D.2.13. Analysis of simulation results and identification of future safety-critical traffic interactions update

Primary Author(s)	Núria Parera | IDIADA Pedro Huertas Leyva | UNIFI, Julia Pelzer | IKA, Fabian Russ | IKA, Arturo Tejada | TNO, Jordi Casas | AIMSUN Xinwei Wang | TUD

Related Work Package	WP2
Version/Status	0.3 | Final version
Issue date	28/04/2023
Deliverable type	R
Dissemination Level	PU

Project Acronym	SAFE-UP
Project Title	proactive SAFEty systems and tools for a constantly UPgrading road environment
Project Website	www.safe-up.eu
Project Coordinator	Núria Parera | Applus IDIADA
Grant Agreement No.	861570

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Document Distribution

Version	Date	Distributed to
0.3	28-04-23	Coordination Team
0.4	28-04-23	Submission in the EC System
		Approved by the EC

Copyright statement

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Executive summary

SAFE-UP's Work Package 2 aimed at understanding the impact of vehicle automation technologies on safety by leveraging newly developed behavioural traffic simulation tools. The developed tools allow to simulate specific road networks with a variable proportion of automated vehicles to non-automated traffic participants (including human-drivers, pedestrians, cyclists, and powered two-wheelers). The simulation models are detailed enough to realistically recreate the effects of unexpected events (like surprise cut-ins) to determine whether these technologies induce changes (positive or negative) in surrogate indicators of traffic safety.

Task 2.5 originally aimed run and analyse the necessary simulations to identify the possible effect of automated vehicles (AVs) on safety. Although not a part of its original mandate, Task 2.5 took upon itself the design of an appropriate simulation methodology that leveraged the models and simulation platform developed in Tasks 2.3 and 2.4. The methodology has been successfully implemented, allowing one to run different simulation scenarios and perform comparative analysis to understand the effect of AVs from several perspectives.

Implementing this methodology posed significant challenges. Several activities took much bigger effort than planned, as for example, the identification of the parameters that needed to be changed in the simulations took several iterations, modifications needed to be done to the models that were already finished and rework the scripts to run the simulations several times. On the other hand, the computational platform over which the simulations were run was changed in mid-2022 due to the need for larger computational power. The simulation system is now hosted on Amazon Web Services, a migration with significant technical challenges, that was necessary to address the necessary increase of AV rate penetration and the large amount of simulation runs needed to obtain the results we were aiming for.

All these challenges, some of which were unexpected, were solved but limited the time and resources left to perform the comparative analysis needed to ascertain the effects of AVs on safety. This was done by comparing baseline simulations without AVs with simulation that contained AVs. Several batches of simulations were done, the starting batch was a set of 100 simulations. Later batches included up to 500 simulations. Due to time and resources, the work planned in the grant agreement has been finished with several analyses but the results have not been as conclusive as expected.

It is recommended that the community sets up a follow-up project focused on continuing the work in this work package, re-using our simulation platform. Such project should support the collection of the data necessary to calibrate and validate the simulation environment so it becomes a true digital twin of reality. It should also help improve the simulation models developed in this project, and perform larger and longer batches of simulations to fully explore the possible future safety-critical situations in mixed traffic.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Table of contents

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

List of figures

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement 861570.

List of tables

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

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

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

1. Introduction

1.1 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 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 be 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 enables to generate most of the important safety-critical situations identified in Task 2.1 (Deliverable 2.6). The simulation results were analysed with a number of safety metrics, which were developed in Task 2.2. Task 2.5 made use of these combined assets to run and analyse interactively multiple simulation experiments.

1.2 Experiment Design

As it is described in deliverable D.2.8, two types of simulation experiments were identified during the first SAFE-UP Simulation Workshop in October 2021: 1) Experiments containing complete road network layouts, allowing several types of driving scenarios and interactions to arise and 2) experiments containing only single driving scenarios, allowing us to focus on specific kinds of critical situations. Given the goals of WP2 and Task 2.5, it was decided that the main focus would be on the first type of experiment, called the "Alpha" experiments.

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.).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

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.

Regarding these experiments, as was mentioned in D.2.8, one must consider the following:

1. It is not clear whether significant changes in safety indicators will be 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.
2. It is also important to remark that although the approach outline above is based on statistical analysis, it will be correct only qualitatively. For the analysis to also be quantitatively correct, the simulation experiment described above should contain a digital twin of a real road network.
3. Due to the lack of data to calibrate and validate the simulation environment, it does not resemble the "real world" closely. Consequently, the analysis can only indicate the validity of our hypotheses but cannot yield results that can applicable beyond the simulation environment.
4. Traffic parameters were adjusted to represent three types of traffic scenarios: low congestion moments of the day (i.e., outside rush-hour), medium congestion (i.e., between morning and afternoon rush hours), and rush hours. The parameters for such moments were adjusted by AIM drawing on their long experience on setting up such simulations.

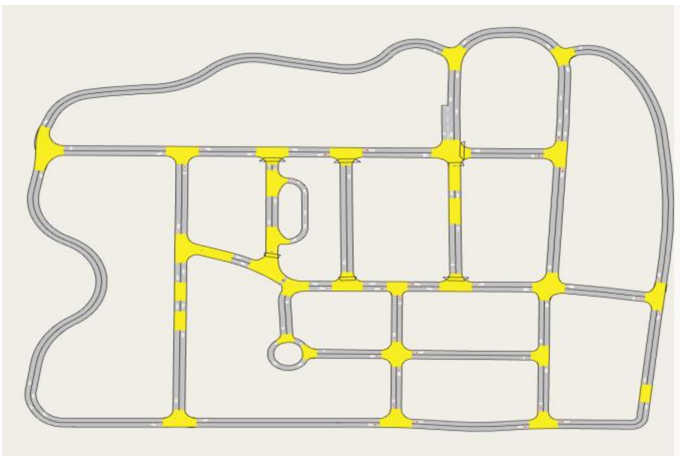


Figure 1: Layout of Town 7

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

2. Metrics baseline

2.1 Simulation Parameters/Metrics to be analysed

The metrics and parameters were defined in Task 2.2. and more information can be found in D.2.14. In T.2.5 the parameters of interest such as 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) were defined and added in tables that can be seen below.

2.1.1 Parameters PTW model

The complete list of parameters for the PTW-model to include variability in PTW rider behaviour can be found in Table 1. These parameters allow the incorporation of human factors related to distraction, response time, field of view (that can be affected by different conditions like hard rain or fog), right of way violation and desired target speed.

Table 1. Parameters for the PTW-model to include variability in PTW rider behaviour.

Parameter Name	AIMSUN interface	Definition	Range	Value for Standard	Distribut.	Type
Delay in Response Time (Amount)	Attributes of Scenario: GKExperiment	Distraction duration: Time added to the braking response time due to distraction (delay time)	[0 - 1.5]	1.5s (+/-0.68s)	No Distribution	Fixed
Delay/Increase in Response Time / Distraction (Probability)	Attributes of Scenario: GKExperiment	Probability to have a “distraction presence” (delay of response time)	[0% – 100%]	0.01 (1%)	lognormal (no literature about mu and sd);	Fixed (response time per each agent defined internally in the model)

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement 861570.

Field of View to detect objects	Attributes of Scenario: GKExperiment	Horizonal angle of view of PTW rider	[20 – 100]deg	60	No Distribution	Fixed - Same value for all the PTW agents
Yield right-of-way violation (Probability)	Attributes of Scenario: GKExperiment	Probability to cross the intersection without stopping, independently of the presence of a vehicle with right of way)	[0% – 100%]	0.001 (0.1%)	lognormal mu =0.0001; sd:16	Fixed (the value per each agent defined internally in the model)
Desired Target Speed	Vehicle Type Menu: *Motorcycle Dynamic Model - Desired Speed*	Desired Speed defined in AIMSUN as "Speed Limit Acceptance" in *Dynamic Model* parameters of motorcycles	30-100 for speed limit (50 km/h)	55km/h (sd. 10) "Speed Limit Acceptance" = 1.1; "Deviation" =10; Min=0.8; Max=1.8	Normal	Distribution: The value for each agent defined by AIMSUN

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

2.1.2 Parameters pedestrian and cyclist

Within the scope of WP2 of the SAFE-Up project, ika has developed two VRU simulation models, the pedestrian and the cyclist model. As described in deliverable D2.9, the model behaviour can be changed according to different parameters. The pedestrian model contains of the following parameters that influence the pedestrians' behavior:

2.1.2.1 Pedestrian model parameters

- **sense_radius**
  - **Description:** Maximal distance to road objects that can be perceived by the pedestrian. The larger the radius, the larger/wider the field of view of the pedestrian. This means that action can be taken earlier and with more anticipation. For critical behavior, the radius must be reduced.
    - Definition range: [0.0 - ∞] [m]
- **blindspot_angle**
  - **Description:** Backwards angle the pedestrian cannot see, in radians, measured sideways to the heading direction. The angle builds up symmetrically from behind areas are excluded from the field of view. Objects located in this area are not perceived. The larger the angle, the less the pedestrian sees.
    - Definition range: [0.0 - π] [rad]

The cyclist model contains the parameters "sense distance", "blindspot angle", "selected driving offset", "ttc and distance" as well as different "driving patterns". By adjusting this parameters, the cyclists' behavior can be modified. In the following, the parameters are explained shortly.

2.1.2.2 Cyclist model parameters

- **sense_distance**
  - **Description**: Maximal distance to road objects that can be perceived by the cyclist. The larger the radius, the larger/wider the field of view of the cyclist. This means that action can be taken earlier and with more anticipation. For critical behavior, the radius must be reduced.
    - Definition range: [0.0 - ∞] [m]
- **blindspot_angle**
  - **Description**: Backwards angle the cyclist cannot see, in radians, measured sideways to the heading direction. Areas are excluded from the field of view.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Objects located in this area are not perceived. The larger the angle, the less the cyclist sees.

- Definition range: [0.0 - π] [rad]

- **selected_driving_offset**
  - **Description**: Desired driving offset to the side of road. The larger the value, the further the driver drives in the lane. Accordingly, overtaking then becomes more difficult.
    - Definition range: [0.0 - ∞] [m]
- **ttc and distance**
  - **Description**: Time to Collision from which the driver moves to the side. The larger the value, the earlier the driver reacts if an interaction with another object is upcoming. For more critical behavior, the value must be reduced, because the cyclist then reacts late to an approaching vehicle.
    - Definition range: [0.0 - ∞] [s]
    - **distance** is used if **ttc** = none
    - Definition range: [0.0 - ∞] [m]
- **driver pattern**
  - **Description**: Percentage distribution of driving patterns of cyclists, influences amplitude and frequency of wiggle whilst driving. All driver patterns are scaled by speed (defined internally in model).
    - **pattern1**: Percentage of cyclists with driving pattern 1; lowest frequency; maximum of amplitude: 0.57m (of main frequency component).
    - **pattern2**: pattern 2 cyclist at mean frequency; maximum of amplitude: 0.72m (of main frequency component).
    - **pattern3**: Percentage of cyclists with driving pattern 3; highest frequency; maximum of amplitude: 1.0m (of main frequency component).
    - Definition range [0.0 – 1.0] [-]

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

2.1.3 Parameters of HDM

The complete list of parameters for the HDM can be found in Deliverable 2.11 [1]. The HDM is composed of a carf-following model augmented with a human perception model that allows the incorporation of a number of human factors. For the purpose of Task 2.5, the human perception model was disabled and all the car-following model parameters were fixed to their fixed calibration values (see [1]), with the exception of two parameters that were allowed to vary:

- Desired time gap (the distance between an HDM and its predecessor in the same lane, divided by the HDM speed). This parameter was modelled as a uniform random variable between 0.5 seconds and 1.5 seconds.
- Desired speed. This parameter was modelled as a Gaussian random variable with a mean of 50kph and a standard deviation of 5kph.

As explained in Sections 3 and 4, for the simulation experiments run in the Amazon Web Services environment, only the desired time gap was allowed to vary (while the desired speed was held constant), and for the analysis performed by TNO the opposite was true (see Sections 3 and 4 for details).

Finally, the metrics used to detect conflicts of interest were the time to collisions and the post encroachment time, with thresholds of 1.5 seconds and 5 seconds respectively.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

3. Methodology & Implementation

The simulation environment, described in deliverable D2.7 and which is summarized in Figure 2, had to be changed due to some challenges during the implementation of the models in the simulation and the computing force needed to carry out the simulation. In this section the challenges faced and the implemented solutions to the simulation will be explained.

The workflow defined previously included the Aimsun Next platform running in a Windows 10 computer, the Human driver and PTW models were implemented as a dynamic library, while the cycling and pedestrians models were run in a UBUNTU 20 computer and the AVs model did run in a UBUNTU 18 computer. The bikes, pedestrians and AVs models used as interface the Aimsun Next platform using the TCP/IP communication through External Agent Interface (EAI).

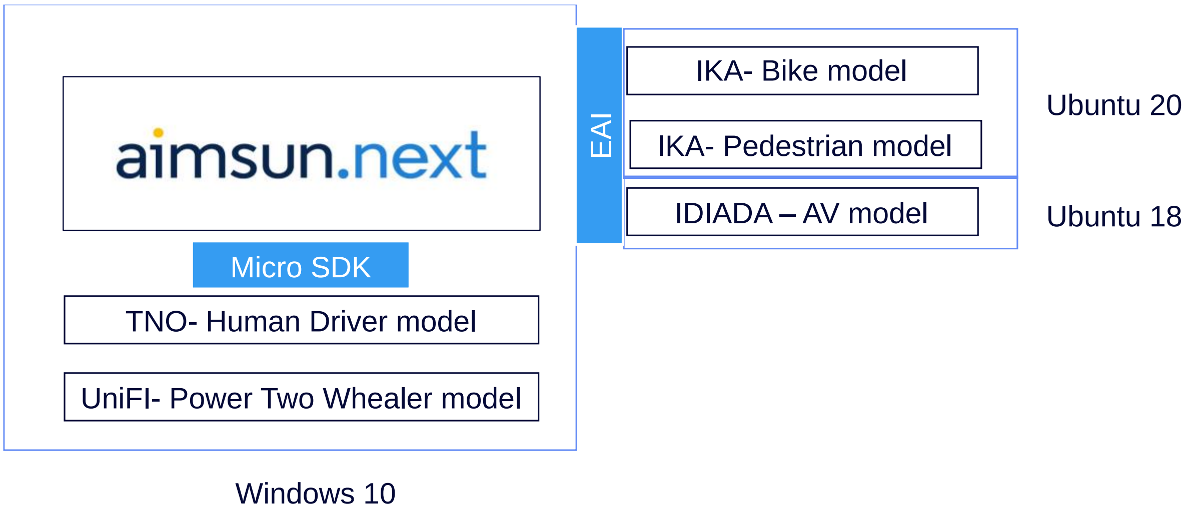


Figure 2: Simulation environment schema

This integration deployed in computers/servers owned by end users, due to problems in scaling this solution into a high-performance computing scheme in private computers, the implementation was moved to a public cloud infrastructure that provides computing scalability on demand. As a result of that some changes have been made into the architecture of the simulation environment with a migration of all processes to Ubuntu 20. The chosen cloud platform is AWS due to ease of deployment, cost competitiveness and scalability. The simulation environment based on AWS is explained in deliverable D2.12

