO,Collision.,15,19/1/15/1,1700,1700,693006.40,5338900.76
INFO,Collision.,15,19/1/15/1,1800,1800,693006.40,5338900.76
INFO,Collision.,15,19/1/15/1,1900,1900,693006.40,5338900.76
INFO,Collision.,15,31/1/15/1,1900,1900,693006.40,5338900.76
INFO,Collision.,19,19/1/31/1,1900,1900,693006.54,5338900.96
INFO,Collision.,15,19/1/15/1,2000,2000,693006.40,5338900.76
INFO,Collision.,15,31/1/15/1,2000,2000,693006.40,5338900.76
```

Figure 21: Text file log example

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The columns represent the following (see previous definitions above):

- Type of message
- Type of event
- Vehicle responsible
- Vehicle 1/Vehicle type of vehicle 1/Vehicle 2/Vehicle type of vehicle 2
- Aimsun Time
- AV time
- Location of event

Reviewing Traffic Simulation Results

Once the replications associated with Aimsun have finished, you can replay the recorded simulation.

Replaying the Log File in Aimsun Next Only

Once you have the network open in Aimsun Next, right-click the replication and select **Aimsun Playback**. This will retrieve the recording file (ARF extension) and a new window called Aimsun Playback Log (t) will be displayed on the right-hand side of the 2D view.

You can now click on each one of the events in the log to pan automatically to its position in the 2D view for further inspection.

Filtering the Detected Events

You can refine the type of event displayed in the log by selecting from the log's drop-down menu (not all possible events are pictured):

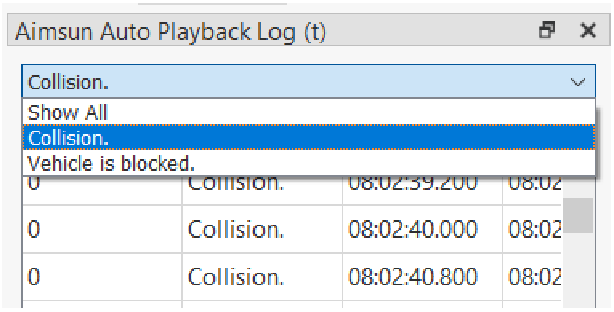

Figure 22: Log's drop-down menu

The List of Relevant Events

The list of events that can be detected by the Aimsun Event Detection plugin includes the following (AV stands for self-driving vehicle):

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- AV is blocked
- AV has passed a red light
- AV hasn't stopped at a stop sign
- AV is speeding
- AV is driving at a consistently slow speed
- AV has changed lane too frequently
- AV made a rapid change in acceleration/deceleration
- AV made a hard brake/start
- A vehicle has changed lane in front of the AV
- AV collision
- AV near collision
- AV keeping a small gap
- AV not yielding to a vehicle
- AV not yielding to a pedestrian
- Vehicle is blocked
- Vehicle is applying non-compliant behaviour
- Collision
- Near collision

2.2.1.4.1 Event Detection Parameters

The Aimsun Event Detection plugin considers three categories of parameter: comfort, safety, and traffic law compliance parameters.

Comfort parameters

The following parameters are used to capture events that could affect passengers' comfort level.

- Maximum jerk [m/s^3]

Jerk is defined as the change in acceleration during one simulation step. The maximum jerk parameter is used to detect situations where the AV makes a rapid change in acceleration/deceleration.

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- Maximum longitudinal acceleration [m/s^2]

Longitudinal acceleration is defined as the change in speed along the direction of vehicle movement during one simulation step when a vehicle is gaining speed. The maximum longitudinal acceleration is used to identify when the AV makes a hard start.

- Maximum longitudinal deceleration [m/s^2]

Longitudinal deceleration is defined as the change in speed along the direction of vehicle movement during one simulation step when a vehicle is braking. The maximum longitudinal deceleration is used to identify when the AV makes a hard brake.

- Maximum lateral acceleration [m/s^2]

Lateral acceleration is calculated by subtracting the longitudinal acceleration component from the two-dimensional acceleration vector. The lateral acceleration is always positive. The maximum lateral acceleration is used to identify when the AV makes a hard start or brake.

- Low speed threshold [m/s]

This parameter is used to identify when the AV is driving at slow speed for a prolonged time.

- Maximum duration of the low-speed condition [s]

This parameter is also used to identify when the AV is driving at slow speed for a prolonged time.

Safety parameters

The following parameters are used to capture events that relate to passengers' safety conditions.

- Front distance to report a near collision [m]

The minimum distance, from the vehicle ahead, that is considered safe. If a vehicle is detected at a distance shorter than this, at any time during the simulation, it is reported as a near collision.

- Side distance to report a near collision [m]

The minimum side distance, to a neighbouring vehicle, that is considered safe. If a vehicle is detected at a lateral distance shorter than this, at any time during the simulation, it is reported as a near collision.

- Minimum time between lane changes [s]

This parameter is used to identify when the AV is changing lanes too frequently.

- Minimum safety gap [s]

The minimum safety gap is used to identify situations where the AV is not yielding to another vehicle that has right of way, or to identify when the AV is maintaining a small gap.

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Traffic law compliance parameters

The following parameters are used to capture events that relate to AVs' compliance with traffic rules.

- Speed threshold to consider the vehicle stopped [m/s]

The minimum speed below which the AV is considered to have stopped. This parameter is used to identify several situations: where the AV is blocked, has passed a red light, has not stopped at a stop sign, is driving at a consistent slow speed, has been involved in collisions, and has been involved in near collisions.

- Maximum distance from stop line to consider being properly stopped [m]

This parameter is used to identify situations where the AV has not made a proper stop, for example when it enters an intersection on a red light or when it complies with a stop sign. Even with a speed reaching zero, a stop is not considered to be *proper* if it takes place beyond a maximum distance from the stop line (upstream and downstream).

- Excess of speed limit to report speeding (%)

As most vehicles will drive at speeds above the posted speed limit, it is common to observe speeds above this limit. This parameter is used to report situations where the excess speed is higher than the acceptable percentage specified.

- Maximum stop time in intersections [s]

This parameter is used to identify situations where AVs or Aimsun vehicles get blocked at an intersection, i.e., they are stopped inside a node for longer than the specified maximum stop time.

- Maximum stop time in road sections [s]

This parameter is used to identify situations where AVs or Aimsun vehicles get blocked on roadways, i.e., they are stopped at a section for longer than the specified maximum stop time.

2.2.1.4.2 Detailed Event Description

This section contains detailed descriptions of the assumptions, parameters, and reporting instances for all the events registered by the Aimsun Event Detection plugin.

AV is blocked

- Assumption: that the AV should frequently move along its path until the end of the route. When the AV's position doesn't change before reaching the end of its route, the stop duration is compared with the specified maximum stop times.
- Parameters:
  - Speed threshold to consider the vehicle stopped [m/s]
  - Maximum stop time in intersections [s]

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- Maximum stop time in road sections [s].

- Event is reported when:
    - The AV is inside a node and the AV speed is below the "stopped" threshold for more than the maximum stop time in intersections [s]
    - The AV is traveling along a section and its speed is below the "stopped" threshold for more than the maximum stop time in road sections [s].

Note: the blockage checker is disabled if one of the maximum stop time parameters is not set.

AV has passed a red light

- Assumption: that the AV will follow the traffic signals and will not enter an intersection (node) when the active phase of the control plan inhibits its movement. Entering an intersection on red is prohibited, with the exception of right turn on red (RTOR). The evaluation algorithm has two components: (a) checking the signal for AV movement and the presence of RTOR and (b) checking if the conditions for a proper stop were met. The latter is examined using traffic law compliance parameters (speed threshold to consider the vehicle stopped, maximum distance from stop line for a proper stop) as well as considering the presence of network elements like a stop line or a crosswalk. The AV is considered to be inside an intersection if it has crossed the stop line and is more than the specified distance downstream from the line. A stop is not considered proper when the AV has already crossed the stop line and stops more than the specified distance downstream from the stop line.
- Parameters:
    - Maximum distance from stop line to consider proper stop [m]
    - Speed threshold to consider the vehicle stopped [m/s].

- Event is reported when:
    - The AV enters an intersection on red except for RTOR
    - The AV doesn't stop properly, including not stopping before making a RTOR and stopping too far (upstream or downstream) from the stop line or crosswalk.

AV hasn't stopped at a stop sign

- Assumption: that the AV will make a stop before proceeding when approaching an intersection with a stop sign. A stop is considered proper if it is made within the specified distance (upstream and downstream) from the stop line or crosswalk. A stop is not considered proper when the AV has already crossed the stop line and it stops beyond the specified distance downstream from the stop line.

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- Parameters:
  - Speed threshold to consider the vehicle stopped [m/s]
  - Maximum distance from stop line to consider proper stop [m].
- Event is reported when:
  - At the stop line, the AV speed is higher than the speed threshold to consider the vehicle stopped
  - The AV stops too far from the stop line or crosswalk, upstream or downstream.

Note: the duration of the stop is **not** evaluated.

AV is speeding

- Assumption: that the AV will follow the section speed limit within reason, as defined by the user. If the AV speed is greater than the specified percentage above the speed limit, speeding is reported. For example, if you define a 10% threshold, an AV traveling at 56 mph in a section with a 50 mph speed limit will be reported as speeding.
- Parameters:
  - Excess of speed limit to report speeding (%).
- Event is reported when:
  - AV is traveling at a speed higher than the specified percentage above the speed limit.

AV is driving at a consistently slow speed

- Assumption: the implementation assumes that the AV is not going to travel at low speed for an extended period of time. If the AV speed is lower than the low speed threshold for longer than a maximum duration, the plugin will report the AV driving at low speed.
- Parameters:
  - Low speed threshold [m/s]
  - Maximum duration of low speed condition [s]
  - Speed threshold to consider the vehicle stopped [m/s].
- Event is reported when:
  - The AV speed stays between the vehicle stopped speed and the low speed threshold for a time longer than the maximum duration of the slow speed condition.

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AV has changed lane too frequently

- Assumption: that the AV will not change lanes unnecessarily. The user-defined parameter, Minimum time between lane changes [s] is used to identify instances where consecutive lane changes occur too frequently.
- Parameters:
  - Minimum time between lane changes [s].
- Event is reported when:
  - The time between consecutive lane changes is lower than the user-specified minimum time.

AV made a rapid change in acceleration/deceleration

- Assumption: that the AV will accelerate smoothly. A maximum jerk parameter is used to identify instances where the change in acceleration is too fast.
- Parameters:
  - Maximum jerk [m/s^3].
- Event is reported when:
  - The AV jerk is higher than the specified maximum value.

AV made a hard brake/start

- Assumption: that the AV will use acceleration or deceleration within the user-specified limits. Longitudinal acceleration or deceleration values are calculated as the change in speed along the direction of vehicle movement during one simulation step. Lateral acceleration is calculated by subtracting the longitudinal component of acceleration from the two-dimensional acceleration vector.
- Parameters:
  - Maximum longitudinal acceleration [m/s^2]
  - Maximum longitudinal deceleration [m/s^2]
  - Maximum lateral acceleration [m/s^2].
- Event is reported when:
  - The AV longitudinal acceleration is higher than the specified maximum longitudinal acceleration
  - The AV longitudinal deceleration is higher than the specified maximum longitudinal deceleration
  - The AV lateral acceleration is higher than the specified maximum lateral acceleration.

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A vehicle has changed lane in front of the AV

- Assumption: that the AV will respond in a reasonable manner to a vehicle moving into its path. To monitor the AV reaction to lane-changing manoeuvres, all instances of Aimsun vehicles changing lanes in front of an AV are reported. The vehicle ID and the distance to the AV are included in the log.
- Parameters:
  - None.
- Event is reported when:
  - an Aimsun vehicle changes lane in from of the AV.

AV collision

- Assumption: that vehicles should follow traffic rules and avoid collisions. All collisions are reported in the log for further investigation. The log includes information on the responsible vehicle, vehicle(s) affected, the time of collision, and the duration of the collision. If one of the vehicles was stopped at the time of collision (speed below the stopped threshold), the moving vehicle is considered responsible.
- Parameters:
  - Speed threshold to consider the vehicle stopped [m/s].
- Event is reported when:
  - The AV and Aimsun vehicle bounding boxes overlap. The vehicle responsible is determined based on their current simulation-step 3D positions, their respective speeds, and their coordinates at the previous simulation step.

AV near collision

- Assumption: that the AV will maintain a reasonable distance from other vehicles.
- Parameters:
  - Speed threshold to consider the vehicle stopped [m/s]
  - Front distance to report a near collision [m]
  - Side distance to report a near collision [m].
- Event is reported when:
  - The distance between the AV and its leading vehicle is less than the front distance to report a near collision
  - The distance between the AV and a neighbouring vehicle is less than the side distance to report a near collision.

AV keeping a small gap

- Assumption: that the AV will maintain a safe distance when traveling behind another car. During each simulation step, the event detection algorithm identifies the AV

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leader – a vehicle traveling in the same lane immediately in front of it – and evaluates the clearance distance between the AV and its leader. When a small gap is detected, the AV speed, vehicle ID, and clearance distance are reported in the log.

- Parameters:
  - Minimum safety gap [s].
- Event is reported when:
  - The clearance between the AV and its leader vehicle is less than minimum safety gap.

AV not yielding to a vehicle

- Assumption: that when entering a node (intersection) the AV will follow the appropriate yield behaviour, i.e., it will stop at a stop sign and yield to vehicle(s) that have the right of way. When the AV is approaching an intersection, the algorithm searches for actors with potential conflicts and examines the AV behaviour using its position, speed, and a minimum safety gap.
- Parameters:
  - Minimum safety gap [s].
- Event is reported when:
  - The gap between the AV and the vehicle with the right of way is smaller than the minimum safety gap, i.e., the AV has not slowed down enough to yield to another vehicle with the right of way.

AV not yielding to a pedestrian

- Assumption: that the AV will yield to pedestrians using crosswalks inside a node. The event detection algorithm uses the AV and pedestrian locations at each simulation step, as well as the positions of other network elements, such as nodes and crosswalks, to evaluate the AV behaviour. The evaluation is performed at each simulation step. When the AV is inside a node, the algorithm searches for all crosswalks that belong to the node. If a pedestrian is already inside the crosswalk polygon as the AV enters, the crosswalk and pedestrian IDs are reported in the log.
- Parameters:
  - None.
- Event is reported when:
  - The AV has entered a crosswalk polygon while a pedestrian is already inside it.

Note: AV interactions with pedestrians using crosswalks that are not inside a node (dummy crosswalks for jaywalking) are not evaluated.

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Vehicle is blocked

- Assumption: that all vehicles will follow their path without performing unnecessarily long stops along their route.
- Parameters:
    - Speed threshold to consider the vehicle stopped [m/s]
    - Maximum stop time in intersections [s]
    - Maximum stop time in road sections [s].
- Event is reported when:
    - The speed of a vehicle is below the "stopped" threshold, the vehicle is inside a node, and it is stopped for more than the maximum stop time in intersections [s]
    - The speed is below the "stopped" threshold, the vehicle is traveling along a section, and it is stopped for more than the maximum stop time in road sections [s].

Note: the blockage checker is disabled if one of the maximum stop time parameters is not set.

Vehicle is applying non-compliant behaviour

- Assumption: that Aimsun Next vehicles will apply non-compliant behaviour according to the test specifications. Currently the following types of non-compliant behaviour can be activated: driving between lanes, hard braking, sharp overtaking, signal violation, speeding, stop-line rollover, stop-line violation, tailgating, turning violation, and unexpected lane change. The type(s) of non-compliant actions to be activated can be specified in the dynamic experiment properties in the Attribute Overrides section or directly in the Vehicle Type editor.
- Parameters:
    - None.
- Event is reported when:
    - An Aimsun Next vehicle applies a non-compliant behaviour. The time and non-compliant action type are reported in the log.

Collision

- Assumption: that Aimsun Next vehicles will follow traffic rules and avoid collisions. All collisions are reported in the log for further investigation, including the responsible vehicle, vehicle(s) affected, time of collision, and duration of collision. If one of the vehicles is stopped at the time of collision (speed below the stopped threshold), the moving vehicle is considered responsible.

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- Parameters:
  - Speed threshold to consider the vehicle stopped [m/s].
- Event is reported when:
  - Aimsun Next vehicle bounding boxes overlap. The vehicle responsible is determined based on the current vehicle locations, their respective speeds, and their coordinates at the previous simulation step.

Near collision

- Assumption: that all Aimsun Next vehicles will maintain a safe distance when interacting with other vehicles.

- Parameters:
  - Speed threshold to consider the vehicle stopped [m/s]
  - Front distance to report a near collision [m]
  - Side distance to report a near collision [m].
- Activation Condition:
  - The distance between a vehicle and its leader is less than the front distance to report near collision
  - The distance between a vehicle and a neighbouring vehicle is less than the side distance to report near collision.

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3. Experiment Analysis

This section summarizes the approach that will be followed by each partner in Task 2.5 to analyse the experiment results. TNO, IKA, TUD, and UNI will base their analysis on the metrics they developed in Task 2.2. IDI will provide the baseline simulation analysis using well-established safety indicators.

Each partner presents below a summary of the techniques behind their metrics[2], a description of their intended analysis objectives, and their initial analysis results obtained during the second SAFE-UP Simulation Workshop held in April 2022.[3]

3.1 Analysis of HD-AV behaviour (TNO)

One of the goals of TNO in SAFE-UP is to develop metrics to identify both safe and safety-critical driving interactions. Both kinds are needed in order to assess the benefits of automate vehicles either via simulation, physical testing, or combinations thereof.

As explained in detail in Deliverable 2.14, in Task 2.2 TNO has developed two metrics that characterize typical human driving as it is known to carry low to medium collision risk (Tejada, Manders, Snijders, Paardekooper, & de Hair-Buijssen, 2020). Both metrics are data-driven. That is, they are derived by training models on NDD using unsupervised, data-driven techniques. One metric, reported initially in (Tejada, Manders, Snijders, Paardekooper, & de Hair-Buijssen, 2020), is based on an autoencoder model and able to recognize typical longitudinal highway driving. The second metric is based on statistical driver profiling and is more suitable for urban scenarios.

In Task 2.5 TNO aims to analyse Alpha-type simulations to understand the impact of automated vehicles on safety. To the best of our understanding, SAFE-UP's state of the art in traffic-participant modelling does not yet represent accurately the behaviours and causal factors that lead to current (let alone future) critical situations in traffic (e.g., human error and distraction, vehicle technology edge cases, etc.). This, coupled with the rarity such events, makes it unlikely to identify them directly in simulations. Consequently, TNO will not seek to identify directly future safety-critical situations but their distal indicators, which are more abundant.

Elaborating on our driver profiling technique, we hope to see on simulation results whether the introduction of automated vehicles in traffic lead to changes in driving profiling. As

[2] Complete details are available in Deliverable 2.14 Description Metrics for Traffic Interactions.

[3] This deliverable contains the partner's initial plans. They may change as more experience and information is gained. The final version of this report, D2.13, is expected in March of 2023.

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explained below, our driving profiling techniques are based on statistics of speed and acceleration over different road segments. These variables are leading measure of safety, as they correlated significantly (in the statistical sense) with hard brakings and (in-turn with) rear-end collisions (Blumenthal, Fraade-Blanar, Best, & Irwin, 2020).

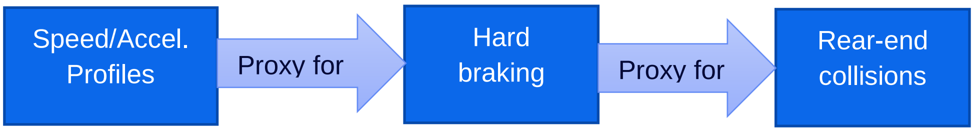

Figure 23: Leading measures and safety.

The specifics of our approach are given next.

3.1.1 Technical Summary: Statistical Driver Profiling

Driver behaviour profiling is defined as *"a normalized score of driver behaviour which serves as a proxy for assessing crash risk by combining a number of measures of risk on a common scale within and across drivers."* (Ellison, 2015). The metric clusters drivers based on how they compare to the norm across road segments, to cope with the variety of urban road networks. This is visualized in **¡Error! No se encuentra el origen de la referencia.**.

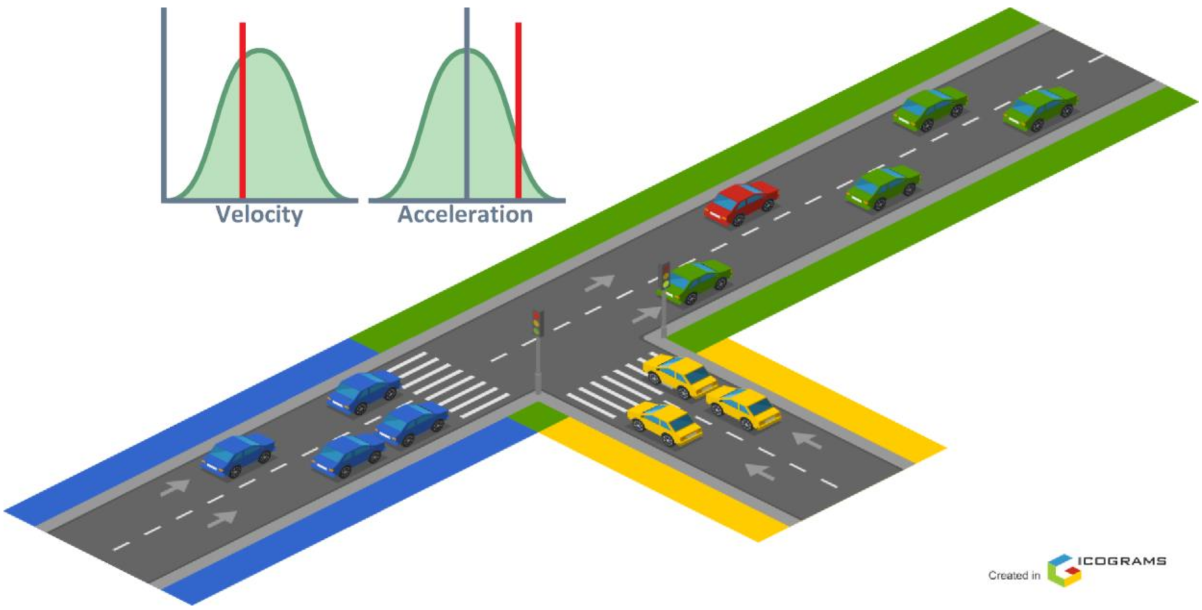

Figure 24 Visualization of comparison of ego vehicle (red) average feature values versus the norm for its current segment (green). Blue and yellow indicate different road segments. Image partially created with icograms.com.

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In order to be able to describe and analyse clustering results, our metric relies on velocity and acceleration, which are both features of driving behaviour and related to crash risk. Higher velocities are associated with an increase in risk of crashes (Kloeden, 1997) (MoRT&H, 2018) (Elvik, 2009) (Taylor, 2000). Besides this, higher velocities are correlated with the impact velocity of a crash, leading to more severe crashes (Elvik, 2012) (Nilsson, 2004). Further, aggressive acceleration and deceleration events, when a driver applies more force to the pedal than during normal driving, are associated with a larger risk of collision (Ellison, 2015) (LeBlanc, 2010).

The K-means (Lloyd, 1982) algorithm is used for the clustering. Finally, the naturalistic driving pNEUMA dataset (Barmpounakis, 2020) was used to develop and validate our metric. A more extensive description of our statistical driver profiling metric will be part of Deliverable 2.14.

3.1.2 Objective of the analysis

As mentioned above, our aim is to use driver profiling to describe and cluster the behaviour of the driving agents in the Alpha-type simulations environment.

Per simulation we will extract the longitudinal velocity and acceleration for each driving agent per timestep. This includes both the agents using the human driver model and those using the AV model. As our metric clusters drivers based on their deviation from the average driving behaviour per road segment, it is necessary to also partition the simulated road network into separate road segments. The network used in the simulations already consists of separate road segments that are joined together. Thus, we will take these segments into account for analysis as well.

We expect the simulated network(s) to have several segments such as straight roads, t-sections, crossings and pedestrian crossings. In clustering behaviour, only data from road segments will be used for which the simulation agents are able to show behaviour which leads to critical driving situations. Deliverable D2.2, Section 2.2, states the following about the human driver models:

> ‘In the implementation, the model overrules the default lane-change, car-following and gap-acceptance driver models in Aimsun Next. However, in order to model other traffic situations in microsimulation, such as giving way and stopping for red light, the Aimsun Next default models are used.’

Because of this limitation we do not expect to use the more complex segments of the network like crossings in our behaviour profiling, as the human driver model is not able to show behaviour in these situations which could become safety-critical. The road segments that are used for feature extraction will only consist of straight one-way sections of the road. A detailed description on how the acceleration and velocity features on these road segments are processed in order to extract the features that are used for clustering will be available in Deliverable 2.14.

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For each variation of the simulation, with and without AV’s, we will cluster the agents based on the previously described features into different clusters. These clusters for each simulation can then be described based on the statistics of the cluster. This way clusters will be interpreted as driver profiles. With these profiles two separate analysis will be executed.

Firstly, we will look at profile clusters within each run of the simulation. Here the main objective is to validate if there is a correlation between parameters of initialized agents which influence the safety of the agent’s behaviour and the found driver clusters. During the initialization of the simulation, there are parameters that can influence the behaviour of driving agents. For example, the human driver model is initialized with a task capacity from a fixed distribution (for reference see deliverable D2.2, Section 2.4.5). This describes the maximum capacity of the driver to do the driving tasks and can be based on driver characteristics such as age or driving experience.

As these parameters influence the behaviour of the driving agent, they should also influence the features that are used for the clustering. We expect to find that there is a relation between the different behaviour parameters and the chance for an agent to fall into a cluster that is identified as a profile which show unsafe driving behaviour. What kind of relation this will be, is not possible to say yet, as this depends on the clusters that will be found during the analysis.

Secondly, the profiles from clusters of different variations of simulations will be compared. The aim is to see if replacing part of the agents for AV’s will change the driving behaviour of both the AVs as well as the other agents in the simulation. We will do this by comparing the kind of clusters that are found in the different simulations.

The analysis will look for differences in the overall statistics of the different clusters of the simulations. This is done with the aim to see if we can map the clusters from one simulation to the other one. Here we try to answer the questions:

- Do we see the same clusters in the different simulations?
- How do the statistics of the same kind of clusters change in the different simulations?
- Do we see new clusters appearing or clusters disappearing when AV agents are added to the simulation?

Besides this, we want to compare the sizes of similar clusters in different simulations and see what kind of agents fall into the different clusters. By doing this we want to answer the questions:

- Do we see a shift in numbers between the simulations for the sizes of driver profiles which are interpreted as safe and unsafe driving profiles?
- Do we see such a shift happening only in the driving profiles of the new AV agents, or also in the agents acting according to the human driver model?

Note that this metric will not directly show safety critical interactions, but at most show that an agent overall behaviour can be described as falling in some driving profiles based on

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features, which serve as proxies to safety critical scenarios. This, however, can already give some insight in how the introduction of the AV model changes the safety situation in the simulation.