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Although considering the current scheme, the workflow defined in the beginning did not change, the experiment execution is described by the following steps (see Figure 3) was not changed:

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

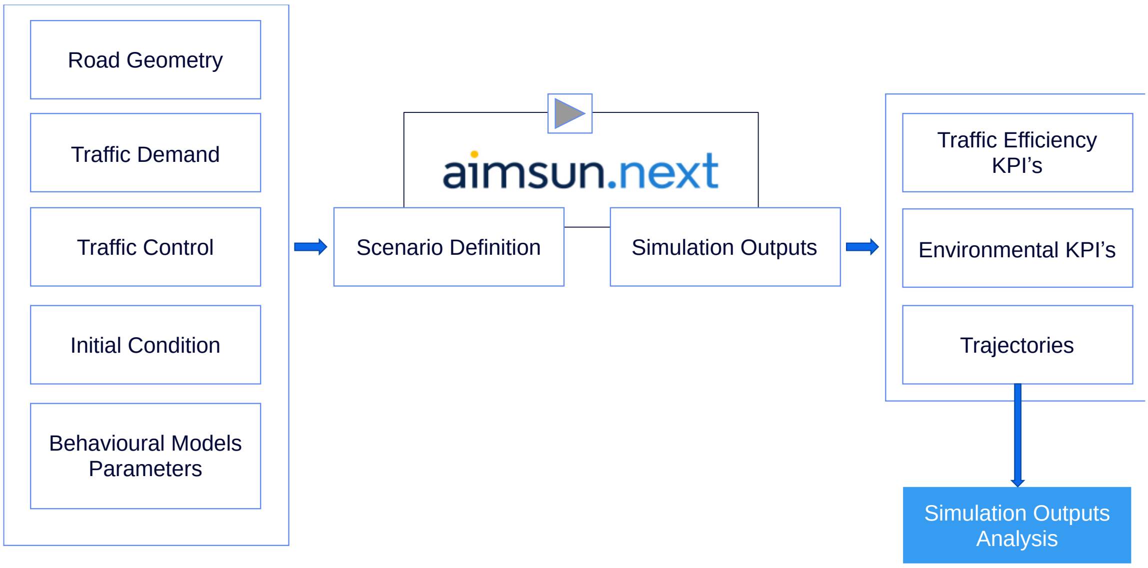


Figure 3: Experiment workflow

The integration was complemented by two python scripts, one to define the simulation parameters (step 1 in Figure 4) and another to generate the folder structure and files required to execute all the experiments (step 1 inFigure 4). They allow the automatization of the work flow in order to deal with a massive number of simulations.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

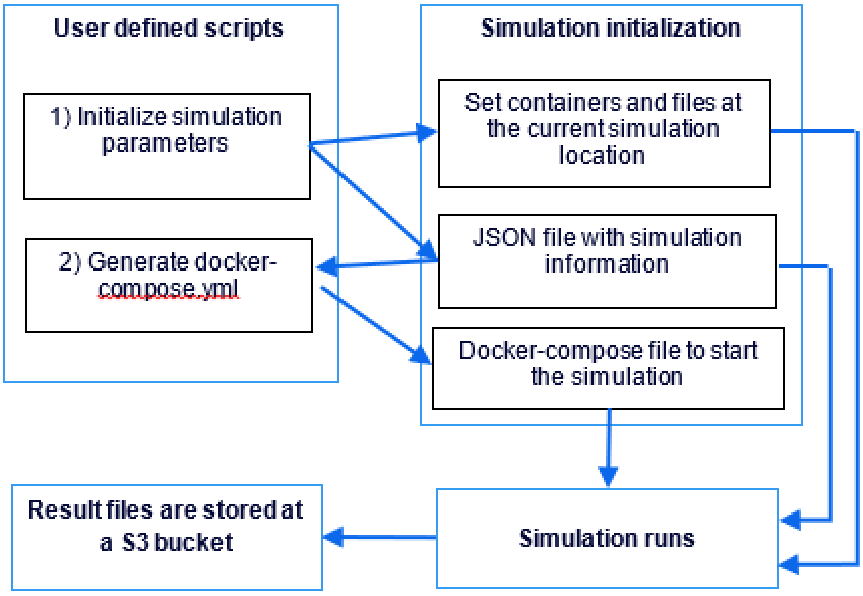


Figure 4 AWS simulations workflow

3.1 Monte Carlo Simulation Procedure

In order to determine whether the presence of automated vehicles do have an influence on the different safety indicators mentioned in Section 2, it was decided early on to conduct only a comparative study between two distinct scenarios: one without the presence of automated vehicles (called the baseline scenario) and another with automated vehicles (the AV scenario).

Both scenarios contain several types of traffic participants including, human drivers, PTWs, cyclists, etc. Each participant is represented in the simulation environment by a(n agent) model. Although each model has a fixed structure, the model parameters can be varied at will.

Each instance of a participant model in the simulation displays different behaviour than any other instance of the same participant in the simulation. Usually, every instance of a participant's model is given a set of parameters that are drawn from prescribed distributions. As a consequence, no two simulation experiments are exactly the same. So, it is to be expected that the number, type and (possibly) severity of critical interactions change from one experiment execution to the next.

In order to compare the baseline and AV scenarios, one first must establish clear statistics for similar safety indicators in each case. That is, one needs to understand the distributions of the safety indicators as a function of the variation of the parameters of every model in both scenarios. To formalize this idea, consider the following definitions:

- In every simulation experiment, the independent variables, $\boldsymbol{X}$, (also known as explanatory or predictor variables) are the parameters of every instance of every participant model in the simulation.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

- In every simulation experiment, the dependent variables, $\boldsymbol{Y}$, (also known as response or outcome variables) are the number of high-risk interactions, crashes or any other event used to study traffic safety, that occur during the simulation events.

Since the independent variables are stochastic in nature, the dependent variables are too. This, the hypothesis we are trying to test with our simulations is:

Hypothesis: $E\{\boldsymbol{Y}|without\ \ AVs\} \neq E\{\boldsymbol{Y}|with\ AVs\}$,

where $E\{.\}$ denotes the expected value. One of the best established, practical methods to test this hypothesis is the Monte Carlo method [2]. The basic Monte Carlo setup is described next.

3.1.1 Basic Monte Carlo setup

The goal of the Monte Carlo method is to estimate the statistics of $\boldsymbol{Y}$ by running a limited number of (statistically independent) simulations.

The basics steps are:

1. Generate N samples of the parameters of every model instance, $\boldsymbol{X}$ by drawing from the knows parameters' distribution f_x. The samples are called $X_1, \dots, X_N$.
2. For each X_i, $i = 1, \dots, N$, run a simulation experiment and compute Y_i
3. Estimate $E\{\boldsymbol{Y}\} \approx \frac{1}{N}\sum_i^N Y_i$,
4. Estimate $\sigma^2\{\boldsymbol{Y}\} \approx \left(\left(\frac{1}{N}\sum_i^N Y_i^2\right) - \left(\frac{1}{N}\sum_i^N Y_i\right)^{\mathbf{2}}\right)\frac{\boldsymbol{N}}{\boldsymbol{N-1}}$,

The estimates of the mean and variance in, respectively, steps three and four generally converge to constant values as N increases.

3.1.2 Practical Monte Carlo Setup

A number of practical challenges were foreseen in applying this simple scheme to our traffic simulations. One was that the vector $\boldsymbol{X}$, which would ideally contain all the parameters from every instance of each participant model, would have been quite large (see Section 2). So, sampling from the parameter distribution f_X would have been difficult to accomplish if all parameters from all models were allowed to vary independently. Another challenge was that the events of interest that are needed to study safety (e.g., crashes) are quite rare, even in simulation. In both cases, the basic method described above would have required to executes a large number of simulation experiments in order to properly estimate the statistics of $\boldsymbol{Y}$.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Since executing a large number of simulations was not feasible even with the use of the Amazon Web Services solution, additional restrictions were imposed to keep the number N of simulations experiments low. The restrictions were:

- In the baseline scenario, within a simulation experiment, all instances of every model were allowed to have different parameter values. However, every model instance had the same parameter values in all simulation experiment, including the initial conditions of the model and the initial location in the map.
  - For example, “pedestrian 1” was different than “pedestrian 2” within simulation experiment 1. But “pedestrian 1” in simulation experiment 1 was exactly the same in simulation experiment 2, and 3, etc.
  - Note that this restriction ensure that every simulation experiment yields exactly the same results down to exactly the same trajectories for every simulated traffic participant.
- The only exception to the above restriction was the human driver model (HDM) because AVs would eventually replace human drivers, so we wanted to explore what happened when some HDMs were replaced by AV models. Two types of HDMs were created as shown in Figure 5

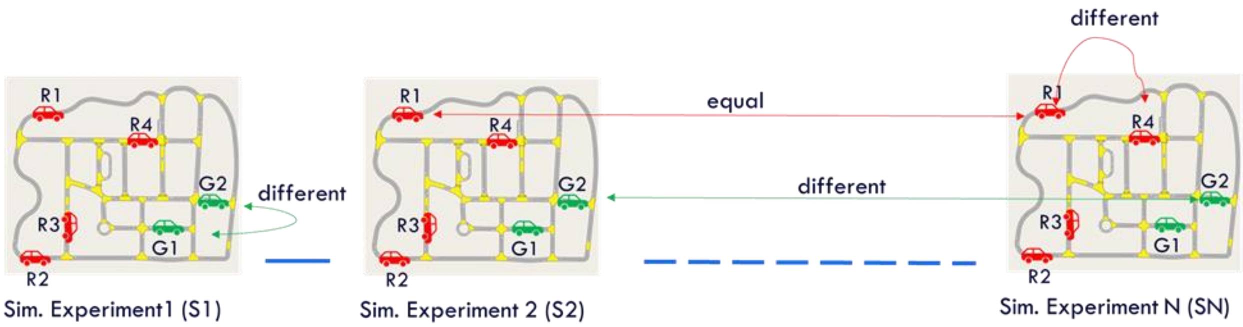


Figure 5: Restricted Monte Carlo simulation setup. See text for a description.

- In every simulation experiment: Red and Green HDMs appear at the same time and location.
- In every simulation experiment: Red and Green HDMs have different parameter values: $R1 \neq R2 \neq R3 \neq \cdots$ and $G1 \neq G2 \neq G3 \neq \cdots$
- However, $R1 \text{ in } S1 = R1 \text{ in } S2 = \cdots = R1 \text{ in } SN$, $R2 \text{ in } S1 = R2 \text{ in } S2 = \cdots = R2 \text{ in } SN, \ldots$
- In contrast: $G1 \text{ in } S1 \neq G1 \text{ in } S2 \ldots \neq G1 \text{ in } SN$; $G2 \text{ in } S1 \neq G2 \text{ in } S2 \ldots \neq G2 \text{ in } SN, \ldots$

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement 861570.

- Approximately 2500 Red HDMs and 250 Green HDMs were considered. Every Green HMD instance had only one parameter that was allowed to change: its "desired time gap", which was assumed to be uniform random variable taking values between 0.5 seconds and 1.5 seconds.
- Based on the above restrictions, and assuming statistical independence between the Green HDMs, we have that $f_X = (Uniform(0.5,1.5))^{250}$.

The AV scenario was set up in exactly the same way. However, in every simulation 1 AV model were added with exactly the same initial condition. In total 500 simulation experiments were executed in both scenarios, and the statistics of $\boldsymbol{Y}$ were estimated as described in Section 3.1.1.

3.2 AWS - Simulation execution and procedure

The simulation has been processed in instances of Amazon Web Services (AWS). To performance this task different configurations and services have been used, the following list is the main services used during the simulations, but there were more services involve.

- EC2: "Amazon Elastic Compute Cloud (Amazon Ec2) offers the broadest and deepest compute platform, with over 500 instances and choice of the latest processor, storage, networking, operating system, and purchase model to help you best match the needs of your workload"
- S3: "Amazon Simple Storage Service (Amazon S3) is an object storage service offering industry-leading scalability, data availability, security, and performance."
- ECR: "Amazon Elastic Container Registry (ECR) is a fully managed container registry offering high-performance hosting, so you can reliably deploy application images and artifacts anywhere."
- CloudWatch: "Amazon CloudWatch collects and visualizes real-time logs, metrics, and event data in automated dashboards to streamline your infrastructure and application maintenance."
- VPC: "Define and launch AWS resources in a logically isolated virtual network. Amazon Virtual Private Cloud (Amazon VPC) gives you full control over your virtual networking environment, including resource placement, connectivity, and security."

This chapter has the following structure:

1. Define the necessaries resources to be able to deploy the simulations.
2. Methodology to deploy a simulation.
3. Methodology to deploy all simulations simultaneously.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

3.2.1 Resources necessaries

The first step was defined the resources necessaries to performance the simulation. If the simulation has autonomous vehicles (AV) demand more resources that it had not.

There are a big number of options of the kind of EC2 instances. Is possible consult all kinds in the web https://aws.amazon.com/ec2/instance-types/?nc1=h_ls

- The instance "t2.medium" was selected to performance the scenarios without AVs. Table 2 shows the characteristics of this type of instance.

Table 2 t2.medium characteristics. Information extract from AWS info

Instance	vCPU	CPU Credits / hour	Mem (GiB)	Storage	Network Performance
t2.medium	2	24	4	EBS-Only	Low to Moderate

- The instance "c5.xlarge" was selected to performance the scenarios with Avs.

Table 3 c5.xlarge characteristics. Information extract from AWS info

Model	vCPU	Memory (GiB)	Instance Storage (GB)	Network Bandwidth (Gbps)	EBS Bandwidth (Mbps)
c5.xlarge	4	8	EBS-Only	Up to 10	Up to 4,750

Also, the storage of the instance had been personalized in each case:

- 8GB for the simulations without Avs.
- 24GB for simulations with Avs.

3.2.2 Methodology to Perform a simulation

To make a simulation, the following steps must be followed:

1. Hire an EC2 machine (according to the characteristics described in the previous section).
2. Choose the operating system that will work with the machine. In this case, an "Amazon Linux x64" image was chosen.
3. Configure the instance to be able to have access to and from outside.
4. Install the necessary tools to run the Docker images.
   - Install and configure Docker, Python 3.7 and amazon-linux specific diagnostic tools and extras.
   - Configure environment variables so that the machine can access AWS services.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

5. Configure the Docker-compose file to be able to find the images previously uploaded to the ECR and find the resources stored in S3.
6. Run the simulation.
7. Wait for the simulation to finish (between 40 min and 2 hours).
8. Upload the simulation output logs to S3.
9. Shut down and destroy the machine, to save resources.

In the project the main objective was run more than five hundred simulations. with this methodology it would have been impossible to do all the simulations in time.

3.2.3 Methodology to deploy all simulations simultaneously.

After search a possible solution to deploy all simulations simultaneously, the consortium decided use Terraform to deploy all simulations simultaneously.

Terraform is an infrastructure as code software developed by HashiCorp. It allows users to define and configure a data center infrastructure in a high-level language, generating an execution plan to deploy the infrastructure to cloud service providers. The infrastructure is defined using a specific syntax where multiple parameters can be defined.