3.1.3 Initial results

In the workshop a first set of simulations was created to test if a comparative analysis is possible, based on the simulations with the agents developed in WP2. More specifically, these simulations were focused on the human driver model developed by TNO in WP 2.3. Two simulations were set up in such a way that there was a difference in the human driver distraction level between them. The first simulation was run with drivers with a normal level of distraction and task capacity. A second simulation was run with “distracted” drivers with a very low task capacity. The aim of this experiment is to see if a comparative analysis with the different developed metrics is possible. For this reason the difference in distraction between the two simulations was set to extreme values to make it easier to analyse.

Here, a small analysis is conducted of these two simulations where we will look more closely at the measured behaviour of the driver agents in parts of the simulation.

We needed to find out if the agents were driving on our segments of interest for each measurement. Only global coordinates are available. However, to create driver profiles, it is important for their comparison to divide the road in segments. For this reason two segments were selected for these simulations. In Figure 25, the trajectories of all agents are plotted as well as the boundaries of the two manually created segments.

For both simulations the acceleration and velocity measurements are aggregated of all human driver agents which drove within segment 0 and 1. We only aggregate measurements for which the velocity is higher than 0.1 m/s. This way we can see the overall velocity and acceleration behaviour of the human drivers in both segments. In Table 3 you can see the number of unique drivers which have driven through these two segments in the two simulations.

Table 3: Unique drivers in each segment for both simulations.

	“Normal” drivers simulation	“Distracted” drivers simulation
Segment 0	77	131
Segment 1	47	73

In Figure 26, Figure 27, Figure 28, and Figure 29 violin plots for the velocity and acceleration for the normal driver simulation and distracted driver simulation in the two segments are given. What we can see is that the distribution of different kinds of accelerations is much broader in the simulation with the distracted drivers. The mean velocity is also higher in the simulation with the distracted drivers. As both more extreme acceleration values and higher

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speed are both proxies for safety critical situations, we could say that the simulation with the distracted divers is more prone to safety critical scenarios.

To really employ the full behaviour profiling technique we would need more information about segment partition of the whole road network in the simulation. Besides this, longer simulations would be helpful to make the amount of data that is used in the normalisation of the driver profiles bigger.

The measurements also show unrealistic acceleration values, especially for the “distracted” drivers. This is expected as the distraction levels in the simulation are set to extreme values, but it also shows the importance to better calibrate the simulations. We will aim to do this by comparing these segment-based distributions to the distributions in natural driving datasets such as PNEUMA.

To conclude, this small simulation with the analysis of only 2 segments shows that some degree of comparative analysis based on driver profiling is achievable using the developed human driver model. But for the final simulations, more attention has to be given to scaling them, and tuning them on natural driving data.

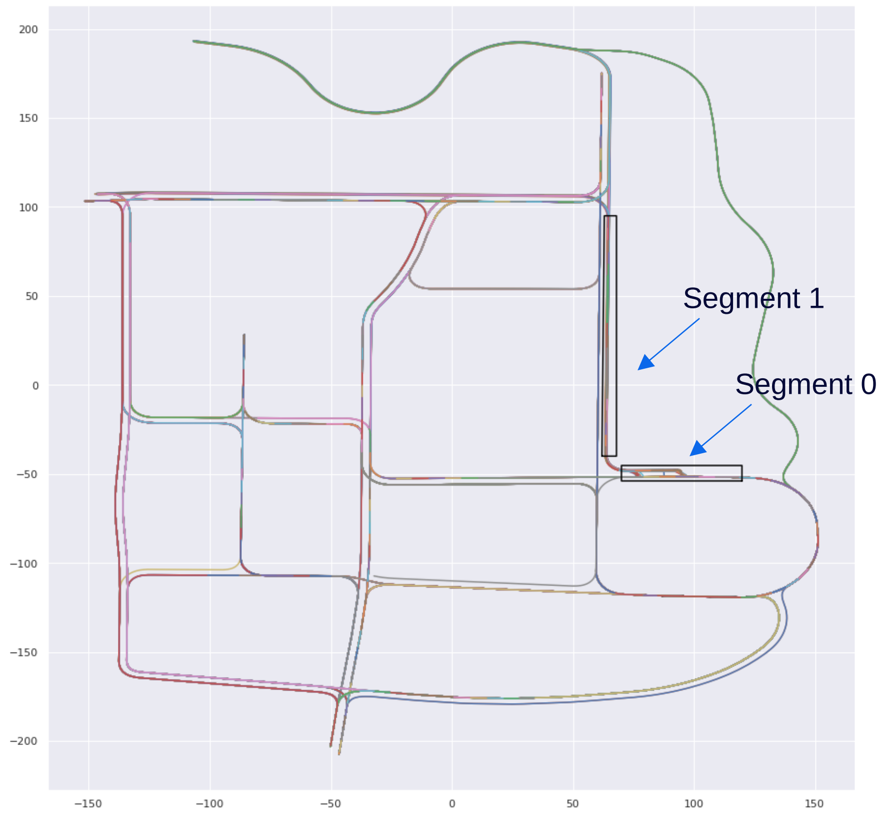

Figure 25: drawn trajectories of Human Drivers in Simulation 1. Also the two extracted segments are drawn in the figure.

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- Acceleration behaviour

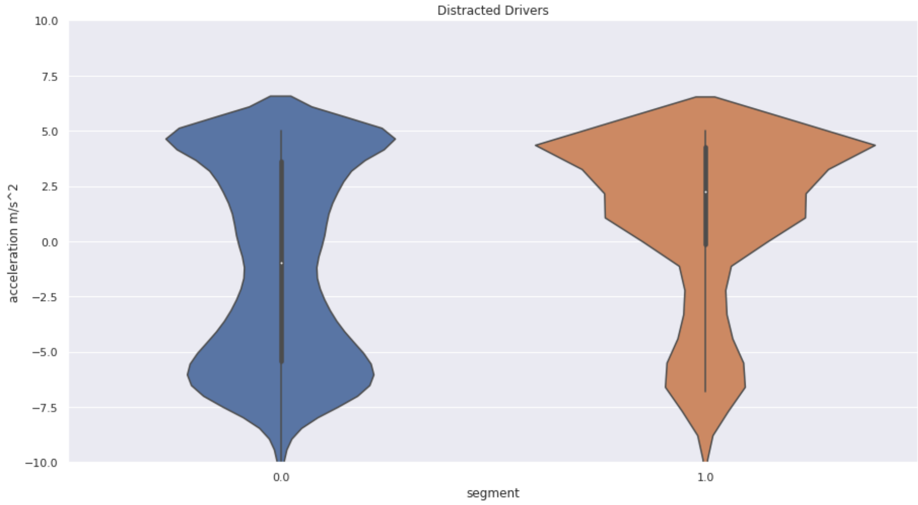

Figure 26: Acceleration behaviour in segment 0 and 1 for distracted drivers.

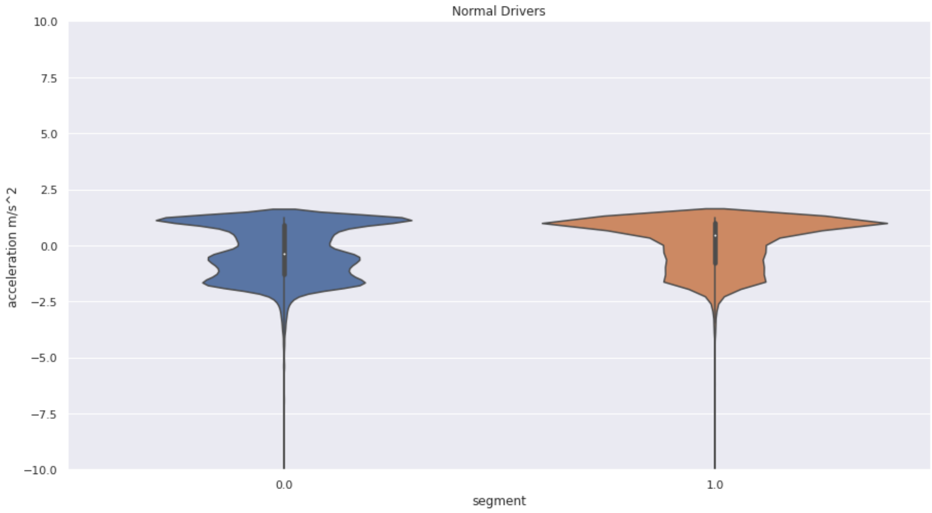

Figure 27: Acceleration behaviour in segments 0 and 1 for normal drivers.

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- Velocity behaviour

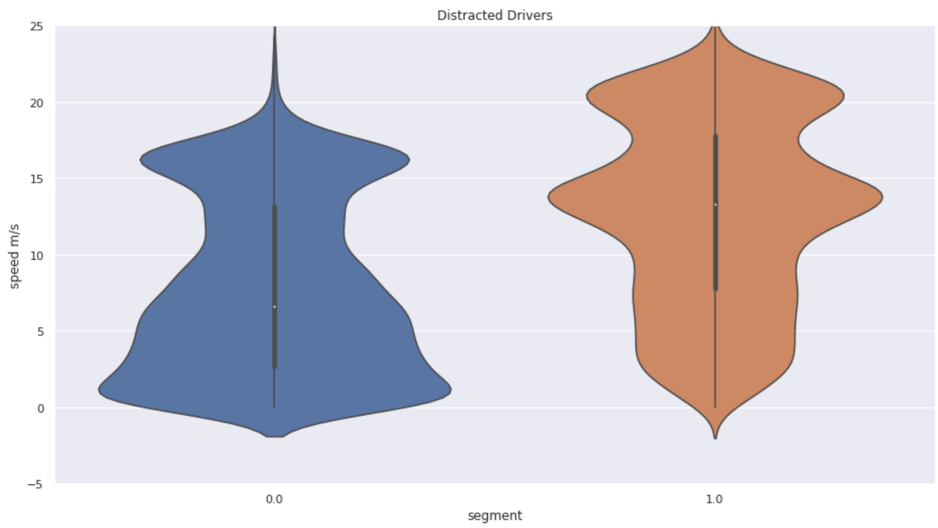

Figure 28: Velocity behaviour in segments 0 and 1 for distracted drivers.

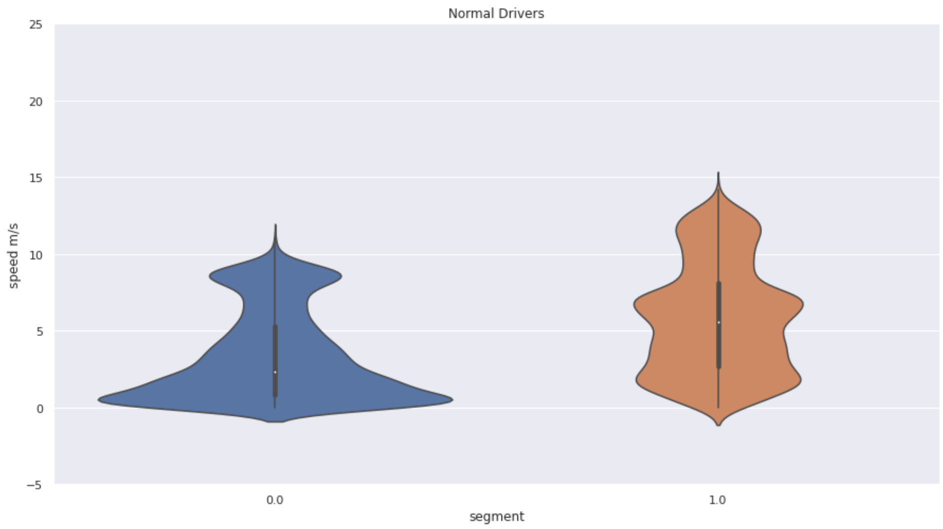

Figure 29: Velocity behaviour in segments 0 and 1 for normal drivers.

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3.2 Pedestrian and bicycle critical situations (IKA)

3.2.1 Technical summary

When considering critical driving scenarios, bicyclists and pedestrians represent a particularly vulnerable group of potential road users. Since they do not have any chassis to protect their body in case of collisions there is a higher risk of being severely injured in Car-VRU interactions (Chaurand & Delhomme, 2013). For this reason, the analysis of the behaviour of the VRUs is of particular relevance for the assessment of future critical scenarios.

Against the background of this, an extensive literature review was conducted as part of Task 2.2. As a result of this research, there are two different aspects to consider.

First, as described in D2.5, human factors such as frustration were shown to have a major influence on road behaviour (Dittrich, 2020), which can lead to critical situations especially in interactions with other road users (Oehl, Brandenburg & Huemer, 2019). Secondly, it was found that literature regarding metrics for assessing critical situations in the Car-VRU interaction are rare. Therefore, classic KPIs adapted to the special situation of car-to-VRU interaction are to be used as surrogate measures of safety (SMoS) to identify critical situations in the further analysis.

The combination of the human factors approach with SMoS that define a critical situation is one goal of the user study conducted in Task 2.3. This study, described more in detail in D2.14, examines the hypothesis of whether the level of frustration alters the VRU behaviour in traffic situations.

In the following, the metrics that should be used for the simulation analysis as well as the planned procedure will be described in detail.

3.2.2 Objective of the analysis

Based on the research in Task 2.2 and the much higher severity of crashes caused by a motorized road user, the focus of the evaluation metric will be on the interaction between motorized road users and VRU's (pedestrians and bicyclists). The risk of injury is much higher for VRU's than motorized road users due to the extreme differences in mass, speed, and object density.

Due to these energetic differences and the hazard potential starting from motorized road users, SMoS are used to determine the safety critical scenarios. The main difference is the determination of the relevant thresholds.

The pedestrian creates a traffic situation as soon as he enters a traffic lane. This is a potential safety-critical scenario, since the pedestrian's trajectory can be crossed by other road users. The following SMoS are used to identify the safety-critical scenarios:

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- Deceleration to Safety Time (DST)
- Time to Headway (THW)
- Time to Collison (TTC)
- Post Encroachment Time (PET)

A detailed definition of each SMoS, the corresponding influence on the model behaviour and the relevance of each metric can be found in Deliverable 2.14.

The cyclist has a lane-independent driving behaviour and is characterized by a much more agile and a more unstable lateral driving behaviour compared to the dynamics of motor vehicles. Especially the continuous observation of the lateral and rear surrounding traffic is much more difficult on a bicycle. The following SMoS are used to identify the safety-critical scenarios:

- Longitudinal:
  - Time to Collison (TTC)
  - Time to Headway (THW)
  - Deceleration Rate to Avoid Collision (DRAC)
  - Proportion of stopping distance (PSD)
  - Post Encroachment Time (PET)
- Lateral:
  - Lateral distance
  - Lateral TTC
  - Lateral THW

Just as for pedestrians, the exact definitions of each SMoS, the corresponding ways to influence the model behaviour, and the relevance of each metric can be found in detail in Deliverable 2.14. Due to the high relative speeds between cyclists and the other road users, overtaking manoeuvres provide new lateral hazard potentials. Thus, in addition to the classical longitudinal SMoS known from the literature, we also have lateral potential collisions. Lateral TTC, lateral THW and lateral distance are used to analyse these lateral collisions.

An essential component for the identification of safety-critical scenarios are the thresholds for the individual SMoS. The determination of the relevant values is based on the known limits in the literature for vehicle to vehicle interactions, road traffic regulations and possibly on potentially relevant datasets from industry partners from the SafeUp project. The exact determination of the parameters can be found with the detailed description of the SMoS in Deliverable 2.14.

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The first step of the analysis is to calibrate the behavioural parameters (such as distraction, state of mind, etc.) of the pedestrian and cyclist models. This is an iterative process in which selected simulations will be performed according to the evaluation from **step c** (listed below) and the parameters of the models will be changed according to an initialization variant.

Basically, the identification of safety-relevant scenarios is carried out according to the following principle:

a. **Implementation of VRU relevant scenarios in the context of a baseline (Aimsun):**
   - For pedestrian, scenarios at crosswalks are relevant.
   - For cyclists, scenarios with potential collision partners in longitudinal and lateral directions are necessary.
   - Recording of all relevant object data.

b. **Repeat VRU relevant scenarios with integration of AV's (Aimsun).**
   - Focus on the same scenarios as step a.
   - Recording of all relevant object data.

c. **Identification of safety relevant scenarios.**
   - Based on the selected SMoS, the corresponding values are calculated.
   - A safety critical scenario is identified as soon as a threshold value of the SMoS has been reached.
   - As part of the analysis, the occurring critical scenarios are listed and a comparison is made between the simulations.

3.2.3 Initial results

This section describes the evaluation algorithm and the visualization form for the VRU's. The algorithm is based on the presented metrics and the fzp file generated by Aimsun Next after a simulation run. Using this file, all potential conflict situations for cyclists and pedestrians are checked. The evaluation process is basically divided into two parts. A calculation algorithm and a visualization software. The schematic structure of the algorithm is shown in Figure 30.

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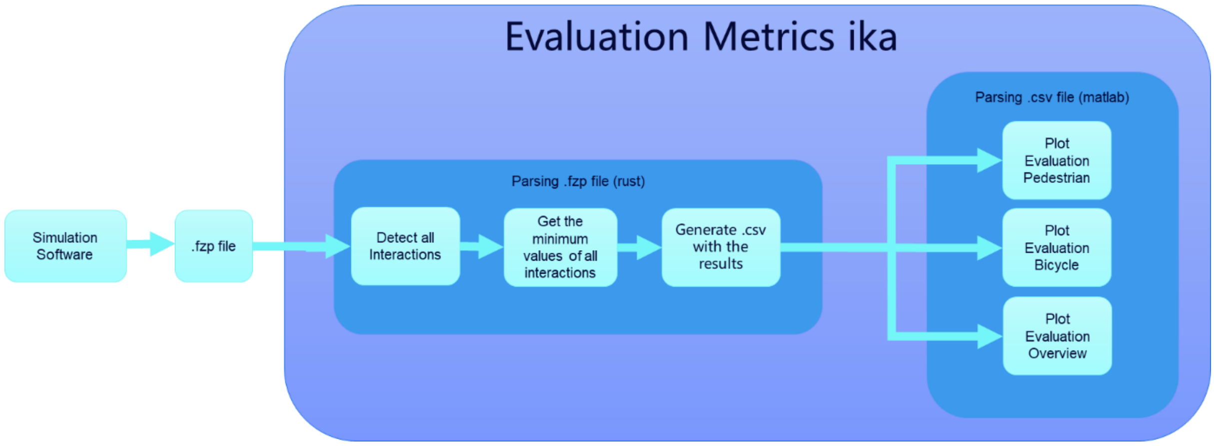

Figure 30: Schematic structure of the evaluation algorithm

Based on the timestamp, the absolute position, and the velocity, the first step is to check which objects in a radius of 100m are potential conflict partners. In the next step, the potential conflict partners are observed over time and the relative behaviour to each other is analysed. On this basis the selected metrics are calculated for each time step and the most critical values of a conflict pair are searched. The output of the calculation algorithm provides a table with the most critical values of all metrics for a conflict pair over the entire simulation period.

The second part of the evaluation deals with the visualization and interpretation of the selected data. Currently, three display variants are possible:

I.) Analysis of conflicts between pedestrians and vehicles based on one fzp-file

II.) Analysis of conflicts between cyclists and vehicles based on one fzp-file

III.) Direct comparison between two simulation runs with at least two fzp-files

In the following, the third representation type for pedestrians and bicyclists is discussed in more detail and the corresponding differences are highlighted by the simulation runs. Two simulation runs with significant parameter variation in the driving behaviour were selected to better underline the differences in the representation form.

In Figure 31, the selected metrics for the pedestrian are represented by histograms. Based on the described algorithm, the critical collision parameters of the simulation run are determined and displayed. The sum of all detected situations and the most critical parameters are shown. In blue the values of the first and in brown the results of the second simulation run are shown, so that they can be directly compared with each other. The red boxes in the diagrams highlight the range that is considered critical. These threshold values are based on the results of D2.6, which has been determined with the help of the GIDAS data.

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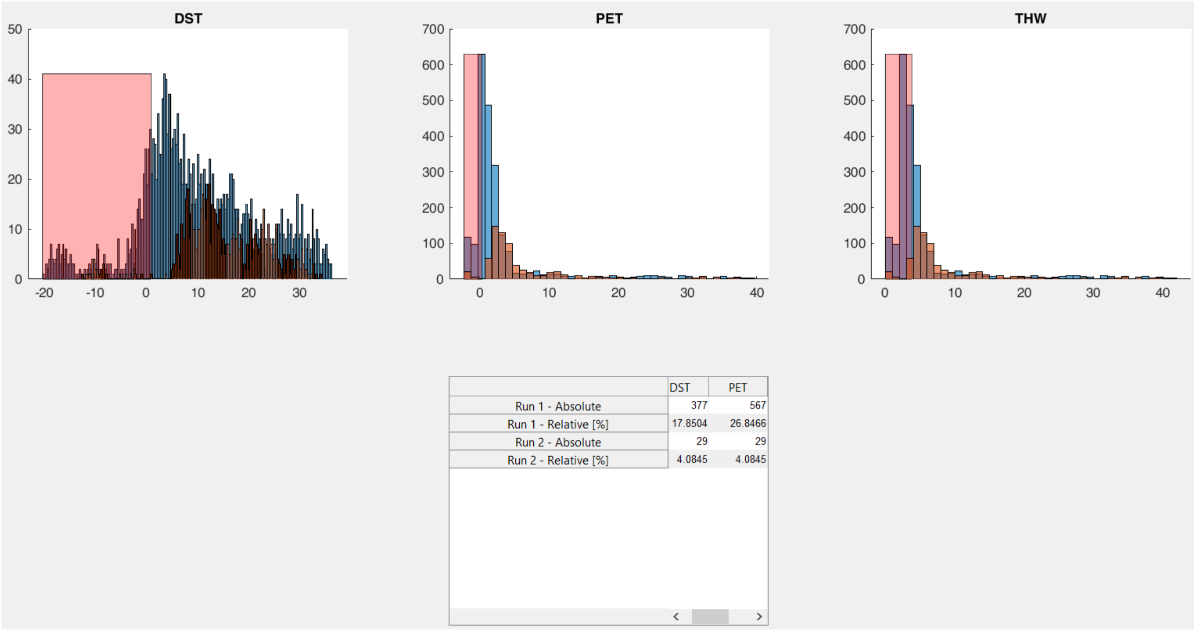

	DST	PET
Run 1 - Absolute	377	567
Run 1 - Relative [%]	17.8504	26.8466
Run 2 - Absolute	29	29
Run 2 - Relative [%]	4.0845	4.0845

Figure 31: Evaluation Overview Pedestrian

In this example, the simulation run with the blue bars shows a much more critical traffic environment than the brown one, since the brown histogram is shifted to the less critical area relative to the blue one and thus has fewer interactions in the red area. In addition to the histograms, there is also a table in the evaluation that supports the analysis with numerical values. The "Absolute" line shows the number of all detected critical situations and the "Relative [%]" line shows the percentage of critical situations in relation to all detected situations. This makes it possible to directly assess how the number of critical interactions has changed and whether there are generally more conflicts due to the parameter variation.

Figure 32 shows the corresponding analysis of the conflict situations for the cyclist based on the sample files. The histograms are similar to the analysis of the pedestrian. The differences are primarily in the selection of the metrics.

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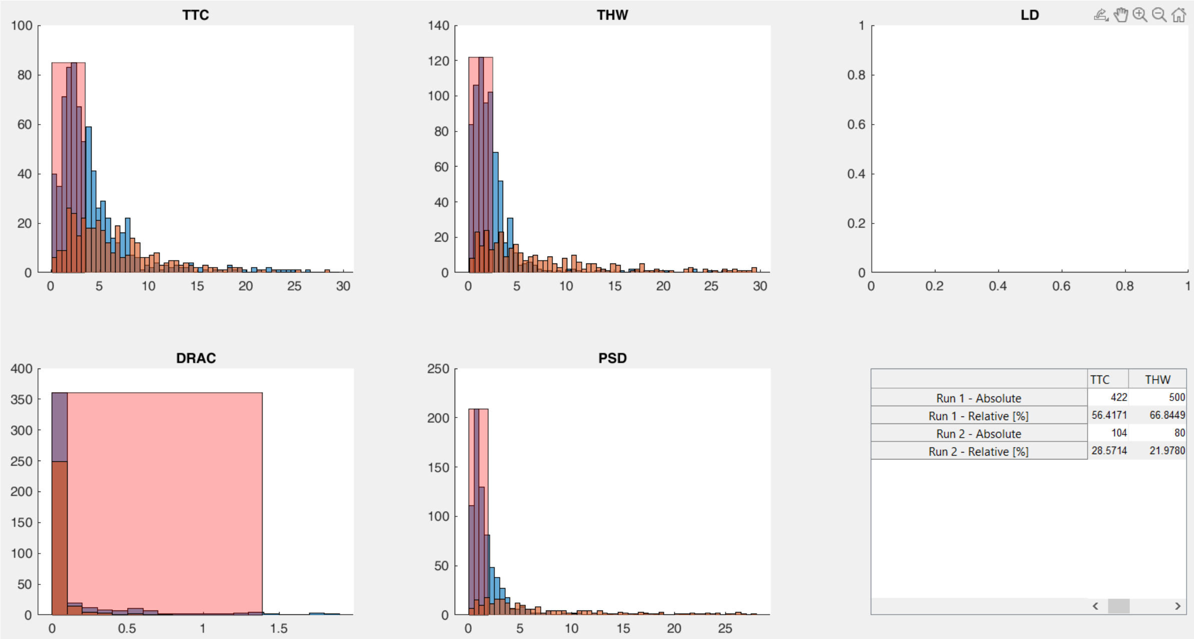

Figure 32: Evaluation Overview Cyclist

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3.3 Driving risk of car-to-car interaction (TUD)

3.3.1 Technical summary

During on-road driving, the neighbouring traffic environment, especially for the neighbouring vehicles, can vary dynamically. The subject vehicle is not certain about the future motion of its neighbouring vehicles and consequent crash outcome. Uncertainty, therefore, is an inherent component of the driving risk estimate. However, SMoS do not typically account for this uncertainty.

Using the paradigm of artificial field theory, we propose an approach to assess the driving risk for car-to-car interactions named Probabilistic Driving Risk Field (PDRF). The proposed car-to-car SMoS PDRF considers the probability of motion predictions of neighbouring vehicles and consists of a crash severity term and a collision probability term. The subject and neighbouring vehicle's possible positions and associated probabilities at discrete future time steps are predicted. The collision probability is modelled as the likelihood of overlap in the predicted spatial configurations of the subject and neighbour vehicle, under the assumption of motion prediction. The risk can be estimated for a single time step or over multiple future time steps, depending on the required temporal resolution.

The PDRF metric at time t is calculated as the product of the collision probability and the expected crash severity,

$$\text{PDRF} = c^{(t+t_f)} \cdot s \tag{1}$$

where $c^{(t+t_f)}$ is the obtained collision probability at time $t + t_f$. The expected crash severity s considering the vehicle mass and velocity is constructed as

$$s = 0.5M\beta^2(\Delta V)^2 \tag{2}$$

where M is the mass of subject vehicle, $\beta = \frac{M_n}{M_n+M}$ the mass ratio with M_n denoting the mass of neighbouring vehicle, and ΔV the relative velocity between subject and neighbouring vehicle.