1. A customized amazon-linux image (Amazon Machine Images (AMI)) was created, in which all the necessary tools to perform a simulation were installed. A system monitoring script was created to detect when the machine had finished the simulation to auto-shut down and thus conserve project resources.
2. Terraform was configured to:
    a. Create an instance for each simulation with the previously customized image, with the characteristics described in section 3.2.1.
    b. Create the appropriate environment to run the Docker-compose.
    c. Load the environment variables needed to run the simulation.
3. Since the number of simulations was much higher than the capacities contracted in AWS and the number of licenses available for the simulator, Python programs had to be developed to launch batches of 25.
    a. The program launched 25 simulations simultaneously (create instances, start docker monitor, launch simulation)
    b. Wait 2 hours to be sure that all simulations are finished.
    c. Stop and destroy all instances.
    d. Start again with the next batch.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

3.2.4 Simulation results download

A custom script was developed to automate the process of downloading simulations from different folders. Due to the large amount of simulations and the size of the data, the script is designed to download the simulations one by one, following the same folder structure. The script is customizable and can be configured to match a regular expression (regex) or a file extension, making it versatile for different types of simulations. This automated script allows the partners to download simulations efficiently and effectively, saving time and effort in managing large volumes of data.

The creation of the custom script for downloading simulations automatically by the partners was developed for several reasons. Firstly, the sheer volume of simulations generated by automotive testing can be massive, resulting in a significant amount of data to be managed and processed. Automating the downloading process through a script allows for efficient handling of this large data volume, saving time and effort compared to manual downloading.

Secondly, different partners may require simulations in various formats or with different file extensions based on their specific needs. The custom script's ability to be customizable and match a regex or file extension makes it highly adaptable to the diverse requirements of different partners. This flexibility allows the partners to efficiently download simulations in the specific format needed by each partner, streamlining the data sharing process and ensuring that the simulations are delivered in the appropriate format for further analysis or processing.

Furthermore, the user-friendly design of the script makes it easy for the partners to utilize it. The script's customization options, such as regex or file extension matching, provide a user-friendly

```python
import time
import logging
import pathlib
import boto3


# User inputs
destination_path = r"D:\safeup_simulations"
root_s3_folder = r"scenarios/February-Experiments-AV/"
file_extension = r"bag"  # None
# str_match = r"all_outputs"
replace = False
```

Figure 6. Inputs required by the script

interface for partners to specify their simulation results requirements without needing to be proficient in coding or scripting. This makes the script accessible to a wide range of users, facilitating efficient data sharing and collaboration between the partners.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

3.2.5 Simulation executions license errors

The primary objective of the script was to identify any license errors, indicating unsuccessful simulation executions, during the iterative process of running multiple simulations in parallel. One of the key advantages of the script is that it does not require downloading the simulation files, as it directly accesses the AWS S3 bucket and reads the body of the docker_execution log file using a GET method.

The first step in developing the script was to establish a connection with the AWS S3 bucket where the simulation files were stored. This involved setting up the necessary authentication and authorization credentials to access the S3 bucket securely. Partner's expertise in working with AWS services and APIs was leveraged to ensure a secure and efficient connection to the S3 bucket.

Once the connection to the S3 bucket was established, the script utilized a GET method to retrieve the body of the docker_execution log file. This log file contains information about the execution status and any errors encountered during the simulation runs. By reading the log file directly from the S3 bucket, the script avoided the need to download the entire file, which could save time and bandwidth in processing large volumes of simulation data.

Next, the script parsed the retrieved log file to search for indices of license errors. This involved using regular expressions or other string manipulation techniques to identify patterns or keywords that indicate license errors.

Once the license errors were identified, the script generated a report summarizing the simulation execution status, including details of any license errors encountered. This report could be in a structured format, such as a CSV file or a JSON file, which can be easily analyzed and interpreted by the partner's.

1	scenario_name	license_error_flg	execution_last_modified	rosbag_size_mb	rosbag_last_modified	date_diff
2	February-Experiments-AV_sc202302280001	False	2023-03-28 16:52:47+00:00	120.53	2023-03-28 16:51:56+00:00	0 days 00:00:51
3	February-Experiments-AV_sc202302280002	False	2023-03-06 14:35:26+00:00	61.62	2023-03-06 14:34:27+00:00	0 days 00:00:59
4	February-Experiments-AV_sc202302280003	False	2023-03-28 16:51:42+00:00	60.5	2023-03-28 16:51:17+00:00	0 days 00:00:25
5	February-Experiments-AV_sc202302280004	False	2023-03-28 16:52:57+00:00	126.62	2023-03-28 16:51:57+00:00	0 days 00:01:00
6	February-Experiments-AV_sc202302280005	False	2023-03-28 16:51:20+00:00	77.33	2023-03-28 16:50:40+00:00	0 days 00:00:40
7	February-Experiments-AV_sc202302280006	False	2023-03-28 16:52:58+00:00	128.56	2023-03-28 16:52:46+00:00	0 days 00:00:12
8	February-Experiments-AV_sc202302280007	False	2023-03-28 16:51:05+00:00	55.95	2023-03-28 16:50:36+00:00	0 days 00:00:29
9	February-Experiments-AV_sc202302280008	False	2023-03-09 10:47:20+00:00	97.69	2023-03-09 10:46:24+00:00	0 days 00:00:56
10	February-Experiments-AV_sc202302280009	False	2023-03-28 16:51:32+00:00	121.39	2023-03-28 16:51:26+00:00	0 days 00:00:06

Figure 7Sample of the results in form of table

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

4. Simulation Results & Analysis

Once all the models and integration were successfully implemented in the simulation and the test runs were executed, different analysis were carried out by each partner. This section summarizes the approach that each partner did in Task 2.5 to analyse the experiment results. TNO, IKA, TUD, and UNI based their analysis on the metrics they developed in Task 2.2. Each partner presents below a summary of the techniques applied and a description of their analysis objectives, and their analysis results.

4.1 Analysis of Car-to-Car critical situations (TNO)

The procedure used by TNO to analyze ca-to-car critical situations was similar to that described in Section 3.1.2. As explained in section 3, the goal of the simulation experiments was to ascertain whether the present of AVs has an influence on traffic safety.

Traffic safety is generally measured by metrics that are aggregated of a large area over sizeable amount of time (e.g., the number of crashes per 100 000km driven in a country). Thus, such metrics could not be computed using the simulation setup developed in WP2. Instead, TNO uses a leading indicator of traffic safety, the number of severe traffic conflicts, which is known to be statistically correlated with traffic safety indicators [3]. In this study, severe traffic conflicts were defined as interactions with a time to collision (TTC) of less than 1.5 seconds and a post encroachment time (PET) of less than 5 seconds (see [4] for definitions).

A preliminary analysis of the baseline simulation experiments run in the Amazon Web Services environment showed that varying the desired time gap, as explained in Section 3.1.2, did not produce any measurable changes in the number of detectable critical car-to-car events (in fact there was only minimal trajectory changes in the Green HDMs). On the other hand, other project partners reported significant changes in the number of conflicts between cars and other traffic participants. As a consequence, to avoid disrupting the workflow already underway in the project, TNO opted for running simulation experiments locally, using a simplified version of the Amazon Web Services environment. The modifications over the setup on Section 3.1.2 were as follows:

- The map selected was City seven under the low-demand settings:
    - Baseline scenario: 20 cyclists, 320 Red HDMs, 40 PTWs, 200 pedestrian, 80 Green HDMs (total: 660 participants)
    - AV scenario: 20 cyclists, 320 Red HDMs, 40 PTWs, 200 pedestrian, 40 Green HDMs, 40 AVs (total: 660 participants)
    - All models, except for the HDM and AV models, were stock AIMSUN models.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

- The HDM models only had one variable parameter: the desired vehicle speed. This was modeled as a Gaussian random variable with a mean of 50kph and a variance of 5kph.
- The AV model was a modified version of the TNO HDM, with a desired time gap constant throughout the (AV) sub-population and smaller than that used by the regular HDM. Furthermore, for the AV, the perception error vanishes, and the desired speed does never exceed the speed limit. All AV model instances used exactly the same parameters in every simulation.
- 500 hundred simulation experiments were run per scenario

Figure 8 shows a plot of the estimate of $E\{\boldsymbol{Y}\}$**,** the average number of severe traffic conflicts, as a function of the number of baseline simulation experiments used to estimate it. As expected, the estimate of $E\{\boldsymbol{Y}\}$ converges to a constant value as the number of considered simulations experiments increases. Note that different colours represent a re-shuffle of the simulation experiments used to estimate $E\{\boldsymbol{Y}\}$**.** In general, the baseline number of severe conflicts is slightly higher than 122.

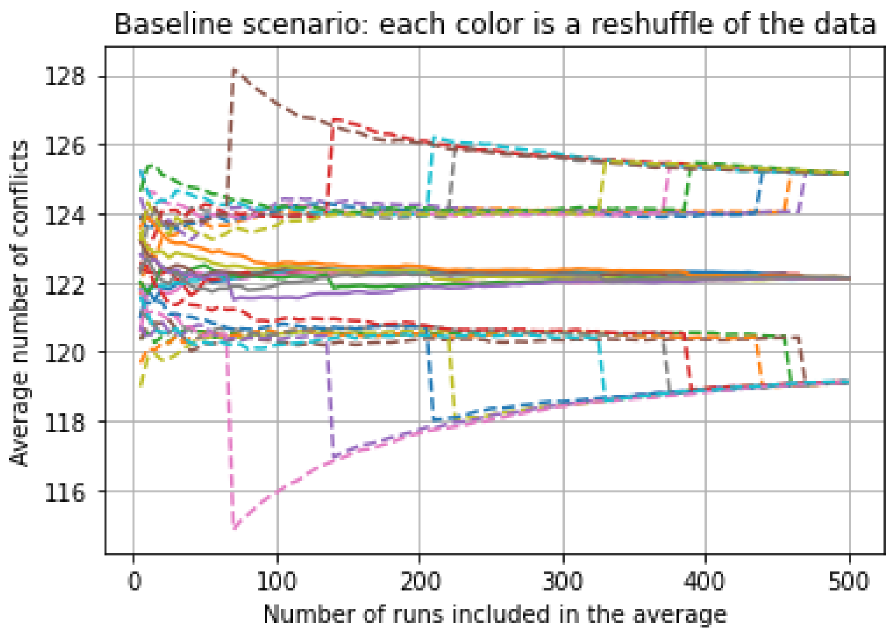


Figure 8: Estimates of the mean and variance of the number of severe traffic conflicts present in the baseline simulation experiments. The plot show how these estimates change with the number of simulation experiments considered.

Figure 8 also shows estimates of $\sigma\{\boldsymbol{Y}\}$**,** the standard deviation of the number of severe conflicts. The variance also seems to converge, although slowly, to a constant value (around 2) as the number of simulation experiment increases.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

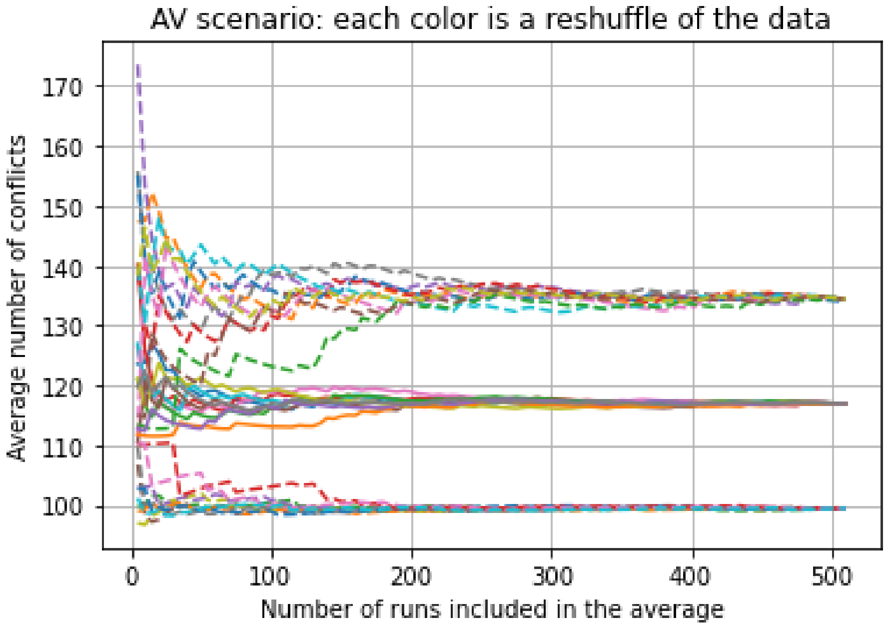


Figure 9: Estimates of the mean and variance of the number of severe traffic conflicts present in the AV simulation experiments. The plot show how these estimates change with the number of simulation experiments considered.

Figure 9 shows the same estimates for the AV scenario simulation experiments. Although the estimated mean number of severe conflicts is lower (116), the standard deviation is much larger (around 18).

To understand this change, consider the histograms shown in Figure 10. They show the number of simulation experiments as a function of the number of severe conflicts. The top histogram corresponds to the baseline scenario. Note that all simulation experiments show a similar number of conflicts tightly distributed around the mean (122). On the other hand, in the AV scenario, when some of the Green HDMs are replaced by AVs (see description above) the effect is split, as shown in the bottom histogram. In many cases the number of severe conflicts decreases, but in other cases, just a few, the number of conflicts actually increases. The net effect is a reduction of the mean number to severe conflicts to 116, but the increase in variance shows that this reductions is not uniform for all experiments.

This change seems to be related to the type of conflicts present in the simulation experiments. Figure 11 show the so-called "violin plots" for three types of severe conflicts: rear-end (left graph), lane change (center graph), and crossings (right graph). The first type of conflict happens when two cars are too close longitudinally (same lane), the second occurs when they are too close while one is changing lanes, and the last type occurs at a crossing (recall that "too close" means either a TTC < 1.5 seconds or a PET < 5 seconds).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

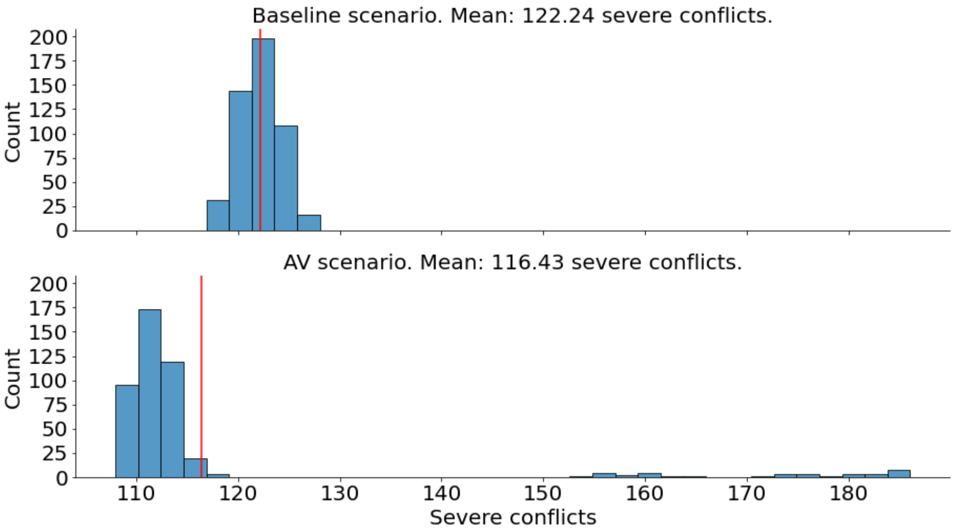


Figure 10: Histograms showing the number of simulation experiments as a function of the number of severe conflicts. Top: baseline scenario. Bottom: AV scenario.

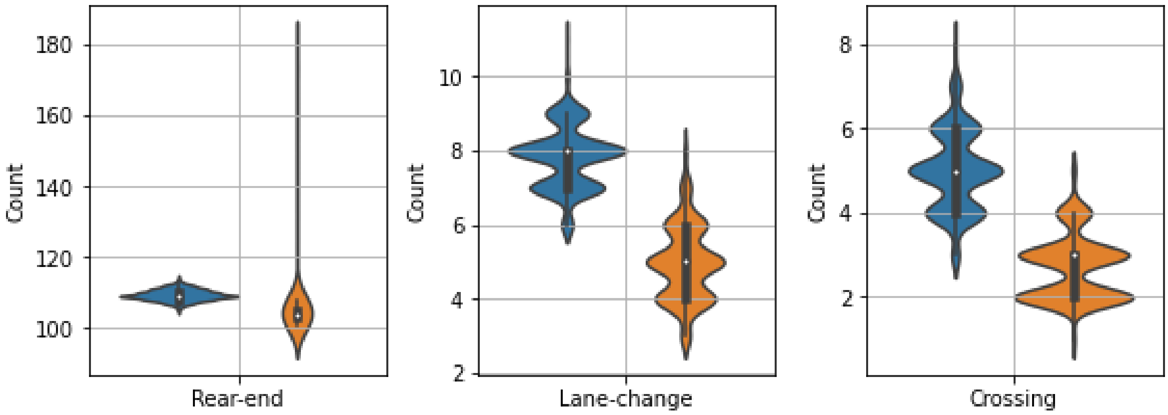


Figure 11: Analysis of the type of severe conflict present in each simulation experiment. In all three graphs, the left (blue) distribution corresponds to the baseline scenario, while the right (organ) distribution corresponds to the AV scenario. Three conflict types were considered: rear-end (left graph), lane change (center graph), and crossing (right graph).

Every violin plot in Figure 11 shows a mirrored, vertical version of the histograms in Figure 10 but for a specific type of conflict only. Figure 11 shows that the presence of AVs led to a reduction in the number of lane change and crossing conflicts, but also to a marked increase in the number of rear-end conflicts.

This basic analysis leads to a preliminary conclusion: although, as mentioned in Section 3, it would be difficult to generalize the results of these simulation to the real-world, these initial results suggest that AVs could indeed potentially alter the number of conflicts present in traffic, both for the better and the worse. More in depth analysis is needed to determine if the same results would be obtained when defining differently what a "severe conflict" is, or when altering how the AVs behave in traffic.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

4.2 Pedestrian and bicycle critical situations (IKA)

As described in deliverable D2.8, the assessment of criticality in interactions between VRUs and vehicles are of major interest. Due to the fact, that crashes have a high probability to cause severe injuries to pedestrians and cyclists [4]. Ika focused their simulation analysis on these critical situations.

To analyze the simulation results, ika used the following metrics to characterize critical scenarios for pedestrian-to-vehicle interactions.

- **Deceleration to Safety Time (DST):**

The DST describes how much an object has to decelerate/accelerate in order to reach the conflict point just after the other object has left it [5]. This evaluation metric is suitable for scenarios in which the trajectories of the two objects cross and can thus be directly transferred to a situation in which a pedestrian crosses the road.

- **Post Encroachment Time (PET):**

PET describes the time difference between a pedestrian leaving the crossing zone and a vehicle entering it. In this case, the trajectories of the pedestrian and the vehicle cross.

- **Time Head Way (THW):**

THW describes the time gap to a preceding object. In our application, the interpretation of THW is modified so that the pedestrian is a standing object on the road. Thus, the THW between the approaching vehicle and the standing pedestrian is evaluated. The calculation of the metric is valid as long as the pedestrian is walking on the road. The modified THW is here theoretically equivalent to the Time to Collision where the pedestrian has no speed.

Next to looking at the metrics characterizing critical situations for pedestrians, ika also identified critical scenarios in cyclist-to-vehicle interactions by using the metrics described below. The simulation analysis was constrained to metrics indicating critical scenarios in a longitudinal direction because of the lane-related behaviour of the other road users in the simulation.

- **Time to Collison (TTC):**

The remaining time to an imminent collision between a vehicle and a cyclist, if the current driving condition (with respect to velocity, direction etc.) does not change.

- **Time Head Way (THW):**

Description of time gap from a vehicle to the preceding cyclist.

- **Deceleration rate to avoid collision (DRAC):**

The rate at which a vehicle must decelerate to avoid a probable collision with a cyclist. Equation for vehicles traveling in the same path.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

- **Proportion of stopping distance (PSD):**

The ratio of distance available between two objects and the distance that is required to avoid a collision with the maximum available deceleration rate (MADR). MADR depends on vehicle type and environmental conditions such as pavement skid resistance.

The same analysis scheme was used for both VRU models. First, we conducted an individual analysis for each metric. As a second step, we performed an overall analysis, which focuses on the total number of all critical scenarios occurring in the simulations with and without the presence of Avs. (see Section3.1).

For the individual analysis the sum of all detected situations were analyzed. As shown exemplarily in Figure 12 for the pedestrian and in Figure 13 for the cyclist, the values of the selected metrics of each situation were plotted. The bars indicate the frequency of occurrence while the critical area is highlighted trough the red boxes. These threshold values defining critical scenarios are based on the results of D2.6, which has been determined with the help of the GIDAS data. The figures show the simulation results of two different simulation runs, which are distinguished by blue and brown bars. Compared to the brown bars, the blue bars represent a much more critical traffic situation. This is due to the fact that the brown histogram is shifted to a less critical area compared to the blue histogram, resulting in fewer interactions in the red area. In addition to the histograms, the specific numerical values are also analyzed. For this purpose, the total numbers of identified critical scenarios and its percentage in relation to all identified situations are considered. This allows a direct evaluation of the changes in the number of critical interactions and whether there are more conflicts in general due to parameter variations.

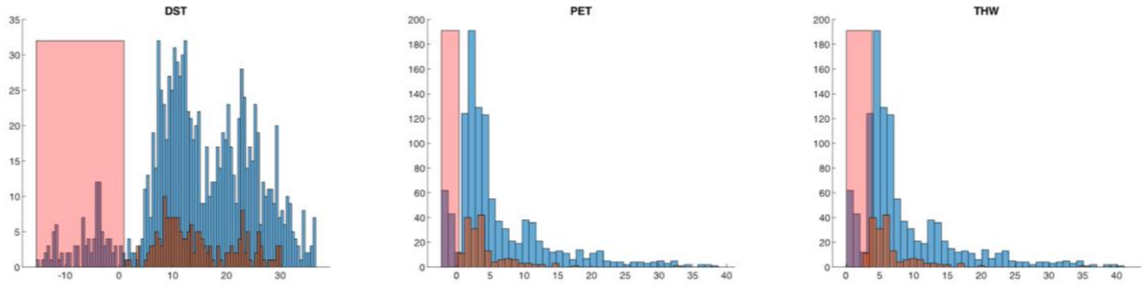


Figure 12: Analysis Overview of two Simulations for Pedestrians

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

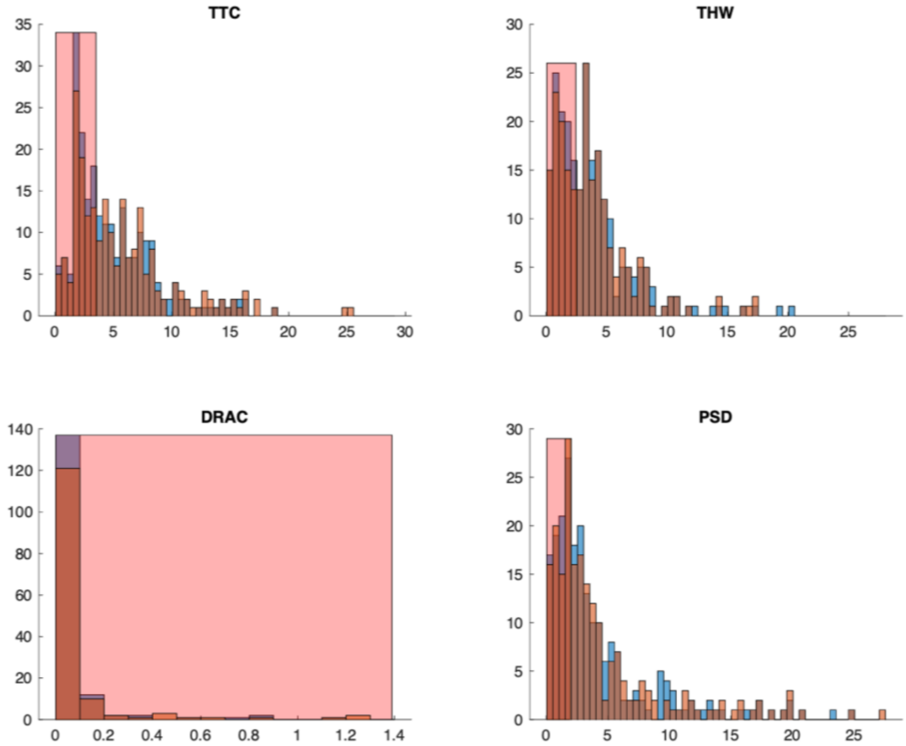


Figure 13: Analysis Overview of two Simulations for Cyclists

For the overall consideration, we conducted descriptive analysis on the absolute frequency of critical situations found in the simulations with and without AV as described in Section3.1. A situation was classified as critical if it was characterized as critical by at least one or more metrics. Figure 12 (Pedestrians) and Figure 13 (Cyclists) show the descriptive distribution (mean, median, quartiles, outliers) of the critical situations' frequency (y-axis). The x-axis indicates the number of simulations carried out.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

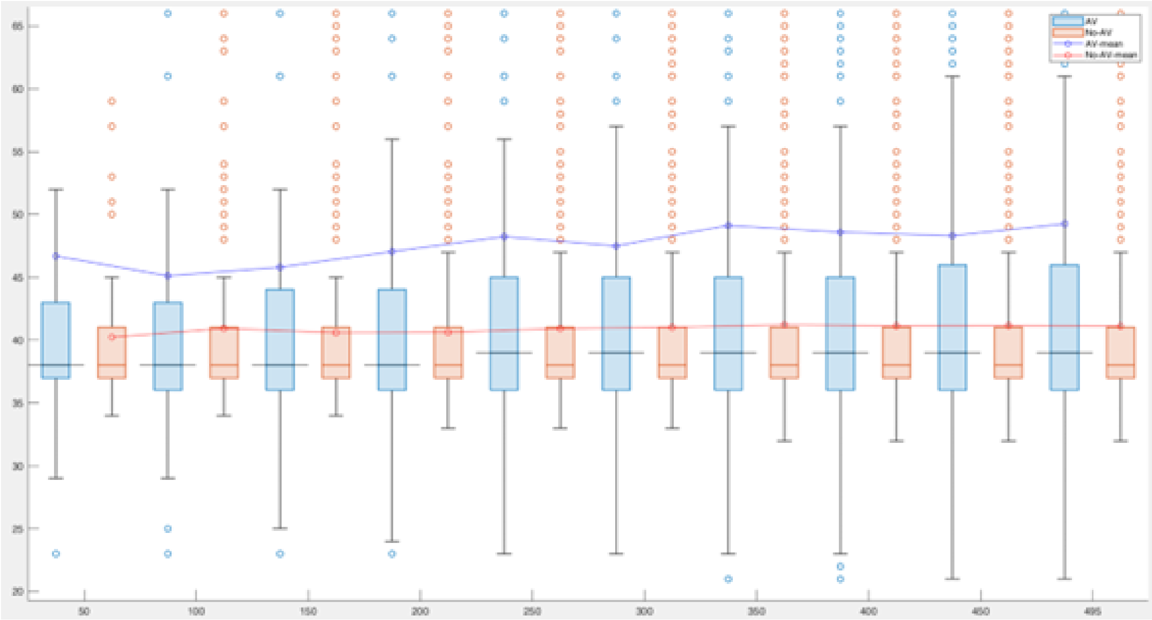


Figure 14: Overall Analysis of the Monte Carlo Simulation for Pedestrians

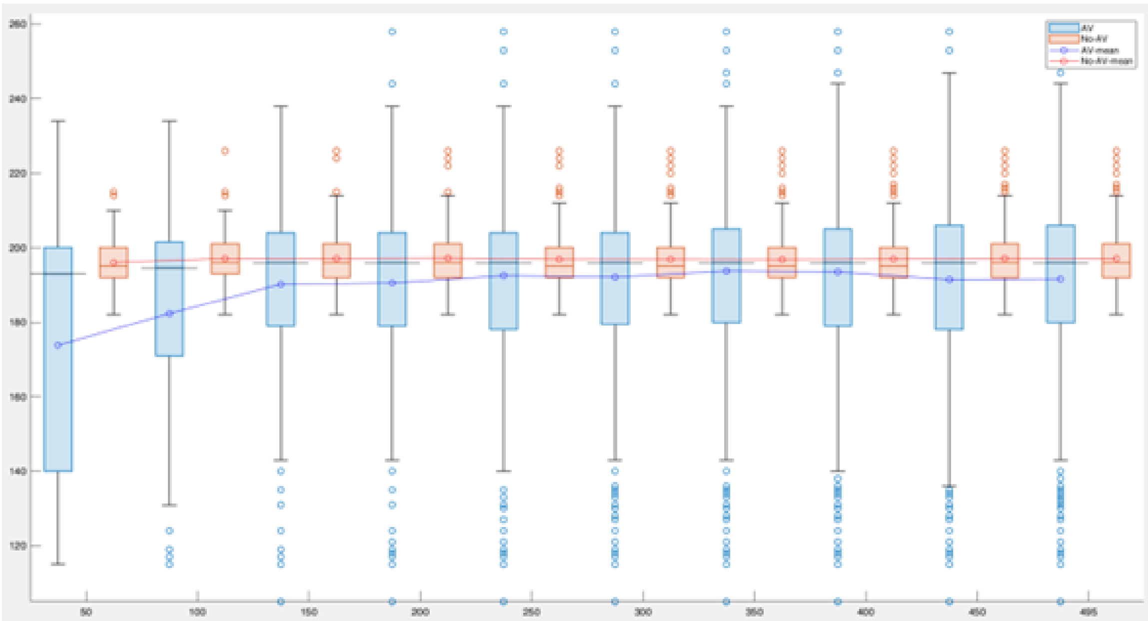


Figure 15: Overall Analysis of the Montecarlo Simulation for Cyclists

Descriptive differences in the data can be seen for both the pedestrians and the cyclists. First, it is noticeable that for both samples, the variance of the data is descriptively larger in the simulations with AVs than in the simulations without AVs. However, the cyclist data show descriptively little difference in the measures of central tendency (mean/median). In contrast, looking at the pedestrian data, a different situation can be seen. In these data, it is noticeable that the median and mean differ greatly. This can be explained by the high number of outliers to which the mean is susceptible. The median, on the other hand, is statistically robust to extreme values. Subsequently, the arithmetic mean descriptively indicates a stronger

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

difference between the two conditions, while examination of the medians indicates small differences in the number of critical events between simulations with and without AVs. It can be assumed that certain parameter variations of the different behavior models led to many critical situations, while the majority of the simulations show a similar frequency.