3.3.2 Objective of the analysis

A general procedure to employ the developed SMoS PDRF for car-to-car interactions PDRF is as follows.

1. Generate benchmark simulation scenarios for calibrations. The safety-critical car-to-car interactions have been identified in advance by manual labelling or other classic SMoSs (e.g., SSAM module).

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2. Pre-process trajectory files from simulation platform Aimsun. To enable offline simulation analysis, the generated trajectory output with labels should be further processed before using as input for PDRF.
3. Calibrate parameters of the PDRF, including prediction time horizon, normal distribution parameters, and the threshold for safety-critical event identifications. Check whether the calibrated PDRF has a comparable/advanced performance compared to the metrics in SSAM.
4. Employ PDRF in line with the overall simulation analysis procedure designed in T2.5. Ideally, PDRF will be employed to identify car-to-car interactions for a set of scenarios, where initial traffic settings, especially the penetration rate of AVs, vary. Distributions of the PDRF corresponding to different trajectory settings are to be obtained, and their corrections are to be analysed. In doing so, certain particular properties in future traffic scenarios involving AVs are expected to be revealed.

To underpin the employment of PDRF and corresponding analysis based on the simulation platform, we introduce each step-in details.

Benchmark Simulation Scenarios

A benchmark of vehicle trajectory dataset including safety-critical/non-safety-critical identification labels is essential to calibration and validation of a car-to-car SMoS. To evaluate the performance of a SMoS we require accurate classifications of car-to-car interaction trajectories. To this end, we not only need to generate trajectories from the integrated traffic simulation platform Aimsun, but also to identify the driving risk for further use.

We may identify the driving risk and manually label a small set of simulated trajectories. However, for a large set of driving trajectories, an automated labelling approach is required. This calls for existing and well-recognised risk indicators.

By further analysing the predicted trajectories and their intersecting points, it is possible to derive some indicators which give more information about the potential collision (Lefèvre, Vasquez, & Laugier, 2014). Popular indicators of the criticality of a potential collision could be the velocity of the vehicles (Kaempchen, Schiele, & Dietmayer, 2009), the amount of overlap between the shapes representing the vehicles (Ammoun & Nashashibi, 2009), the probability of simultaneous occupancy of the conflict area by both vehicles (Seeliger, et al., 2014), and the configuration of the collision (Kaempchen, Schiele, & Dietmayer, 2009). The information provided by these indicators can 9be used to classify the simulated trajectories. Popular risk indicators are based on a measure of the “Time-To-X” (or TTX) where X corresponds to a relevant event in the course toward the collision. Besides, we can also introduce risk indicators based on unexpected behaviours. For example, a vehicle proceeding in an intersection when only a very short gap is available will not necessarily result in a collision, but most drivers will consider it to be dangerous since they expected the vehicle to wait for a larger gap. Two types of approaches, i.e., detecting unusual events

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(Worrall, Orchansky, Masson, & Nebot, 2010) and detecting conflicting manoeuvres (Aoude, Desaraju, Stephens, & JP, 2012), could be considered.

In conclusion, along with the trajectory generation from the traffic simulation platform Aimsun, we also select a bunch of classic and well-recognised SMoSs to identify and label safety-critical events in the simulated trajectory benchmark. The thresholds for the selected SMoSs are determined in line with recommendations in T2.2 Deliverable 2.5. One trajectory sample is labelled as safety-critical once *n* out of *N* selected SMoSs are identified as risky (here *n* could choose 1, and *N* is the number of entire selected SMoSs).

Pre-process trajectory files

To enable offline simulation analysis, the generated trajectory output with labels should be further processed before using as input for PDRF. In doing so, several issues are to be addressed.

A careful selection and process of trajectory output format should be first considered. The current Aimsun simulation platform provides several formats for trajectory output, including FZP and TRJ formats with different attributes. It is observed that the FZP output file has a clear head file and contains more attributes than that of TRJ for each vehicle at each time step. Thus, in line with the current settings, we select FZP output file and extract information from it for the proposed PDRF.

A suitable coordinate transfer is also necessary for correctly employing the proposed car-to-car SMoS PDRF. The current formulation of PDRF assumes that the road longitudinal direction is along the X-coordinate, while the lateral is along the Y-coordinate. However, the realistic road network generating from the simulation platform Aimsun cannot always match the global X-Y coordinate, and a transformation from the global coordinate to the local road coordinate is required to align with the vehicle acceleration distributions along the longitudinal and lateral directions of the road.

Besides, the current calculation of PDRF does not consider the impact on road curves. An additional output file including road network geometry information may be also included to enhance the calculation accuracy of PDRF.

PDRF Calibration and Validation

We have calibrated PDRF with simulated highway cut-in events in T2.2. To underpin the employment of PDRF for simulated trajectories, further calibration and validation is required. The parameters associated with PDRF to be tuned include a threshold value and the normal distribution parameters along two directions and the prediction horizon.

It is worth noting that PDRF is calibrated over an imbalanced benchmark, since safety-critical events are rare and constitute only a small portion of the driving trajectories in practice. It has been demonstrated that classification probability calibrated with imbalanced scenarios systematically underestimate the probabilities for minority class instances, despite ostensibly overall good calibration (Wallace & Dahabreh, 2014). To ensure an accurate identification of the rare safety-critical events, which we are more interested in, two potential solutions are proposed.

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The first approach is to balance the number of safety-critical and non-safety-critical samples in the benchmark, and then use F score as the optimisation objective during the calibration process. Here F-score is a measure of PDRF's performance. It is calculated from the precision and recall.

$$F_1 = 2\frac{\text{precision}\cdot\text{recall}}{\text{precision}+\text{recall}} \tag{3}$$

Where the precision is the number of true positive results (i.e., those safety-critical events that have been correctly identified) divided by the number of all positive results, including those not identified correctly. The recall is the number of true positive results divided by the number of all samples that should have been identified as positive.

The alternative approach is directly using a more general F score calculation over the imbalanced benchmark, and the importance of safety-critical events can be reflected by a positive real factor β:

$$F_\beta = (1+\beta^2)\frac{\text{precision}\cdot\text{recall}}{\beta^2\cdot\text{precision}+\text{recall}} \tag{4}$$

We plan to combine the calibration and validation process by using a *k*-fold cross validation (Rodriguez, Perez, & Lozano, 2010). We shuffle the generated benchmark randomly and split the benchmark into k groups. For each unique group, we repeat the same procedure: take the group as a validation dataset and take the remaining groups as a calibration (training) dataset. Then calibrate the PDRF on the training set and evaluate it on the validation set. After the separate validation over each unique group, we finally average the calibrated parameters.

Note that we conduct offline analysis with PDRF at the current stage, while we expect using PDRF in an online manner at the final stage. Therefore, the computational efficiency of PDRF is a key factor to evaluate PDRF and the online computation of PDRF needs to be realised and validated at the final stage.

PDRF Utilisation and Analysis

We aim to use PDRF for more accurate and efficient safety-critical events identifications. It is expected that the PDRF after calibration and validation can both accurately identify risky events and well represent the severity extent. The results will be obtained under various traffic flow and vehicle initial state condition settings and compared to that using other car-to-car SMoSs.

For further analysis, it is also interesting to analyse the distributions of PDRF under different simulation settings. Moreover, the correlations between PDRF and other SMoS distributions are to be investigated. While a single SMoS is probably not sufficient to completely identify all safety-critical events, multiple SMoS can (Lu, et al., 2021). To better capture the probability of events that are more extreme than any previously recorded (i.e., the safety-critical events), the extreme value theory or extreme value analysis (EVA) is adopted to

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address the extreme deviations of the safety-critical events from the median of probability distributions. Specifically, an EVA with multiple SMoS is thus to be conducted, since evidence has shown the outperformance of multivariate extreme value analysis compared to the univariate and bivariate counterparts for safety-critical scenarios (Bakhshi & Ahmed, 2022). We plan to use and compare both two EVA approaches, the block maxima approach to extract the maxima from divided boxes and the peak over threshold method to extract records whose probabilities exceed a certain threshold. We expect not only to accurately identify safety-critical events, but also to understand potential factors featured by SMoS leading to these events.

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3.4 PTW critical analysis results (Unifi)

3.4.1 Technical summary

- Motivation

Riders of powered-two-wheelers (PTW) are vulnerable road users who represent a significant proportion in the urban environment and should be considered when assessing the safety effects of new traffic conditions, such as the inclusion of autonomous vehicles (AVs). However, most surrogate measures of safety (SMoS) and thresholds for identifying safety-critical events are based on car driving behaviour and typically do not consider the different interactions between PTWs and motor vehicles. Among other characteristics that differentiate PTWs they have a non-lane-based behaviour swerve (Nguyen, Hanaoka, & Kawasaki, 2012). Their dimensions are smaller in width, and they have greater manoeuvrability, so they frequently use shorter safety distances than other classes of larger vehicles such as passenger cars (Walton & Buchanan, 2012; Amrutsamanvar, Muthurajan, & Vanajakshi, 2021).

- Technical description

The Motorcycle Collision Probability Index (MCPI) developed for PTW-car interactions in SAFEUP to identify safety-critical events is based on the Crash Potential Index (CPI) proposed in previous studies for car conflicts (Cunto and Saccomanno, 2008; Wang and Stamatiadis, 2014) and considers multiple factors such as TTC, time Headway and DRAC and establish the risk index based on a distribution of maximum available deceleration rate (MADR) for different rider performances. The MCPI is defined as the probability that a given DRAC for a PTW rider exceeds its MADR during a given time interval. The MCPI index is obtained using an equation of the form

$$MCPI_i = \frac{\sum_{t=ti_i}^{tf_i} P\left(MADR^{(PTW)} \leq DRAC_{i,t}\right) \cdot \Delta t \cdot b}{T_i}$$

Where:

$$\begin{aligned}
&MCPI_i = crash\ potential\ index\ for\ PTW\ i \\
&DRAC_{i,t} = deceleration\ rate\ required\ to\ avoid\ the\ crash \\
&MADR^{(PTW)} = truncated\ distribution\ of\ PWT\ rider \\
&\qquad\qquad performance\ during\ emergency\ braking \\
&ti_i = initial\ simulated\ time\ interval\ for\ vehicle\ i \\
&tf_i = final\ simulated\ time\ interval\ for\ vehicle\ i \\
&\Delta t = simulation\ time\ interval \\
&T_i = total\ event\ time\ for\ vehicle\ i
\end{aligned}$$

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MADR depends on many factors such as vehicle, rider skill or the pavement conditions. To consider the braking performance of PTW riders with different abilities, the MADR is included as a stochastic component where PTW riders with different skills are expected to perform differently during a braking event. The proposed MCPI metric considers the braking performance of PTW riders, so MADR has been adapted by using a truncated normal distribution obtained from 149 emergency braking tests with PTW performed by 13 riders of different skills running at 50km/h in straight section and dry conditions (Huertas-Leyva et al., 2019). The MCPI has been calibrated and tunned using the dataset of naturalistic trajectories pNEUMA which was collected in urban environment (Barmpounakis and Geroliminis, 2020).

The identification of car-following events on and the most important object (MIO) has been done implementing algorithms based on Kusano et al. (2014) methods. Every car-following event with braking is related with a maximum value and an average value of the MCPI. Since the MCPI result is a probability index, the threshold value for determining unsafe and safe events will be defined after analysing the MCPI distributions. This makes this metric more flexible, since in case no collisions or near collisions occur during the simulations, the MCPI results could still be used to compare the safety of different traffic conditions.

Figure 1 shows an example of a safety-critical event identified on a one-lane road section. The example represents a car-following event where the MIO is the leading vehicle (car), and the following vehicle is a PTW (ego vehicle). In this instance, the MCPI identifies an unsafe event, because when the vehicle in the lead (MIO) brakes, the headway distance of the PTW traveling at 40km/h is about 2m before the overtaking. Despite the high risk, this event did not end in a collision because the PTW overtook with minimal swerving and with the minimum possible distance between vehicle centroids corresponding to 1.5m.

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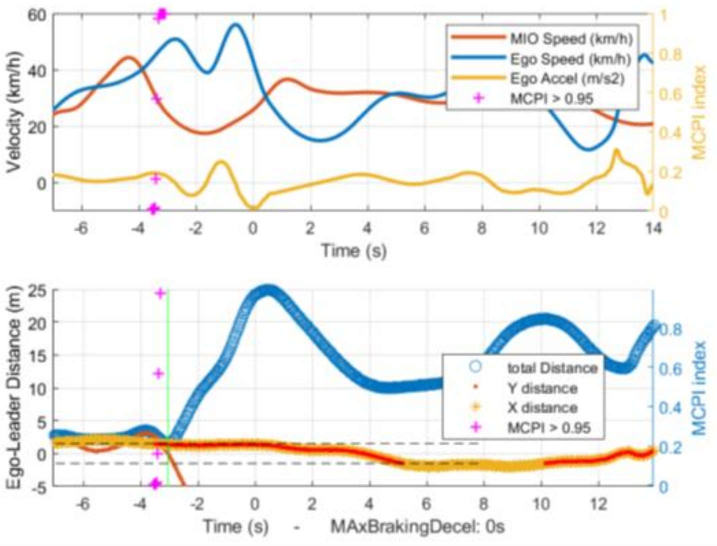

Figure 33: Example of a safety-critical event. Maximum braking deceleration corresponds to T=0s

Additionally, a widely extended standard surrogate measures such as Surrogate Safety Assessment Model (SSAM) will be used to analyse PTW-to-vehicle interactions to identify conflict events during micro-simulations with AIMSUN platform. SSAM calculates several surrogate safety measures for each event, including the following: Minimum time-to-collision (TTC); Minimum post-encroachment (PET); Initial deceleration rate (DR); Maximum deceleration rate (MaxD); Maximum speed (MaxS); Maximum speed differential (DeltaS). Once the trajectory files extracted from AIMSUN have been processed, the number of safety critical events from SSAM will be obtained using the default threshold filters (maximum TTC of 1.50 s and maximum PET of 5.00).

3.4.2 Objective of the analysis

This analysis will generate metrics to identify safety-critical events related to PTW-car interactions occurred during the micro-simulations in AIMSUN platform. First, the baseline of traffic scenarios will be defined during simulations running in an urban traffic network without the inclusion of autonomous vehicle in the traffic conditions. In a second stage, the metric will identify the safety-critical events of the same traffic network with the inclusion of AVs. The objective of this analysis is to evaluate the changes in the baseline traffic scenarios with PTW-car interactions once the behavioural models developed in T2.3 are integrated in T2.4. The safety analysis will be performed through microscopic traffic simulation models based on surrogate measures of safety. Based on the simulated vehicle trajectories exported from AIMSUN, a PTW-car conflict analysis through a standard metric such as SSAM and the metrics defined in T2.2 (MCPI) will be completed.

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The simulation network corresponds to urban roads with mainly one-lane roads. To identify safety-critical PTW-car interactions, three different sections of the simulation urban network (Figure XX), corresponding to straight roads with intersections regulated by traffic signals, will be analysed. The critical events to identify are related mainly to rear-end conflicts and eventually, in case of right of way violations, crossing conflicts with PTW and car driving in perpendicular directions. The identification of safety-critical events will be performed off-line.

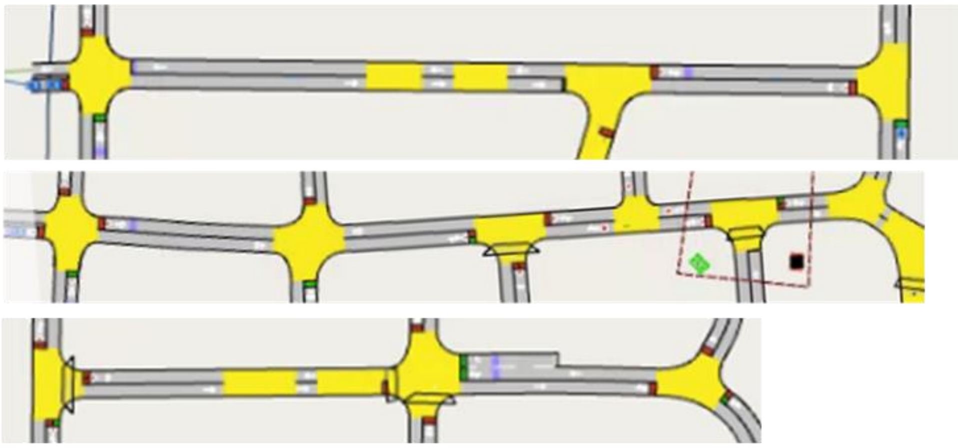

Figure 34: Three road sections selected from the network for traffic micro-simulations

At the end of each simulation the detailed parameters about trajectories generated during the simulation (such as time step, speed, and position) will be extracted and the data will be postprocessed to identify safety-critical events both with SSAM and with the MCPI developed in SAFE-UP. Road-network geometry and traffic states such as traffic lights will be required to improve accuracy of the metric. The metric will focus mainly on rear-end conflicts and conflicts at intersections when

Considering the stochastic nature of the simulation model, simulations will be run as long as required to obtain a more accurate representation of traffic conditions and to extract a significant number of safety-critical/unsafe events with a time step of 0.1s, also taking into account the computational demand of the traffic models. In order to avoid a low accident environment, and to capture a higher quantity of safety-critical events, eventually, the behaviour of the road users modelled will be set to behave in non-compliant way with occasional speeding or long reaction times simulating distraction. Violations such as running red-light will be considered.

A detailed comparison between simulation results will be done following the process described below:

- Run a set of three micro-traffic simulations with AIMSUN platform with three different traffic volumes.
- Repeat the previous microsimulations with AIMSUN platform considering the inclusion of AV as a percentage of the cars.

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- Identification of the safety-critical events according to SSAM and MCPI methods for each traffic simulation. An example of what the results of the identification of safety-critical events may look like for one direct comparison and for the whole set of simulations is presented in Figure 35 and Table 4 respectively.

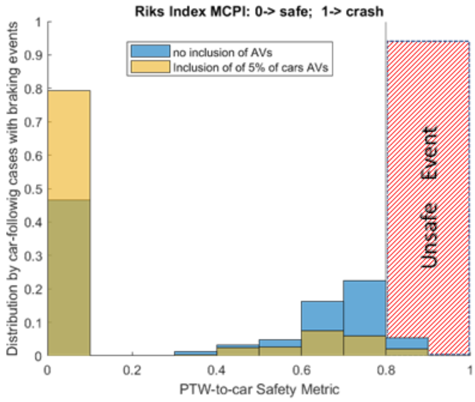

Figure 35: Example of a possible output of the risk analysis with 0.8 as threshold value

Table 4: Table layout of the results to be completed after running the micro-simulations with Aimsun.

AV inclusion	Demand Factor	Unsafe PTW-to-Car Events (Quantity N)		Unsafe PTW-to-Car events per hour (Mean)		Unsafe PTW-to-Car events per hour (Standard deviation)	
		SSAM	MCPI	SSAM	MCPI	SSAM	MCPI
NO (baseline)	50%						
YES	50%						
NO (baseline)	100%						
YES	100%						
NO (baseline)	150%						
YES	150%						

a. To compare the SMoS as recorded by SSAM and by MCPI, the student's t-test will be performed. To evaluate the effect in safety terms of the inclusion of AVs, the t-test will calculate the probability of the difference of the average values of total conflicts for each section under the *baseline* conditions and *the AV inclusion*

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conditions. The possible correlations between SSAM and MCPI results will be analysed. Additionally, the type of conflicts identified will be explored to check if there are significant changes between traffic conditions.

b. Since the MCPI has been calibrated with naturalistic data on one-lane and four-lane road sections, it will require calibrating the MCPI will be calibrated to be adapted to the conditions of the simulation environment designed for the task and readjusting the thresholds to identify unsafe events with higher accuracy.

c. To validate the results, a subset of the identified unsafe events of the results done running a simulation of the critical events found to assess qualitatively the collision risk evaluating the behaviour of the agents involved in the conflict.

d. To validate the results and check whether false positives have been identified, visual audits will be carried out by means of reproductions of the event in which the agents involved, and their trajectories will be simulated (see example of Figure 4). This validation will be performed with a subset of the identified unsafe events.

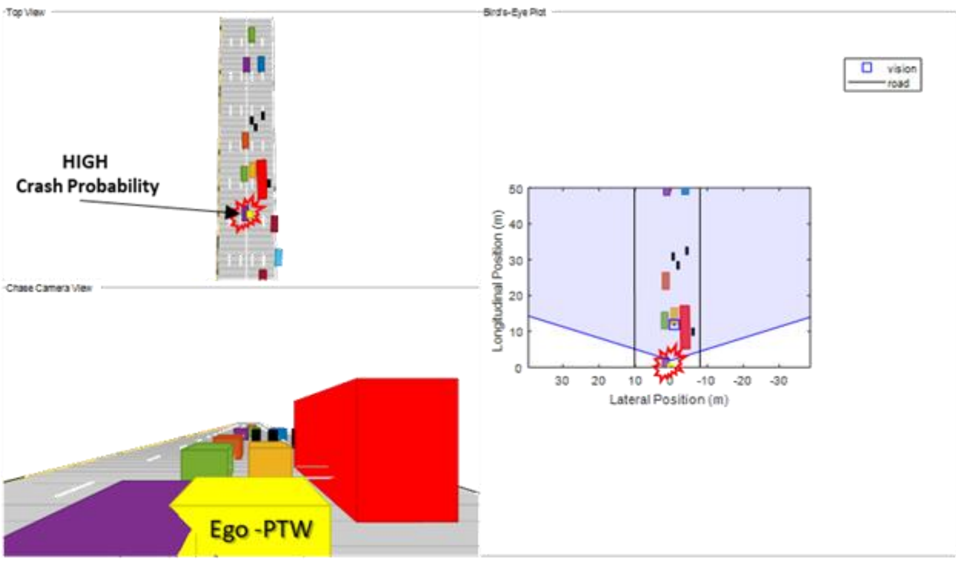

Figure 36: Example of a case where an identified safety-critical event with PTW-car interaction is validated after reproducing a simulation.

3.4.3 Initial results

A first set of preliminary results was obtained during a workshop of the WP2 partners where the different agents were integrated to analyse the safety critical events. Two runs of 10 minutes each were performed with two different conditions: 1) network with Human Drivers running with a normal behaviour; 2) network with Human Drivers running with a "*distracted*" behaviour. The rest of the agents (PTW, bicycles and pedestrians) were running with a normal behaviour in both simulations. From the point of view of PTWs, the aim of the

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simulation was to assess if the change of behaviour of the Human drivers of cars could have an effect on the safety metric linked to PTW-to-car interactions, where the car is in front of the PTW in a car-following scenario. For this a comparative analysis was done on three selected segments of the network (S1, S2 and S3), after extracting the trajectories of all the agents involved and identifying the PTW with braking events (Figure 37).

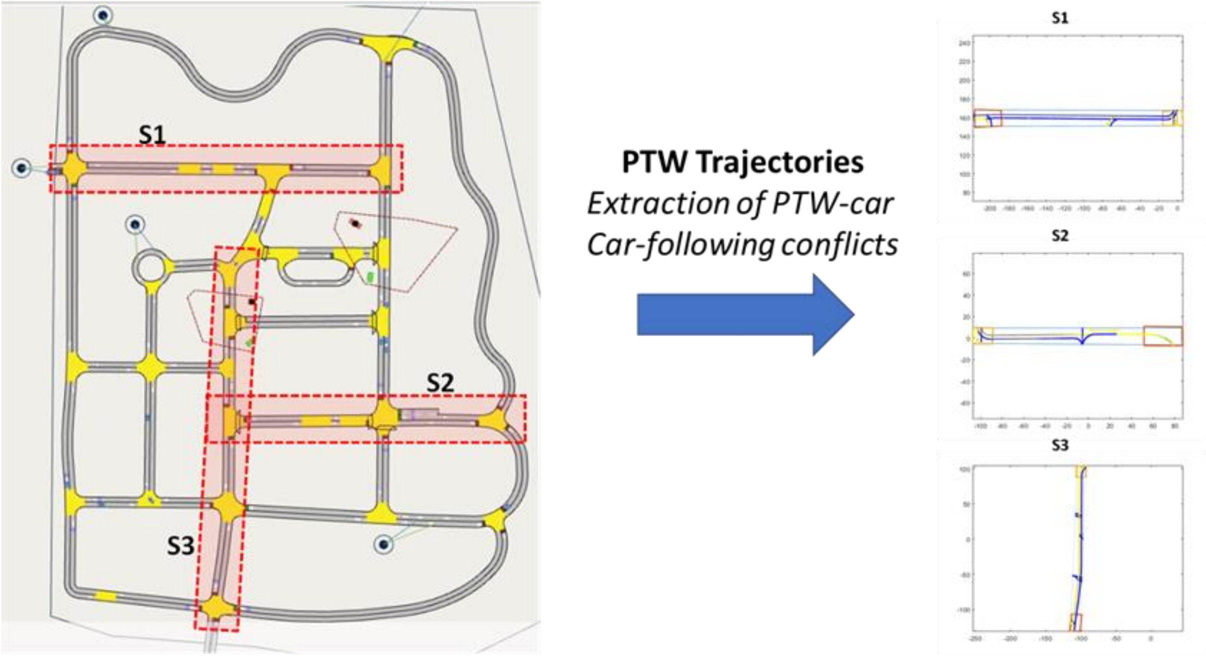

Figure 37: Identification of the segments S1, S2 and S3 for the MCPI analysis by segment and their trajectories during the simulation

For the two simulations performed, the number of PTW braking events identified and the respective number of safety critical events is presented in Table 5 and Figure 38.

Table 5: Results of safety critical events in relation to total events identified with MCPI by section of road and by human driver condition

	Sim 1 (normal drivers)	**Sim 2 (distracted drivers)**
S1	0/4	0/15
S2	0/3	5/13
S3	0/6	0/13

As expected, the condition of ‘normal’ human driver generated no safety critical events in any of the sections analysed. On the contrary the condition ‘distracted’ human driver, could generate 5 safety critical events where the PTW had to brake to a deceleration level that was related to high probability of crash. All the safety critical events were identified on section S2, what could be interpreted as a more potentially risky section than S1 and S3.