This shows how strongly different parameter variations and combinations of the different road users influence the number of critical situations occurring. When interpreting the data, it is therefore essential to take a differentiated look at the parameter variations carried out in order to be able to make reliable conclusions.

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

4.3.1 Analysis of the two simulations

Two simulation datasets are employed to conduct safety analysis. The first simulation set includes human driving (HD) vehicles with normal behaviours, while the HD vehicles have distracted behaviours in the second set. The simulation period is 10 minutes for both datasets, and an overview of the two simulation datasets is displayed in Table 4.

Table 4. General information in the two simulation datasets.

Dataset	No. cars	No. car pairs	No. PDRF calculation	Analysis time (s)
D1-normal	256	898	52,646	265.67
D2-distracted	260	926	40,952	182.53

As shown in Table 4, despite the difference of human driving behaviours, the two datasets (D1 and D2) contain a close number of cars, indicating a similar traffic density. To speed up the simulation analysis, we set a distance threshold as 100 metres for car-car interactions. Given ego car A, if a surrounding car B has a minimum relative distance with car B less than 100 metres, the two cars (A, B) are identified as a pair. Note pairs (A, B) and (B, A) are different, as the calculation of PDRF (the safety metric developed by the project partner TU Delft) depends on whether a car is regarded as an ego or surrounding one.

We calculate PDRF for each pair at each time step when the relative distance of the pair is less than 100 metres. Although the number of car pairs in D1 is slightly less than that in D2, more PDRF calculations are conducted for D1, leading to overall larger analysis time. However, real-time implementation for safety evaluation with PDRF is still promising, as the simulation period is 600 seconds, which is 2 or 3 times of the analysis time.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

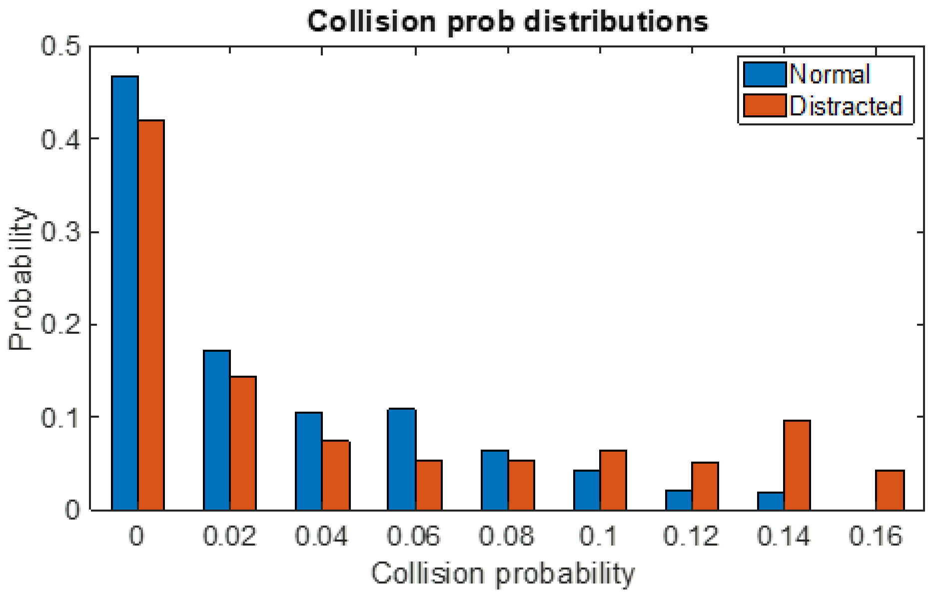


Figure 16 CP distributions over two datasets.

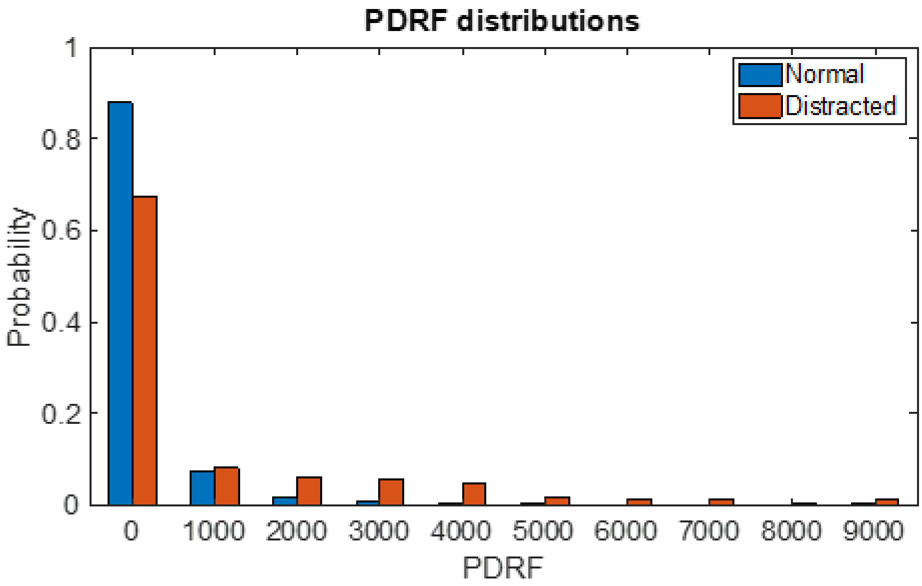


Figure 17 Safety metric PDRF distributions over two datasets.

For convenience, we only report the maximum collision probability (CP) and corresponding PDRF values for each pair. The CP and PDRF distribution comparison results over D1 and D2 are illustrated in Figure 16 and Figure 17, respectively. Clearly both figures present the same trend between D1 and D2, i.e., car-car interactions in D1 are more risky than that in D2. This is reasonable, as the human drivers in D2 are simulated with distracted behaviours. We also observe that for the same dataset, the distributions of CP and PDRF are different.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

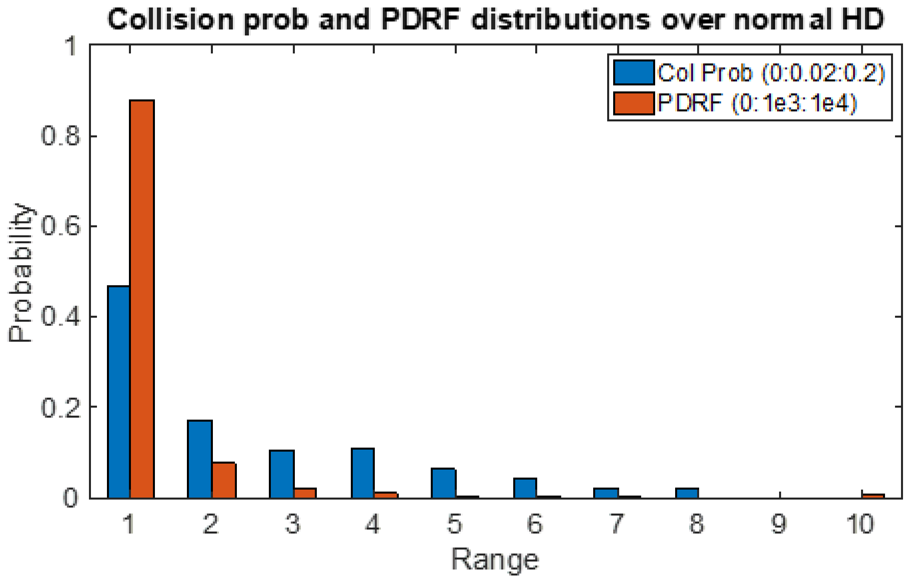


Figure 18. CP and PDRF distributions comparison over D1.

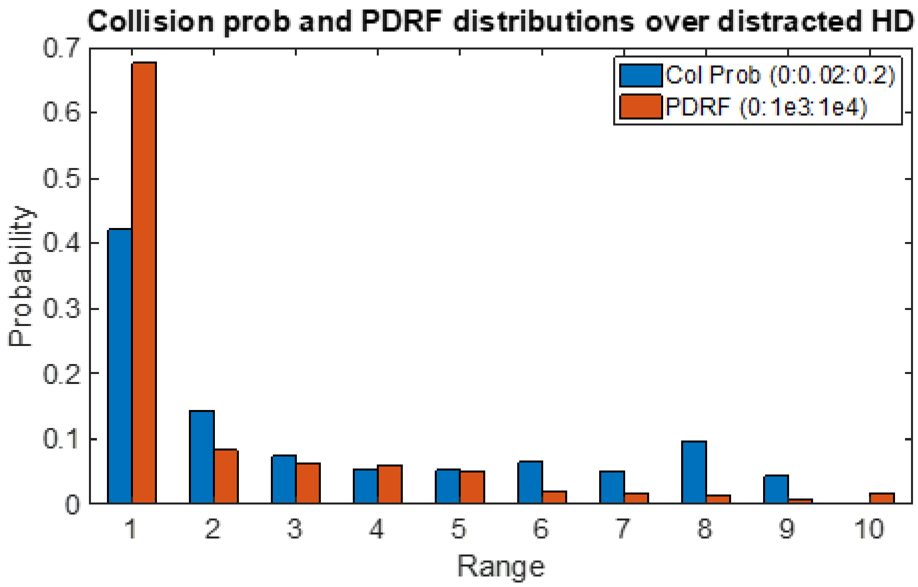


Figure 19 CP and PDRF distributions comparison over D2.

For clearer comparison, we plot the distributions of CP and PDRF in the same frame, both for D1 and D2 in Figure 18 and Figure 19, respectively. Indeed, in both datasets, the distributions of PDRF are more concentrated. This is because PDRF is calculated as a product of a CP and a crash severity, where the severity is relevant to the vehicle mass and relative speed between the two cars. Thus PDRF has a larger distribution range; when PDRF is evenly divided into 10 subintervals, the first interval then has a higher distribution probability. In conclusion, the CP distributions have clearer physical meanings and easy to interpret for safety analysis. For PDRF distributions, a safety-critical threshold matters.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Nevertheless, PDRF contains not only CP but also crash severity information and is promising to accurately estimate the driving safety for car-car interactions.

4.4 PTW critical analysis results (Unifi)

The Analysis of PTW-car critical interactions was done with the simulations conducted for the Monte Carlo method explained in Section 3. Thus, this analysis identified the high-risk PTW-car interactions for both the baseline scenario (without the presence of automated vehicles) and the AV scenario (including automated vehicles). The conditions of the simulations for each scenario (network, number of simulations, number of different agents and values changed in the parametric models) are those defined in Section 3. The risk metrics used to identify high-risk PTW-car interactions is the Crash Probability Index for Motorcycles (CPIM). How the CPIM is computed and the methodology for the analysis of CPIM using the output of the simulations are defined in deliverable D2.14.

4.4.1 CPIM Risk Analysis

The CPIM analysis identifies PTW-car interactions with a high risk of crash (i.e., near-crash or crash) to assess traffic safety. As commented in previous sections, this type of events are quite rare in real-life, so the possibility of finding a crash in a realistic simulation of traffic is very low. Figure 20 shows how the risk metrics using the CPIM index identified cases where the interaction PTW-car was completely safe in 99.2% and 99.4% of the events for the simulation without (baseline) and with AV respectively.

The CPIM identified just over 100 cases with high crash risk (CPIM > 0.8) for each condition in a total of 500 simulations involving more than 50,000 PTW-car interactions, making it difficult to conduct a reliable comparison between the two conditions (Figure 21). Overall, PTW-car interactions with high crash risk accounted for 0.3% and 0.2% of the cases in the simulations without and with inclusion of AV respectively. Based on this result, the inclusion of AVs in the simulations developed in AIMSUN Next did not add significant changes in the PTW-car interactions in terms of increase/reduction of high crash risk cases.

It is important note, that a few of the planned simulations with AVs were not completed due to some errors during the simulation, so despite having more agents involved (same quantity of human driven vehicles, PTWs, bicycles and pedestrians plus the new autonomous vehicles) the total number of PTW-car interactions is slightly lower with AVs (52,398 cases) compared to the total case of the baseline conditions (56,721 cases).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

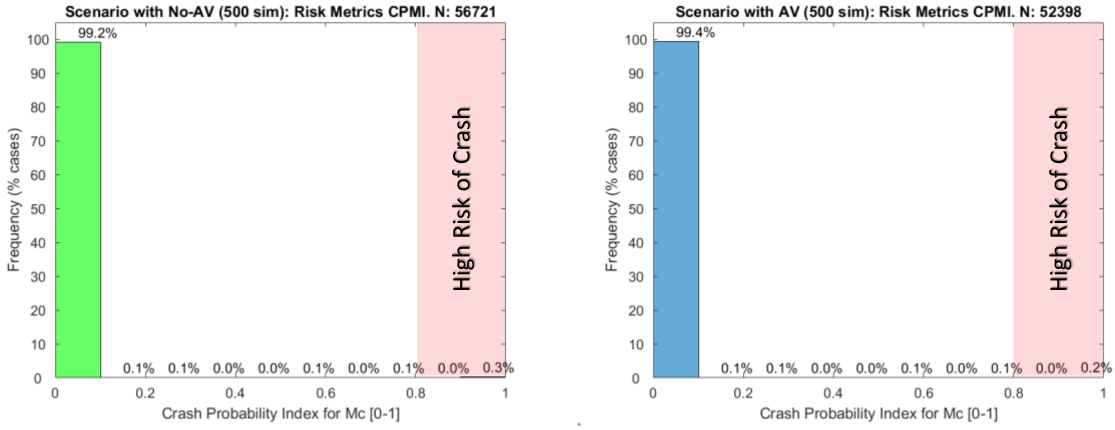


Figure 20. Distribution of CPIM (percentage) after running 500 simulations with baseline condition (No-AV) and with the condition including Avs. Unavoidable crash is considered for CPIM =1. *High Risk of crash* for CPIM > 0.8.

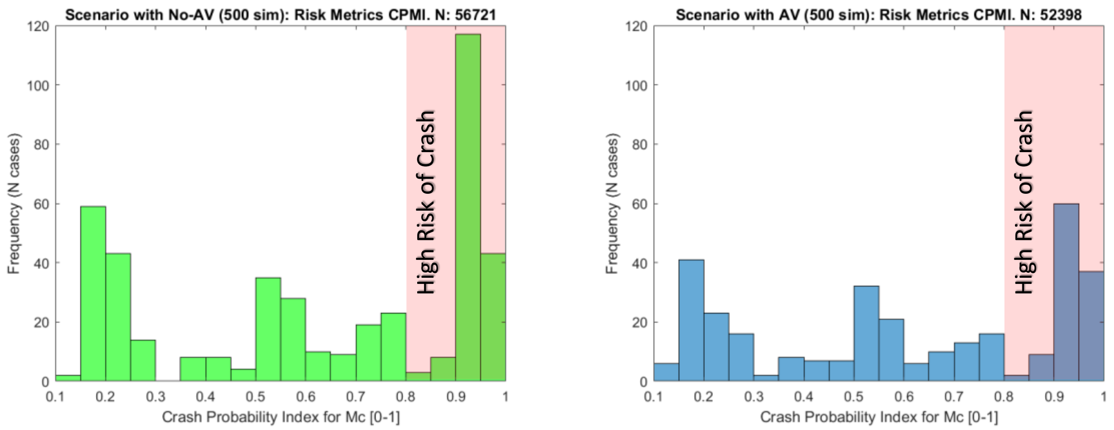


Figure 21. Frequency distribution of CPIM (quantity of events) after running 500 simulations with baseline condition (No-AV) and with the condition including AVs. *High Risk of crash* for CPIM > 0.8.

4.4.2 Mixed Index Risk Analysis: Fuzzy Inference Systems model

In order to understand the variance between simulations in terms of risky PTW-car interactions, we decided to apply a new mixed index (MI) risk metric based on fuzzy inference system (FIS) models using time-to-collision (TTC) and Time Gap (TG) between the PTW and the leading car as input. This MI risk metric follows the methodology of previous studies [6][7]. or the case of our analysis, which explores PTW-car interactions with car-following scenario, the inclusion of the TG brings a potential hazard component to the TTC (more related to a real and imminent danger), which increases the number of cases considered unsafe without the need to end up becoming a crash or near-crash.

Thus, MI risk metric is less reliable than CPIM in identifying actual crash events, but it is able to identify medium risk events with interactions that could potentially become high risk in case of changing conditions (e.g., possibility of rear-end collision if the car in front brakes sharply due to a short time gap of the PTW during car-following). The fuzzy rules of the model connecting TTC, TG and risk in the PTW-car interaction are based on the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

relationships defined in previous studies (Nadimi et al., 2016; Vogel, 2003). Table 5 and Figure 22 show the fuzzy rules and membership gaussian functions for the defined TTC and TG inputs respectively.

Table 5 Fuzzy rules for MI risk determination of PTW-car interactions based on TTC and TG.

	TG: VS	TG: S	TG: M	TG: L	TG: VL
TTC: VS	MI RISK: VS	-	-	-	-
TTC: S	MI RISK: VS	MI RISK: S	-	-	-
TTC: M	MI RISK: S	MI RISK: M	MI RISK: M	-	-
TTC: L	MI RISK: M	MI RISK: M	MI RISK: L	MI RISK: L	-
TTC: VL	MI RISK: L	MI RISK: L	MI RISK: VL	MI RISK: VL	MI RISK: VL

VS: very small; S: small; M: moderate; L: large; VL: very large; '-': not possible. Source: Nadimi et al (2016)

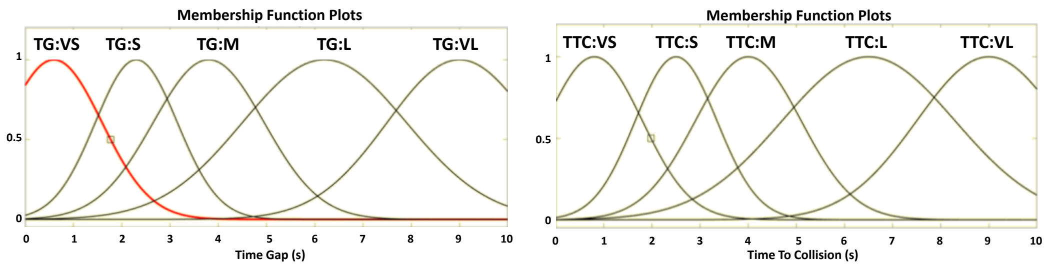


Figure 22. Gaussian membership functions for TTC and GT

After applying the MI risk to the interacttions for the 500 simulations without/with AVs, the threshold that could classify the different levels of risk was determined with the Cumulative Distribution Function (CDF). Figure 23 shows the CDFs and the three different thresholds defined, where the *unsafe events* were determined by MI risk > 0.8, which represents more than Percentil 97 for both conditions. The thresholds of MI Risk 0.4 and 0.6 were also added in case the planned analysis required to increase the subsample with cases considered not completely safe.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

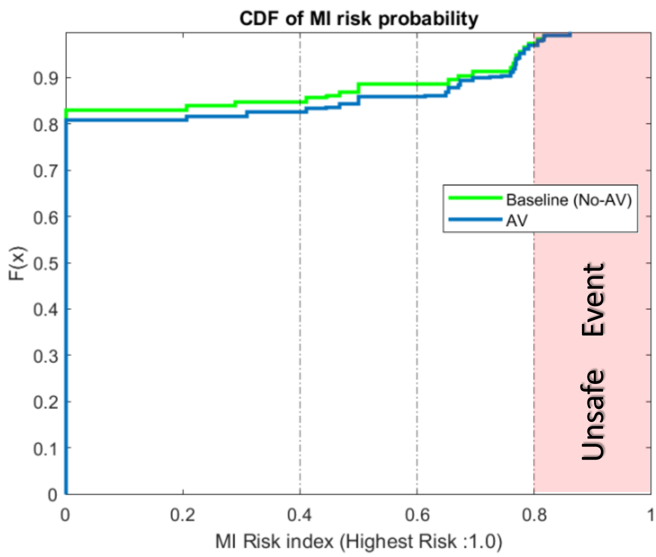


Figure 23. Cumulative Distribution Function (CDF) of MI risk for 500 simulations. Dotted lines represent the different thresholds related to risk PTW-car interactions.

The results of the new MI risk metric for the 500 simulations and the te two conditions of the study are showed in Figure 24 and Figure 25. The MI Risk identified more than 1500 unsafe events (MI Risk > 0.8) for each condition in a total of 500 simulations. Overall, unsafe PTW-car interactions accounted for 2.5% and 2.9% of the cases in the simulations without and with inclusion of AV respectively. Based on this result generated with MI Risk (in contrast to the results with CPIM), the inclusion of AVs in the simulations developed in AIMSUN Next increased overall unsafe PTW-car interactions by 0.4% compared to the baseline without AVs, representing a relative increase of 16% more unsafe cases.

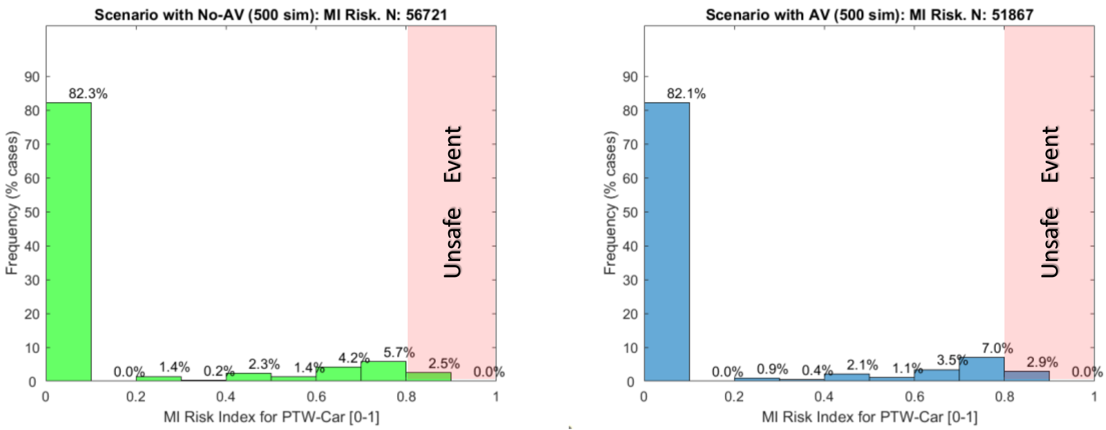


Figure 24. Distribution of MI Risk (percentage) after running 500 simulation with baseline condition (No-AV) and with the condition including AVs. *Unsafe Event* for MI Risk > 0.8.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

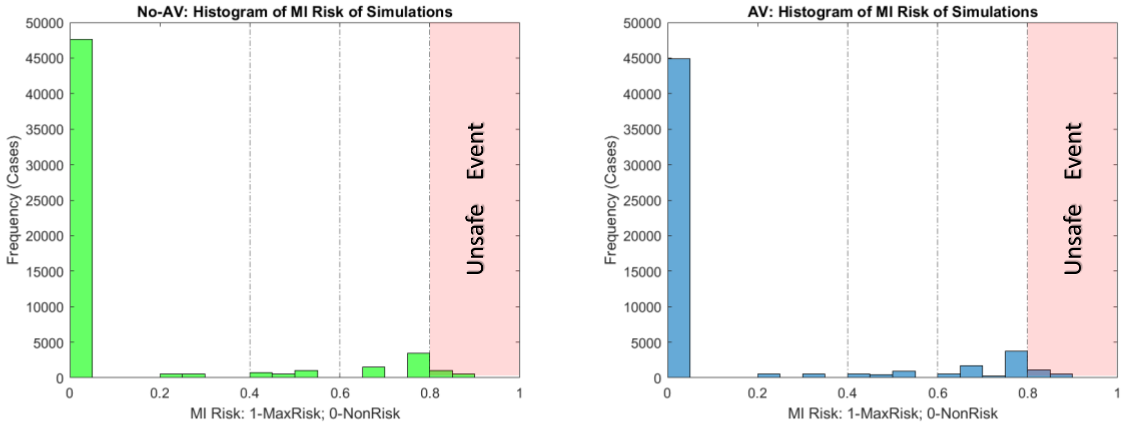


Figure 25. Frequency distribution of MI Risk (quantity of events) after running 500 simulation with baseline condition (No-AV) and with the condition including AVs. *Unsafe Event* for MI Risk > 0.8

4.4.3 Monte-Carlo Results (PTW-car interactions)

As only one high crash risk case (CPIM > 0.8) was identified in every three simulations, it was not feasible to perform the Monte Carlo analysis with the variation of crash or near-crash cases. For this reason, we used the variation between the number of cases that exceeded three defined thresholds of the MI risk metric developed with a fuzzy model, to determine at what point (number of simulations) the number of unsafe PTW-car events stabilized. For this purpose, the average and variance were calculated for each new simulation performed. Thus, the procedure followed was to add the cases of each new simulation to the cases of the previous simulations, and then calculate the new variance value and the new average number of unsafe PTW-car interactions per simulation.

Figure 27 shows the curve of the variance as the number of simulations increased. As can be seen, in the baseline condition (no AVs) the variance is minimal from the first simulations, from which it can be deduced that the variation in the time gap parameter of the human driver model had little influence in bringing about changes in the number of *unsafe* events between simulations. On the contrary, the simulations with the AV condition experienced some variability for the cases identified with more conservative thresholds (0.4 and 0.6) that tends to stabilize between 200 and 300 simulations, although from the first simulations the variance is already very low. In the case of events considered *unsafe* (MI Risk > 0.8), the number of events found oscillates between 3 and 4 per simulation, so the variance found is very low from the beginning.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

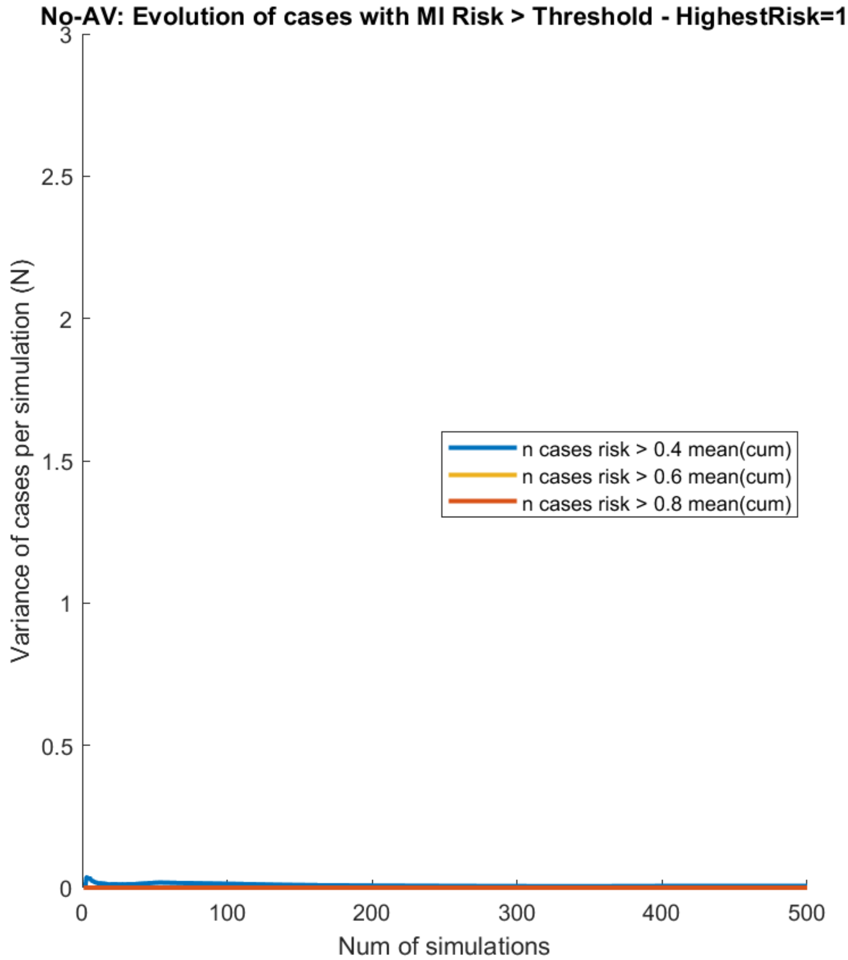


Figure 26. Variance of cases identified as the number of simulations increased

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

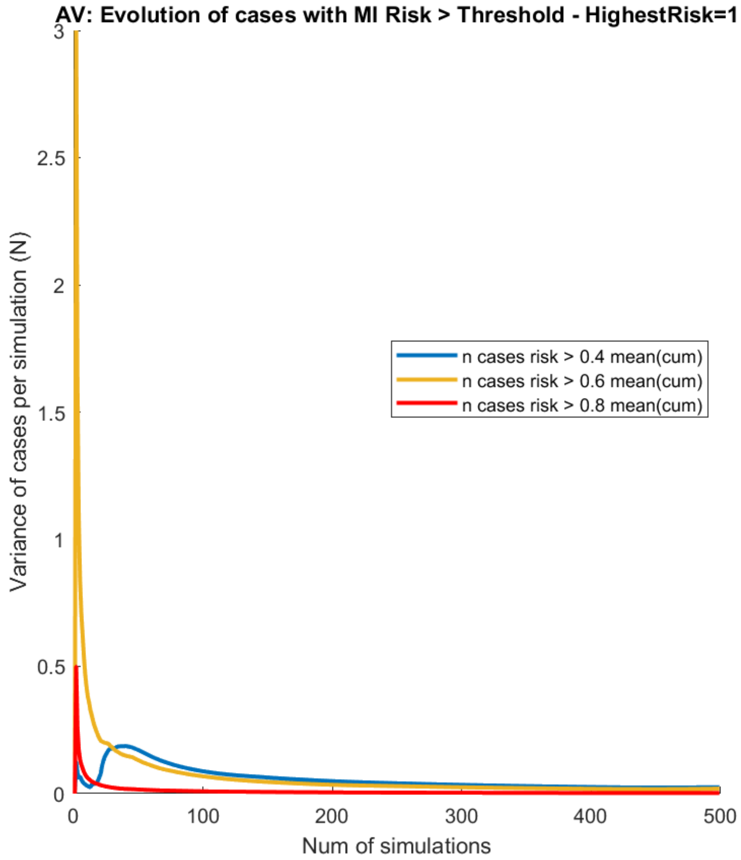


Figure 27. Variance of cases identified as the number of simulations increased

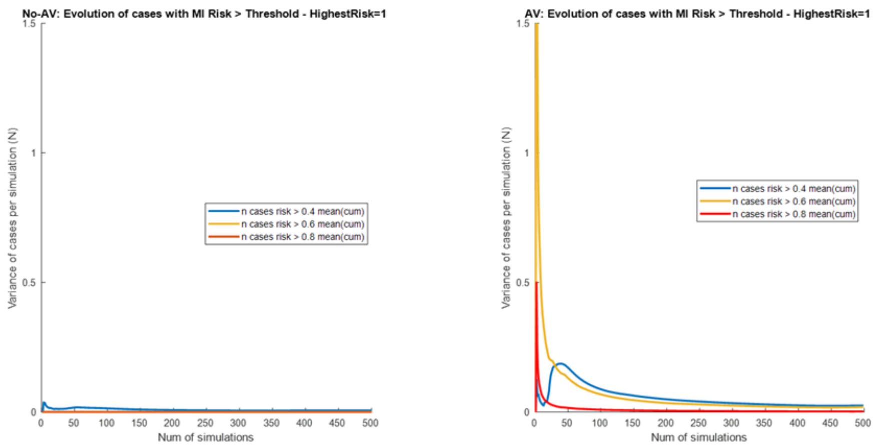


Figure 28 shows the trends of the average number of cases encountered above the different thresholds defined, where it can be seen how the variability of the simulations with VAs included is higher than that without VAs. It is important to note that, considering that the simulations including AVs increased the number of cars in the simulation network, the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

number of interactions also increased and, consequently, the probability of having more unsafe cases also increased. Thus, the results in Figure 27 help to understand the variance of the results as the number of simulations increases, but cannot be used to directly compare the two study conditions. For a direct comparison it is necessary to use the results in Figure 20 and Figure 24 already discussed.