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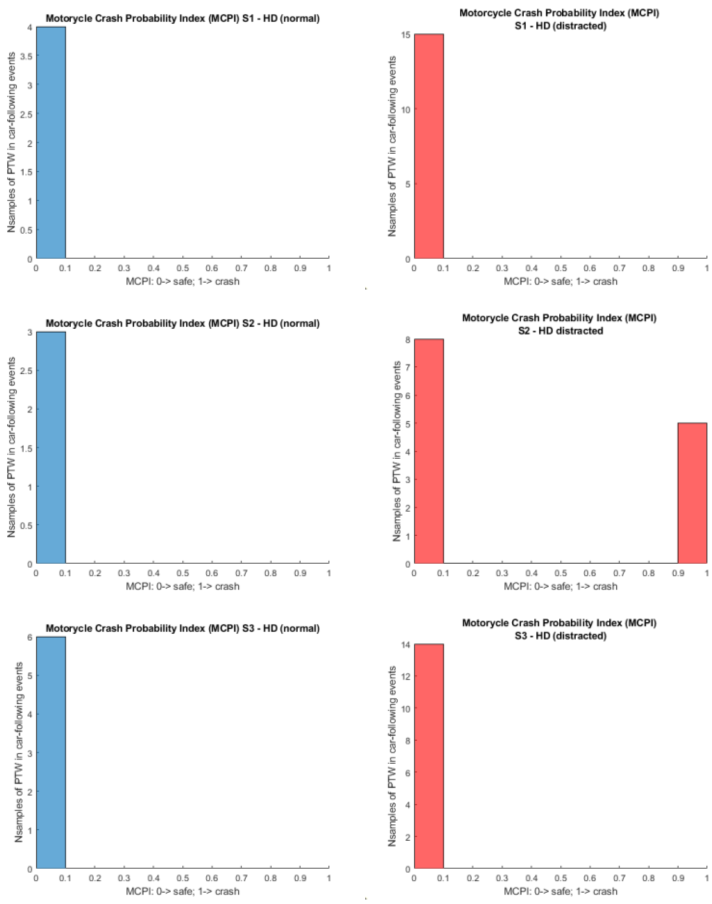

Figure 38: Histograms of MCPI by Section and by human driver condition

Since the sample of PTW was shorter than that of cars, only as an exploratory approach we have used the MCPI for braking car events in S2 supposing the human car drivers were PTW drivers. As Figure 39 shows, the condition human driver distracted identified 14 safety critical events, and 5 cases where there was a slight risk (0.5 > MCPI > 0.1).

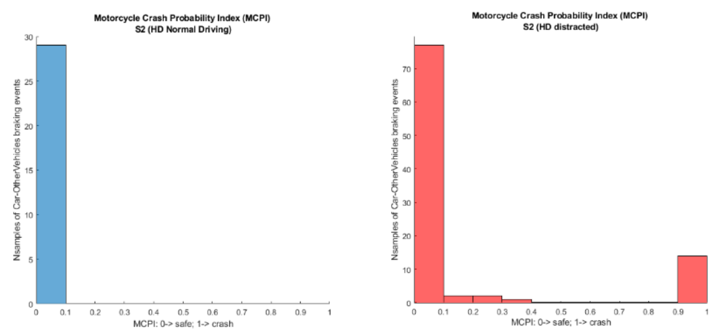

Figure 39: Example of MCPI applied to Car braking events during car-following

Finally, we have to point out that these are preliminary results with short simulations and a small sample of interactions. Besides the models have to be tuned for a better performance

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on the conditions of AIMSUN platform. Nevertheless, the results can be considered as a way of how to use our methodology to identify safety critical events and, consequently, to compare different traffic conditions with a road safety approach.

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3.5 Baseline critical situation analysis (IDI)

3.5.1 Technical summary

Searching for future critical scenarios poses a research challenge in many fronts. To this end, state-of-the-art metrics developed though the WP2 provide novel point of views to analyse traffic scenarios and road users behaviour. To provide T2.5 partners with more analysis tools and data, IDIADA will provide baseline SSAM-based analysis and critical scenario detection.

To this end, a tool provided by USA DoT will be used. This tool provides TTC, PET, and direct metrics of speed and acceleration.

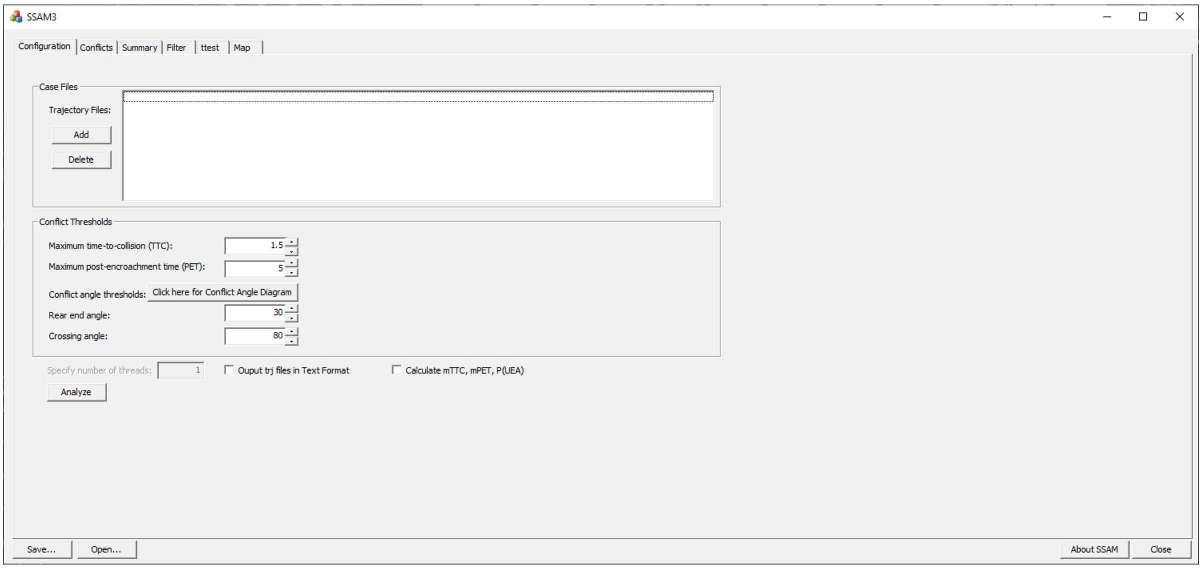

Figure 40: SSAM3 DoT tool

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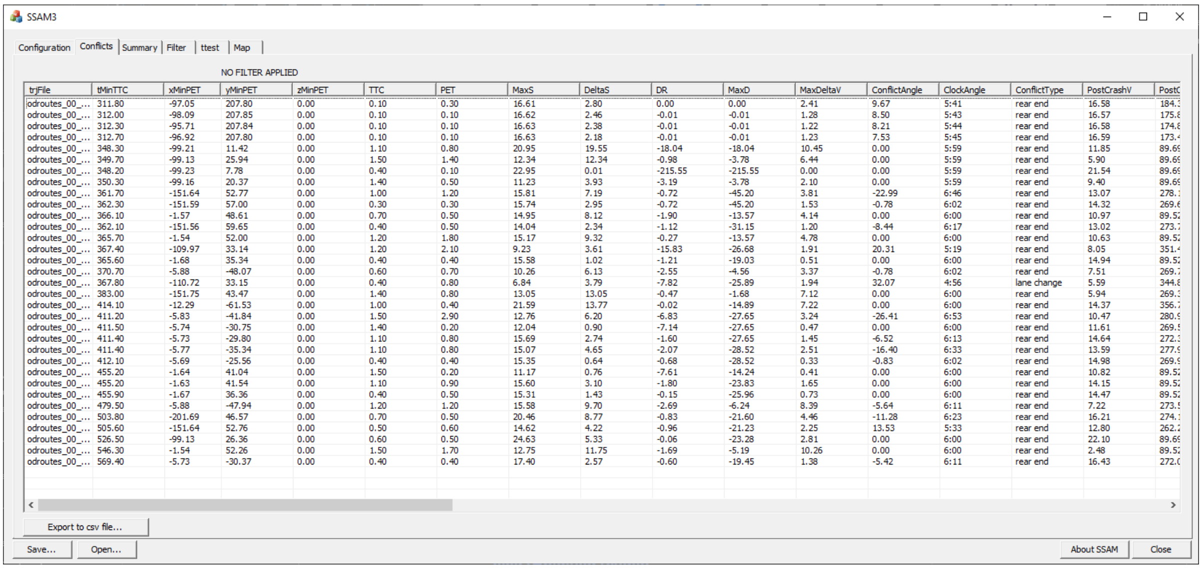

trjFile	tMinTTC	xMinPET	yMinPET	zMinPET	TTC	PET	MaxS	DeltaS	DR	MaxD	MaxDeltaV	ConflictAngle	ClockAngle	ConflictType	PostCrashV	PostC
odroutes_00_...	311.80	-97.05	207.80	0.00	0.10	0.30	16.61	2.80	0.00	0.00	2.41	9.67	5:41	rear end	16.58	184.
odroutes_00_...	312.00	-98.09	207.85	0.00	0.10	0.10	16.62	2.46	-0.01	-0.01	1.28	8.50	5:43	rear end	16.57	175.8
odroutes_00_...	312.30	-95.71	207.84	0.00	0.10	0.10	16.63	2.38	-0.01	-0.01	1.22	8.21	5:44	rear end	16.58	174.8
odroutes_00_...	312.70	-96.92	207.80	0.00	0.10	0.10	16.63	2.18	-0.01	-0.01	1.23	7.53	5:45	rear end	16.59	173.
odroutes_00_...	348.30	-99.21	11.42	0.00	1.10	0.80	20.95	19.55	-18.04	-18.04	10.45	0.00	5:59	rear end	11.85	89.69
odroutes_00_...	349.70	-99.13	25.94	0.00	1.50	1.40	12.34	12.34	-0.98	-3.78	6.44	0.00	5:59	rear end	5.90	89.69
odroutes_00_...	348.20	-99.23	7.78	0.00	0.40	0.10	22.95	0.01	-215.55	-215.55	0.00	0.00	5:59	rear end	21.54	89.69
odroutes_00_...	350.30	-99.16	20.37	0.00	1.40	0.50	11.23	3.93	-3.19	-3.78	2.10	0.00	5:59	rear end	9.40	89.69
odroutes_00_...	361.70	-151.64	52.77	0.00	1.00	1.20	15.81	7.19	-0.72	-45.20	3.81	-22.99	6:46	rear end	13.07	278.
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odroutes_00_...	362.10	-151.56	59.65	0.00	0.40	0.50	14.04	2.34	-1.12	-31.15	1.20	-8.44	6:17	rear end	13.02	273.7
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odroutes_00_...	370.70	-5.88	-48.07	0.00	0.60	0.70	10.26	6.13	-2.55	-4.56	3.37	-0.78	6:02	rear end	7.51	269.7
odroutes_00_...	367.80	-110.72	33.15	0.00	0.40	0.80	6.84	3.79	-7.82	-25.89	1.94	32.07	4:56	lane change	5.59	344.8
odroutes_00_...	383.00	-151.75	43.47	0.00	1.40	0.80	13.05	13.05	-0.47	-1.68	7.12	0.00	6:00	rear end	5.94	269.3
odroutes_00_...	414.10	-12.29	-61.53	0.00	1.00	0.40	21.59	13.77	-0.02	-14.89	7.22	0.00	6:00	rear end	14.37	356.7
odroutes_00_...	411.20	-5.83	-41.84	0.00	1.50	2.90	12.76	6.20	-6.83	-27.65	3.24	-26.41	6:53	rear end	10.47	280.9
odroutes_00_...	411.50	-5.74	-30.75	0.00	1.40	0.20	12.04	0.90	-7.14	-27.65	0.47	0.00	6:00	rear end	11.61	269.5
odroutes_00_...	411.40	-5.73	-29.80	0.00	1.10	0.80	15.69	2.74	-1.60	-27.65	1.45	-6.52	6:13	rear end	14.64	272.3
odroutes_00_...	411.40	-5.77	-35.34	0.00	1.10	0.80	15.07	4.65	-2.07	-28.52	2.51	-16.40	6:33	rear end	13.59	277.9
odroutes_00_...	412.10	-5.69	-25.56	0.00	0.40	0.40	15.35	0.64	-0.68	-28.52	0.33	-0.83	6:02	rear end	14.98	269.9
odroutes_00_...	455.20	-1.64	41.04	0.00	1.50	0.20	11.17	0.76	-7.61	-14.24	0.41	0.00	6:00	rear end	10.82	89.52
odroutes_00_...	455.20	-1.63	41.54	0.00	1.10	0.90	15.60	3.10	-1.80	-23.83	1.65	0.00	6:00	rear end	14.15	89.52
odroutes_00_...	455.90	-1.67	36.36	0.00	0.40	0.50	15.31	1.43	-0.15	-25.96	0.73	0.00	6:00	rear end	14.47	89.52
odroutes_00_...	479.50	-5.88	-47.94	0.00	1.20	1.20	15.58	9.70	-2.69	-6.24	8.39	-5.64	6:11	rear end	7.22	273.5
odroutes_00_...	503.80	-201.69	46.57	0.00	0.70	0.50	20.46	8.77	-0.83	-21.60	4.46	-11.28	6:23	rear end	16.21	274.1
odroutes_00_...	505.60	-151.64	52.76	0.00	0.50	0.60	14.62	4.22	-0.96	-21.23	2.25	13.53	5:33	rear end	12.80	262.2
odroutes_00_...	526.50	-99.13	26.36	0.00	0.60	0.50	24.63	5.33	-0.06	-23.28	2.81	0.00	6:00	rear end	22.10	89.69
odroutes_00_...	546.30	-1.54	52.26	0.00	1.50	1.70	12.75	11.75	-1.69	-5.19	10.26	0.00	6:00	rear end	2.48	89.52
odroutes_00_...	569.40	-5.73	-30.37	0.00	0.40	0.40	17.40	2.57	-0.60	-19.45	1.38	-5.42	6:11	rear end	16.43	272.0

Figure 41: SSAM3 tool example output

3.5.2 Initial results

The first set of simulations run in the workshop were analysed by all the partners thought the metrics they developed. In this regard, IDIADA also ran the SSAM3 tool with the generated outputs.

The simulation was intended to try a comparative analysis between a simulation with normal HD (i.e., normal model parameters) and “distracted” HD (i.e., tweaking parameters to force poorer behaviour). Otherwise, both simulations are identical.

The metrics analysed were TTC, PET and maximum deceleration (MaxD). The thresholds selected for critical situations were the defaults of the tool: TTC < 1.5s, PET < 5s.

As can be seen comparing normal HD results (Figure 42, Figure 44 and Figure 46) with “distracted” HD results (Figure 43, Figure 45 and Figure 47), the behaviour of the altered HD creates more critical situations, as expected.