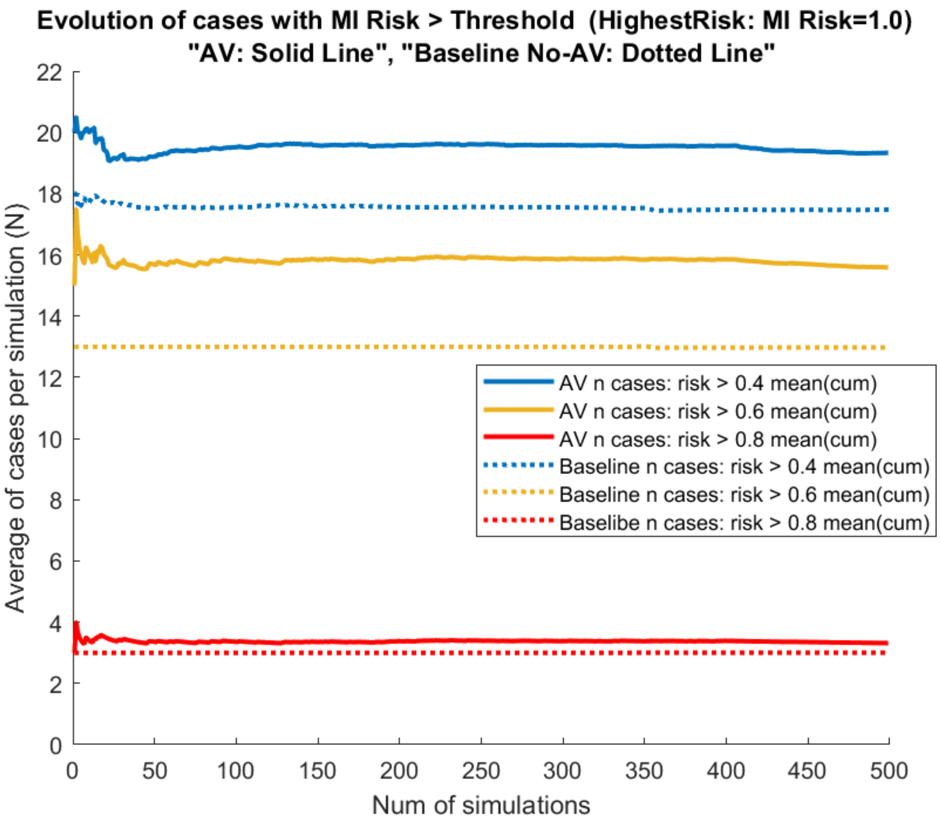


Figure 28. Average of cases identified per simulation as the number of simulations increased

As a conclusion, the 500 simulations following the Monte Carlo method for two conditions (collision risk with/without inclusion of AVs) in the network with mixed traffic (cars, PTWs, bicycles and pedestrians) indicates that the values obtained from the MI risk metric analysis are stable after 200 simulations. Therefore, although the 500 simulations are not sufficient to analyze events that rarely occur in a simulation (i.e. crash or near-crash), they do guarantee reliable results if the objective is to evaluate the probability of potentially unsafe interactions under the two study conditions.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

4.5 Av scenario analysis (IDIADA)

In the study, 500 simulations were conducted using an automated vehicle in the presence of pedestrians and powered two-wheelers. The purpose of these simulations was to analyze the behavior of the automated vehicle's algorithm in critical situations that could potentially lead to malfunctions or errors.

The simulations were designed to replicate real-world scenarios in which an automated vehicle may encounter challenging situations involving pedestrians and powered two-wheelers. These scenarios included scenarios such as pedestrian crossing, and other complex traffic situations. The simulation environment considered various factors, such as road geometry, traffic flow, and sensor data that the automated vehicle would perceive.

The simulations were executed multiple times to obtain a statistically significant sample size of 500 simulations, which allowed for a comprehensive analysis of the automated vehicle's performance in different scenarios. The simulations varied in terms of input parameters to capture a wide range of potential scenarios that the automated vehicle may encounter in real-world driving conditions.

The analysis focused on identifying any potential critical situations or scenarios in which the automated vehicle's algorithm could potentially malfunction or make errors. These could include scenarios where the vehicle failed to detect a pedestrian or powered two-wheeler, misjudged their movements, made incorrect decisions, or exhibited unsafe behavior. By analyzing the simulations from the perspective of the automated vehicle, the study aimed to identify potential areas of improvement in the algorithm's performance and safety.

The analysis revealed that the automated vehicle algorithm was not as mature as anticipated in terms of decision-making and behavior planning. Several factors were identified as responsible for these limitations.

One key factor was the coexistence of different behavioral models within the simulation environment. With multiple road users, including pedestrians and powered two-wheelers, exhibiting diverse behaviors, the algorithm struggled to accurately predict and respond to their actions. The lack of clear understanding between the behavioral models of different road users led to challenges in decision-making and behavior planning for the automated vehicle.

Another challenge arose from unexpected traffic signaling situations, such as intersections with stop signs in each incoming lane. The algorithm applied a right-hand rule, but it encountered malfunctions due to the unpredictable behavior of other actors, leading to uncertainties and errors in decision-making.

The long flow of pedestrians in certain scenarios also posed challenges for the automated vehicle. The conservative programming of the algorithm led to prolonged waiting times as the vehicle prioritized pedestrian safety. This resulted in delays and disruptions to the flow of traffic, affecting the efficiency and performance of the automated vehicle.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Furthermore, the conservative nature of the automated vehicle's programming sometimes caused pedestrians to get stuck in a particular area, leading to accumulations and further delays. The vehicle's cautious approach to avoid potential collisions resulted in extended waiting times until sufficient clearance was detected, further impacting the vehicle's performance. These situations can be categorized in the most common problems as follows:

4.5.1 Scenario vehicles ignoring AV presence

It was found in multiple cases where the vehicles surrounding the AV were overlapping the AV, even not respecting sometimes the traffic lights, and moving laterally without modifying their heading.

These situations reflect a leak of maturity on the interaction between scenario actors, and meanwhile are expected to happen the planning algorithm hasn't been tested so deep in the scope of this project to manage these situations.

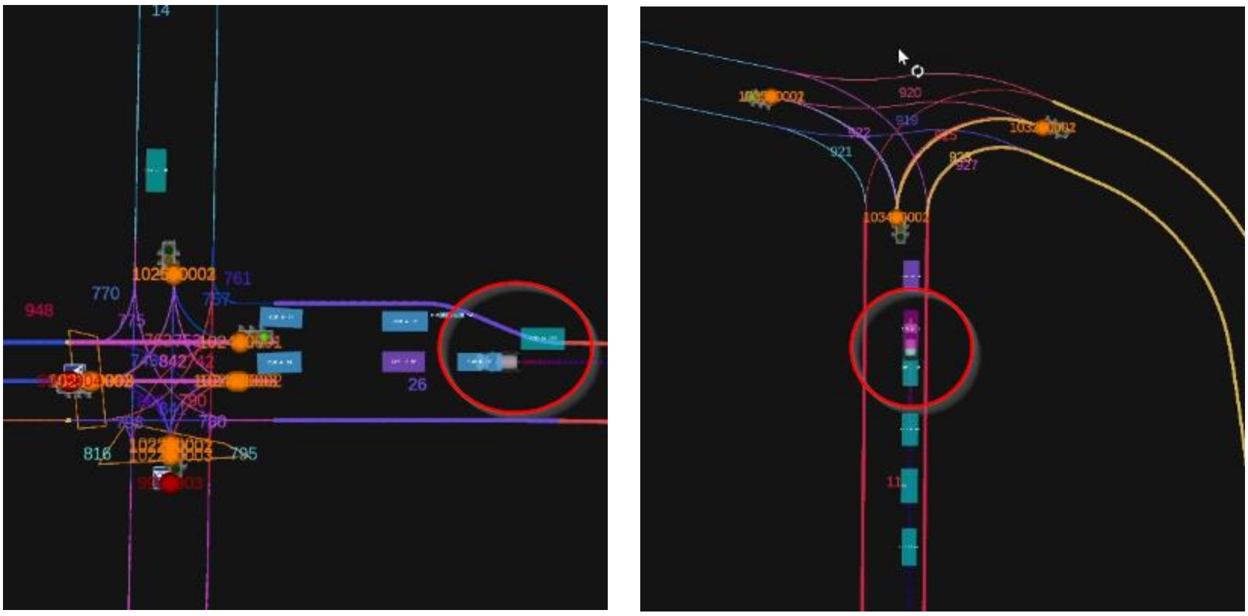


Figure 29. vehicles ignoring AV presence

4.5.2 The AV is stuck for the rest of the simulation

There were multiple cases where the AV got stuck during the rest of the scenario without any external vehicle interaction. Among the reasons, the main one is the low maturity of the AV algorithm behavioral model to manage complex digital maps and deal with this unexpected situation.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

For instance, below we can see an example where the AV found a “ghost” junction; We found out that these situations can be avoided properly managing them.

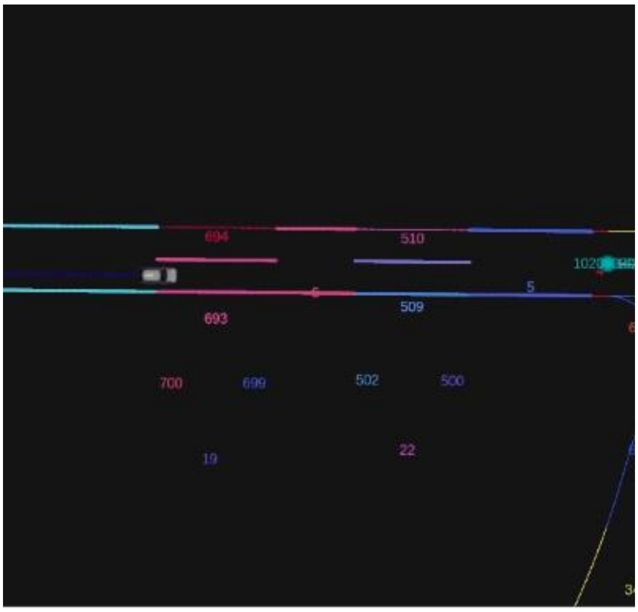


Figure 30. the AV found a “ghost” junction

4.5.3 Crosswalks management

Crosswalks have been a conflictive spot, because our AV had to interact with the pedestrian model, and our behavioral model towards pedestrians is too basic and conservative, leading to situations of the AV being stopped for too long or during the rest of the scenario.

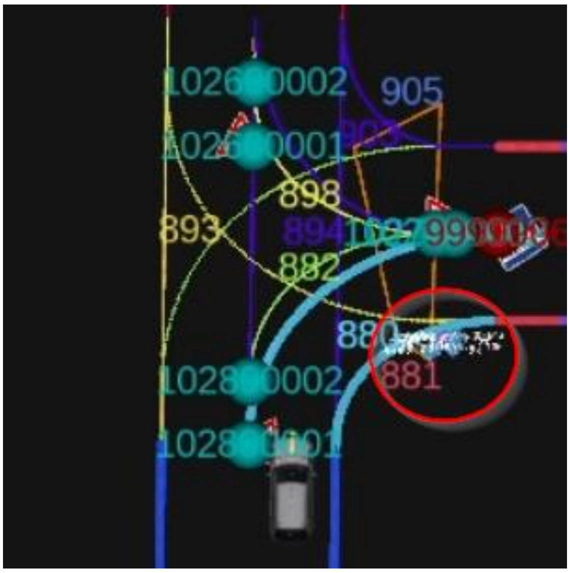


Figure 31. the pedestrian model accumulating too many pedestrians

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement 861570.

In figure 31 can be seen an example of the pedestrian model accumulating too many pedestrians in the same spot near a crosswalk and confusing the AV, which leads to a permanent stop until there is full clearance. These situations are something that can happen in the real world and shall be improved in the AV behavioral models.

4.5.4 Junction management

Another conflictive spot are junctions, mainly the junctions that don't have a clear priority established, e.g. "Four road junctions with a STOP in every road". Where the AV had to establish the right-hand rule, but since other actors are working together these rules should be very well defined for all models.

As the example below it can be seen that these situations led to other actors invading the junctions while the AV was on Drive mode, leading to the AV getting stuck for the rest of the scenario. There are some cases that the AV algorithm can manage and continue after the conflictive spot, and other ones that are simply breaking the algorithm state machine. The behavioral model shall be deeply tested for this conflictive situations.

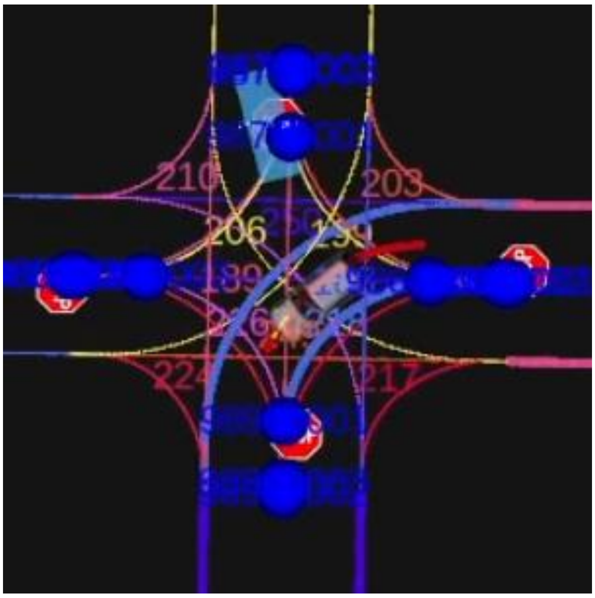


Figure 32. other actors invading the junctions while the AV was on Drive mode

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

5. Conclusions

Task 2.5 had to achieve an ambitious objective: to perform a set of simulations to find out the safety critical scenarios that we will encounter in mixt traffic in the future.