This is also in line with all other WP2 metrics, since all of them succeeded in a comparative analysis, obtaining results compatible with SSAM ones.

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In Figure 42 and Figure 43 we can see the TTC of both simulations for critical scenarios detected by SSAM3 tool. It can be seen that normal drivers not only had less critical situations, distracted drivers are also more reckless, as can be seen by the amount of critical scenarios of TTC > 0.5.

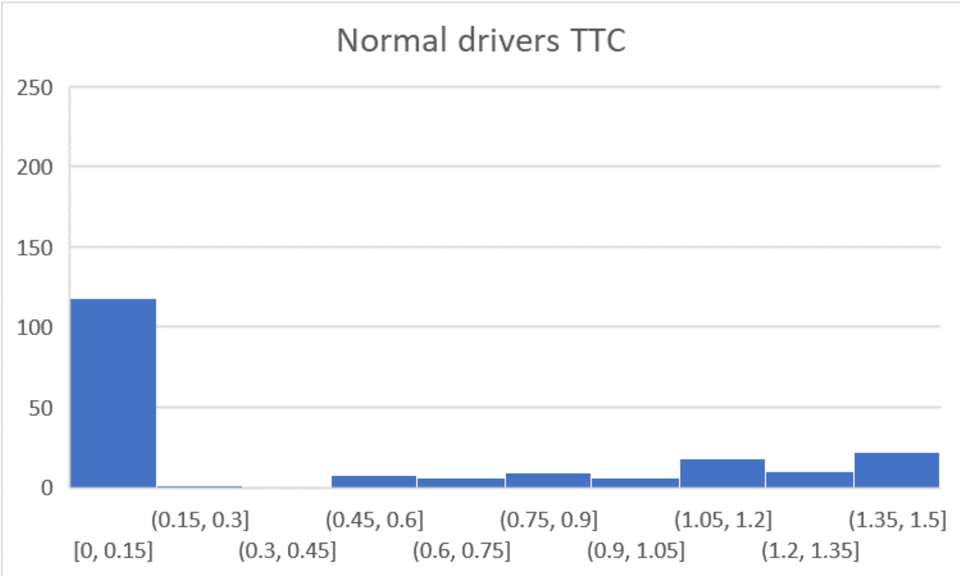

Figure 42: Normal drivers TTC Histogram

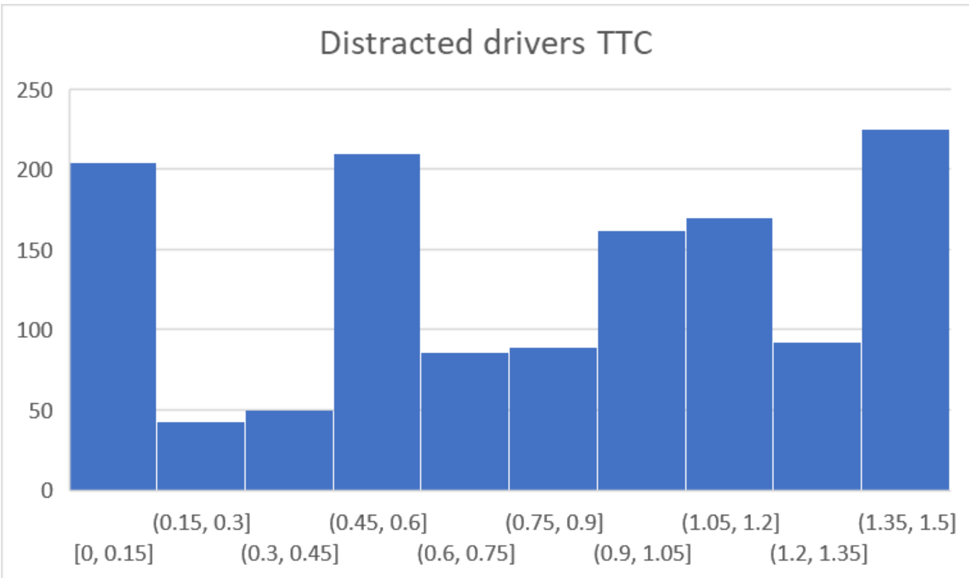

Figure 43: Distracted drivers TTC Histogram

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In Figure 44 and Figure 45 we can see PET of both simulations. As seen with the previous figures, the distracted drivers not only had more critical scenarios, we can also corroborate that their behaviour is the issue by the distribution of events.

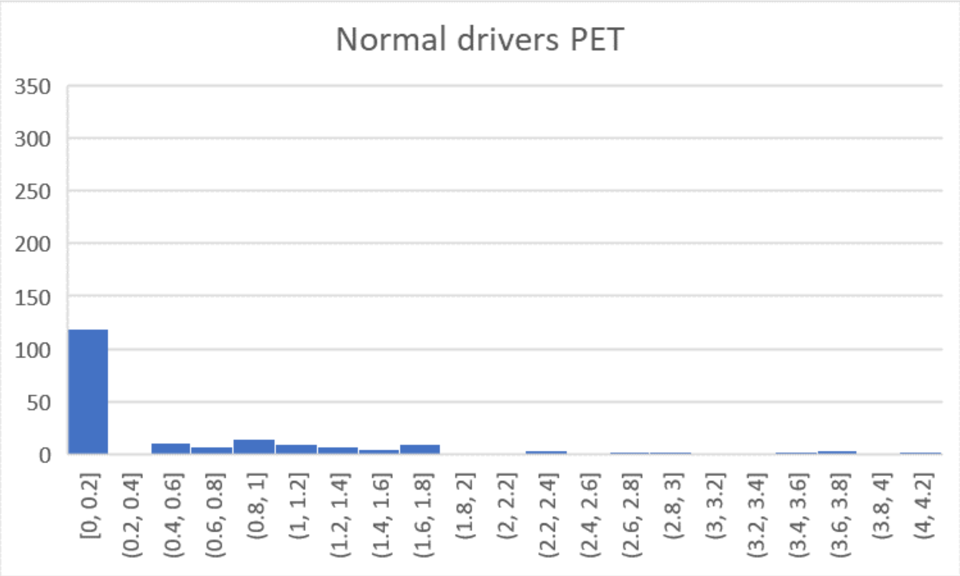

Figure 44: Normal drivers PET Histogram

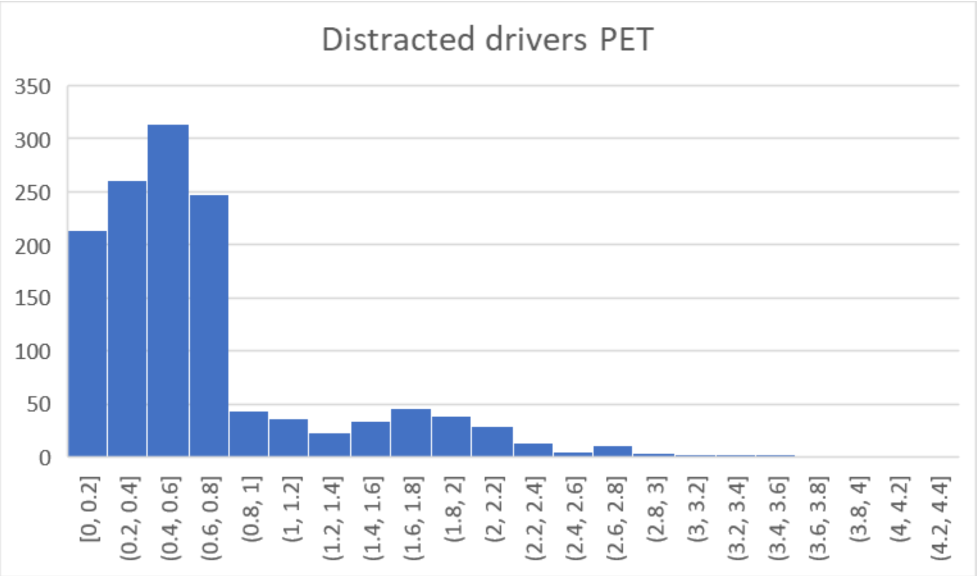

Figure 45: Distracted drivers PET Histogram

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In Figure 46 and Figure 47 we can see the maximum deceleration of cars in the critical scenarios detected by the SSAM3 tool. Here we can see that the behaviour of normal drivers is much more predictable and consistent than the behaviour of the distracted drivers.

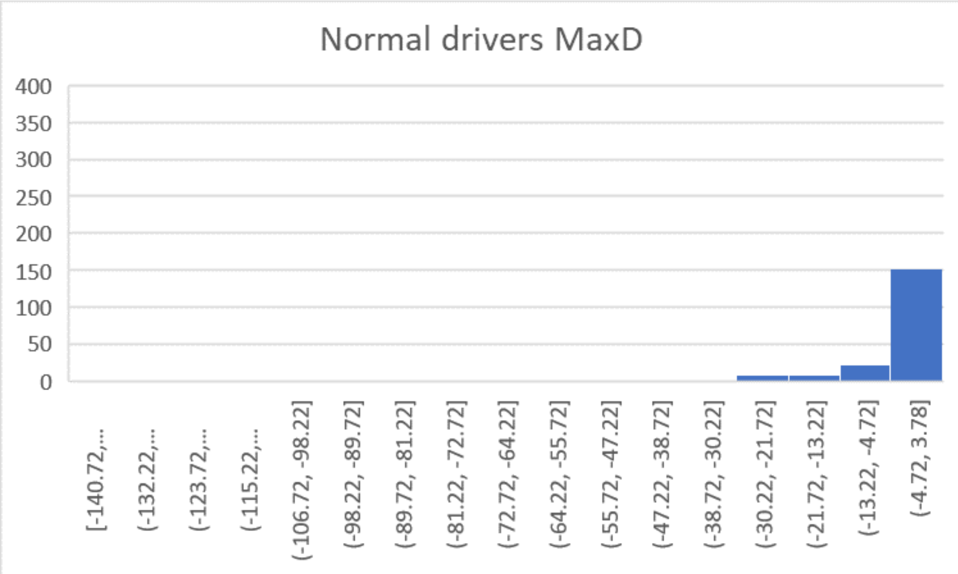

Figure 46: Normal drivers MaxD Histogram

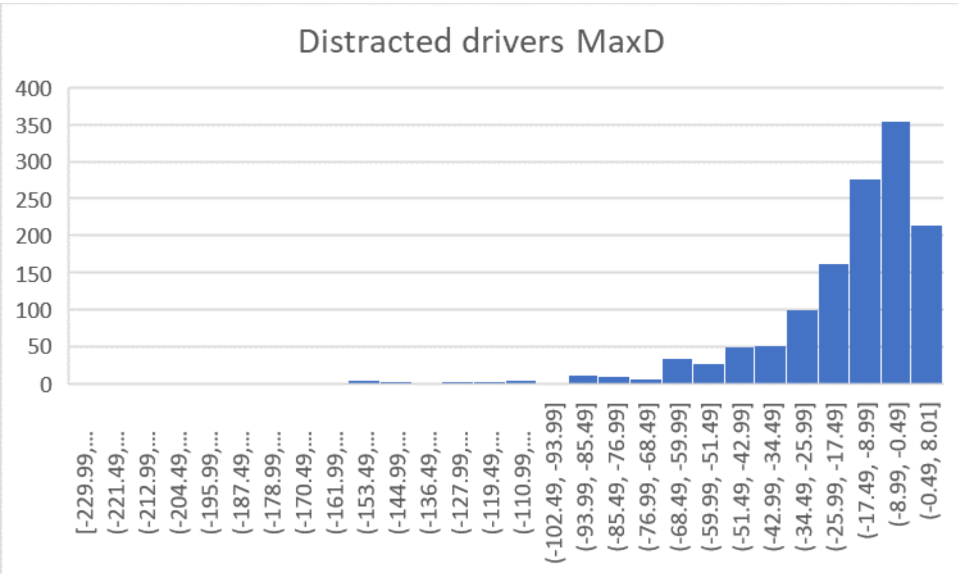

Figure 47: Distracted drivers MaxD Histogram

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4. Conclusions

This document presents the initial design of the simulation experiments needed to explore possible future safety-critical situations in traffic that may arise when human drivers are replaced by automated vehicles.

The experiment was designed in collaboration with all partners from WP2 via a number of online discussions and two physical Simulation Workshops held in October 2021 and April 2022. The experiment will make use of the all the results produced so far in WP2: safety-critical scenarios identified in Task 2.1, safety metrics developed in Task 2.2, simulation models developed in Task 2.4 and the simulation environment created and integrated into Aimsun Next simulator in Task 2.4.

Our experiment analysis approach is based on differential analysis. That is, we first create a baseline simulation of a "typical" (urban) environment populated with a typical mix of traffic participants (e.g., human driven vehicles, pedestrians, powered two-wheelers, cyclists, etc.). Such baseline simulation produces over time a number of traffic interactions that can then be classified as non-safety-critical or safety-critical according to a different safety indicators. After the baseline simulations are established, they are repeated with only one difference: a number of human driven vehicles are replaced by automated vehicles (AVs). In this way, we theorize that any changes in the statistics of safety indicators can be attributed to the presence of AVs.

This document proves an overview of the elements and data required to create the simulation experiments, the kind of hypothesis than can bested with it, the initial choices of parameters for some of the simulation parameters, and the initial experiment analysis plans for each partner in Task 2.5. TNO, IKA, TUD, and UNI will base their analysis on the metrics they developed in Task 2.2. IDI will provide the baseline simulation analysis using well-established safety indicators.

Task 2.5 will continue running the experiment, analysing the simulation outputs and iterating into the experiment parameters, even considering specific microsimulations for detected corner critical scenarios. The outputs of Task 2.5 will be provided to WP5, and an updated version of this deliverable (D2.13) will be available by the end of the task with the final results.

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