The activities in this task consisted in defining a methodology to plan the execution of the simulations (a necessary activity that was unassigned in the project proposal), define the parameters that needed to change during the different simulations (aggressive or standard driver, standard PTW, aggressive PTW, pedestrian and cyclist attention to the surroundings, AV penetration rate, etc.), define the batch of simulations for each run, and analyse the simulations performance and their results. Below, you can find the main conclusions of each study that was carried out in Task 2.5

5.1 Car-to-car conflicts (TNO)

The basic comparative analysis performed in the framework of the Monte-Carlo method described in Section 3.1.2 leads to a preliminary conclusion: although it would be difficult to generalize the results obtained via the simulations to the real-world, the initial results suggest that the presence of AVs could indeed alter the number of conflicts present in traffic, both for the better and the worse.

It was observed that some conflict types increased (rear-end conflicts) while other types decreased (lane changes, crossings). It is not clear at this point whether these results would be replicated if, for example, the thresholds on TTC and PET used to define severe conflicts were changed, or if the behavioral rules for AVs were altered, or if the number of traffic participants increases. Future projects should explore more fully these variations.

5.2 AV model performance conclusions

Significant effort was put into establishing a pipeline for parallel simulation in AWS, involving multiple partner models, to assess the limitations of automated vehicle algorithms. Through these simulations, valuable insights have been gained, particularly in identifying the areas that require special attention and reinforcement in the automated vehicle algorithms. These areas include the interaction with behavioral models, as well as the need to enhance the interaction between different algorithms operating in the same scenarios.

Furthermore, an important aspect that has emerged from the development and design of automated vehicle algorithms is the need to account for completely unexpected situations, and to create robust behavioral models that can handle worst-case scenarios, such as prompting the driver to take over control of the vehicle.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

5.3 PTW-to-car conflicts

The work conducted has been able to provide new information to understand more about PTW-car interactions, the effect of different parameters related to driving behaviour and the probability of critical events in a realistic environment such as the one developed in the simulations with the AIMUN Next platform. The analysis of the effect of AV inclusion on the safety of PTW-car interactions did not show large differences when compared to the baseline condition (no-AVs). PTW-car interactions with high crash risk accounted for 0.3% and 0.2% of the car-following events found in the simulations without and with inclusion of AV respectively, and unsafe PTW-car interactions with potential risk of collision accounted for 2.5% and 2.9% of the cases without and with inclusion of AV respectively.

Varying over the simulations the desired time gap of the human drivers' vehicles, as explained in section 3.1.2, resulted in small changes in the number of PTW-car critical events. Therefore, the 500 simulations were not sufficient to analyse the collisions or near-collisions identified by the CPIM metric using the TTC, the speed of the vehicles and the distribution of the braking ability of the motorcycle riders. In contrast, if the objective is to assess the probability of potential unsafe interactions in the two study conditions as a surrogate safety indicator, the 500 simulations performed following the Monte Carlo method on the network with mixed traffic indicated that the values obtained from the MI risk metric analysis for PTW-car interactions (based on TTC and Time-Gap) were stable after 200 simulations.

For a better understanding of PTW-car interactions and the effect of including AVs in collisions and near-collisions, the findings of our work suggest for future studies to include a wider range of variation of parameters such as time gap or right-of-way violation in human drivers of cars and motorcyclists.

5.4 Pedestrians and Cyclists

In this work package, ika focused on the development of behavioral models for cyclists and pedestrians. VR simulators were developed to calibrate and verify the models, so that the relevant behavioral characteristics could be investigated in the context of subject studies. By integrating these models into the shared simulation environment consisting of various road users, critical scenarios between VRUs and vehicles could be identified using selected metrics and related thresholds.

Simulations have shown that the specific parameterization of VRU behavior produces corresponding behavior in the simulation. For example, restricting pedestrian visibility generally increased the number of critical incidents. The Monte Carlo simulation clearly showed that replacing human drivers with AVs influences the number of critical situations. Whether this has a negative or positive effect depends on the specific model parameters for each simulation.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

In further studies, it is important to focus on VRUs as they are the most vulnerable to collisions with future AVs. Especially the future challenges regarding AVs in urban areas require the identification and analysis of edge cases. A key aspect is to create a validated traffic simulation that serves as a reference or baseline situation. The challenges here are mainly in the ground truth data and the correlation of the individual model parameters to each other, so that the behavior in the real world can be reproduced through stochastic variation of the parameters. Subsequently, the effect of Avs or specific functions in future traffic scenarios can be investigated in detail based on the validated reference simulation.

5.5 Challenges and lessons learned

The overall achievement of the T.2.5 task was in line with the grant agreement, the methodology defined was implemented, the models developed in the other tasks were integrated in a platform and simulations were executed and analyzed.

On the other hand, several challenges were faced and activities took much bigger effort than planned, the definition of the model's parameters that needed to be changed in the simulations took several loops and modifications to the models that were already finished and rework on the scripts to run the simulations. Also, the computational platform over which the simulations were run was changed in mid-2022 due to the need for larger computational power. The simulation system is now hosted on Amazon Web Services, a migration with significant technical challenges, that was unavoidable to address the necessary increase of AV rate penetration and the large amount of simulation runs needed to obtain the expected outcomes

All these unexpected challenges were solved but limited the time and resources available for the final step which was performing a comparative analysis between the baseline with no AV to an elevated big penetration rate of AV. Several batches of simulations were done, the starting point was a set of 100 simulations, and it increased to up to 500 simulations. But each time a set of simulation was finished we found several things to improve on models or on the performance to the simulation.

Due to time and resources, the work planned in the grant agreement had been finished with several analyses but the results had not been enough to provide a clear picture of future safety-critical situations. The work related to improving the models and the parameters of the simulation is a never-ending cycle of improvements.

It is recommended that the community sets up a follow-up project focused on continuing the work in this work package, re-using our simulation platform. Such project should support the collection of the data necessary to calibrate and validate the simulation environment so it becomes a true digital twin of reality. It should also help improve the simulation models developed in this project, and perform larger and longer batches of simulations to fully explore the possible future safety-critical situations in mixed traffic.

.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

References

[1] K. Adjenughwure, N. Deschle, G. Klunder and C. Birkner, "Enhanced Human Driver Behavioral Microsimulation Model Update," in *Deliverable 2.11, SAFE-UP Project*, 2022.

[2] I. M. Sobol, "A primer for the Monte Carlo method," 1994.

[3] M. S. Blumenthal, L. Fraade-Blanar, R. Best and J. L. Irwin, "Safe Enough: Approaches to Assessing Acceptable Safety for Automated Vehicles," *RAND Corporation,* 2020.

[4] K. Adjenughwure, P. Huertas Leyva, F. Prinz, A. Tejada and X. Wang, "Description Metrics for Traffic Interactions," in *Deliverable 2.5, SAFE-UP Project*, 2021.

[5] J. Kotte and A. Pütz, "Methodology and Results for the Investigation of Interacations Between Pedestrians and Vehicles in Real and Controlled Traffic Conditions," in *UR:BAN Human Factors in Traffic*, Springer Fachmedien Wiesbaden: Wiesbaden , 2018, pp. 291-310.

[6] N. Nadimi, H. Behbahani and H. Shahbazi, "Calibration and validation of a new time-based surrogate safety measure using fuzzy inference system," *Journal of traffic and transportation engineering,* vol. 3, no. 1, pp. 51-58, 2016.

[7] K. Vogel, "A comparison of headway and time to collision as safety indicators," *Accident Analysis and Prevention,* vol. 35, no. 4, pp. 427-433, 2003.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

Appendix

6. Manual for safety metric PDRF programme developed at TU Delft

6.1 Introduction

This manual is created to help SAFE-UP project partners and other potential users to understand and use the safety metric the probabilistic driving risk field (PDRF) programme developed by SAFE-UP partner TU Delft, for car-car interaction risk assessment. Detailed information of PDRF is referred to relevant SAFE-UP project deliverables.

6.2 Two programs

PDRF_fzp_process.py

Purpose: to calculate PDRF value for every vehicle pair at each time step, and output the maximum PDRF value for each vehicle pair.

Required packages: sys, numpy, shapely, quadpy, time, math, mat4py

Input: trajectory file generated from the AIMSUN traffic platform. The supported file format is *.fzp.

The definition of the format is as follows.

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

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.

ToD: Simulation Time as Time of Day [hh:mm:ss]

DistX: Total Distance Traveled in the Network [m]

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)

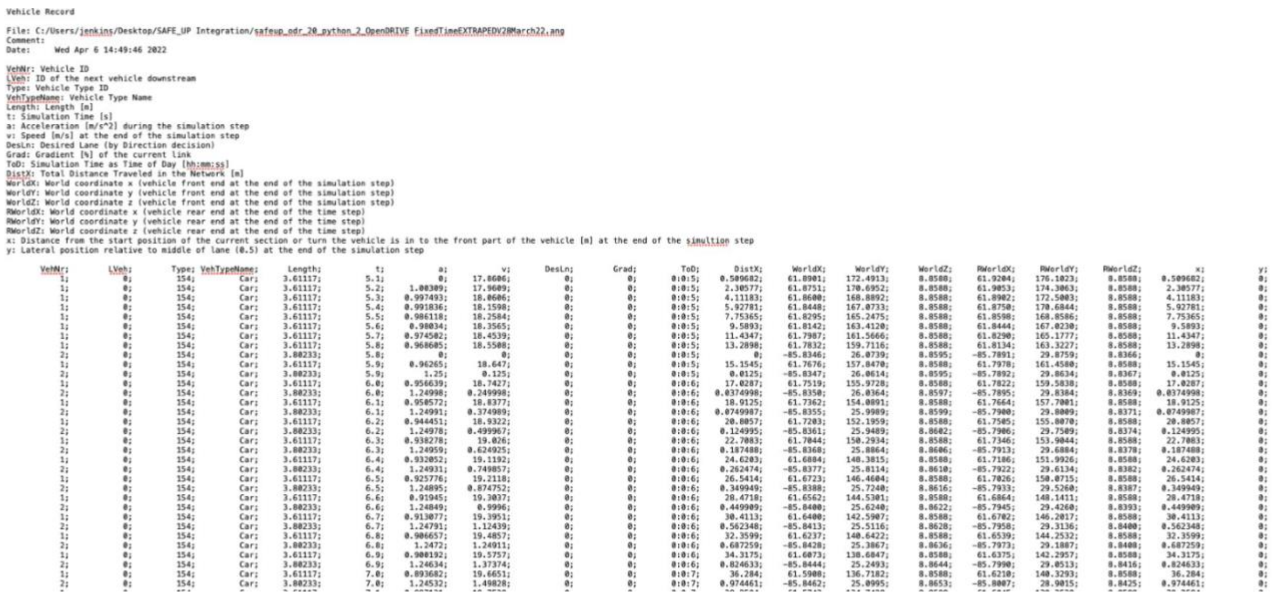
RWorldX: World coordinate x (vehicle rear end at the end of the time step)

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 [m] at the end of the simulation step

y: Lateral position relative to middle of lane (0.5) at the end of the simulation step



Vehicle Record

File: C:/Users/jenkins/Desktop/SAFE_UP Integration/safeup_odr_20_python_2_OpenDRIVE FixedTimeEXTRAPEDV20March22.ang
Comment:
Date: Wed Apr 6 14:49:46 2022

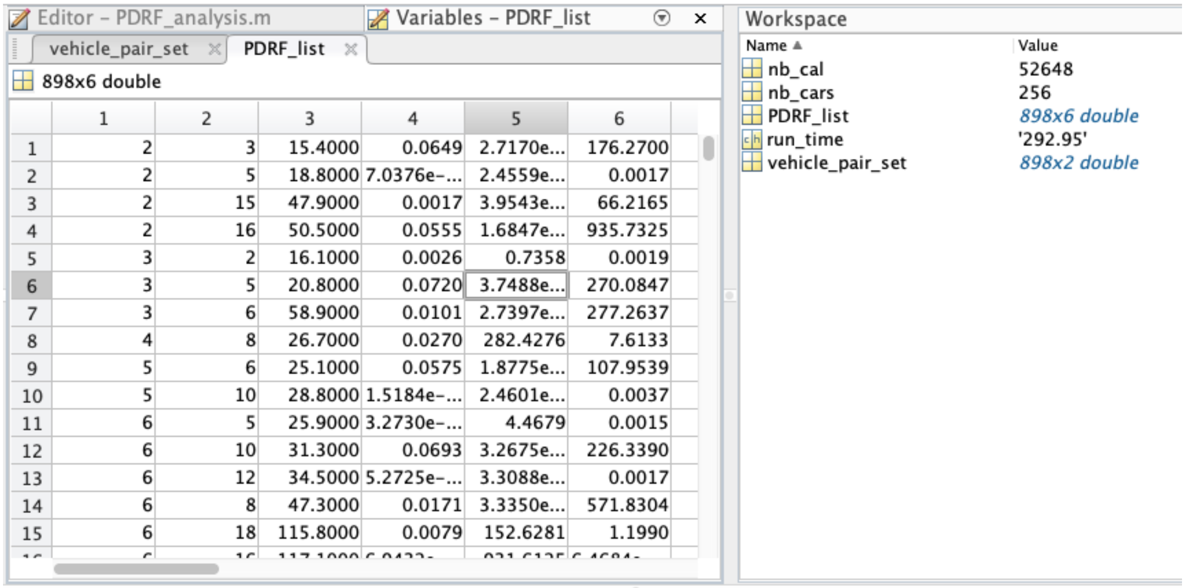
VehNr: Vehicle ID
LVeh: ID of the next vehicle downstream
Type: Vehicle Type ID
VehTypeName: Vehicle Type Name
Length: Length [m]
t: Simulation Time [s]
a: Acceleration [m/s^2] during the simulation step
v: Speed [m/s] at the end of the simulation step
DesLn: Desired Lane (by Direction decision)
Grad: Gradient [%] of the current link
ToD: Simulation Time as Time of Day [hh:mm:ss]
DistX: Total Distance Traveled in the Network [m]
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 [m] at the end of the simultion step
y: Lateral position relative to middle of lane (0.5) at the end of the simulation step

VehNr;	LVeh;	Type;	VehTypeName;	Length;	t;	a;	v;	DesLn;	Grad;	ToD;	DistX;	WorldX;	WorldY;	WorldZ;	RWorldX;	RWorldY;	RWorldZ;	x;	y;
1;	0;	154;	Car;	3.61117;	5.1;	0;	17.8606;	0;	0;	0:0:5;	0.509682;	61.8901;	172.4913;	8.8588;	61.9204;	176.1023;	8.8588;	0.509682;	0;
1;	0;	154;	Car;	3.61117;	5.2;	1.00309;	17.9609;	0;	0;	0:0:5;	2.30577;	61.8751;	170.6952;	8.8588;	61.9053;	174.3063;	8.8588;	2.30577;	0;
1;	0;	154;	Car;	3.61117;	5.3;	0.997493;	18.0606;	0;	0;	0:0:5;	4.11183;	61.8600;	168.8892;	8.8588;	61.8902;	172.5003;	8.8588;	4.11183;	0;
1;	0;	154;	Car;	3.61117;	5.4;	0.991836;	18.1598;	0;	0;	0:0:5;	5.92781;	61.8448;	167.0733;	8.8588;	61.8750;	170.6844;	8.8588;	5.92781;	0;
1;	0;	154;	Car;	3.61117;	5.5;	0.986118;	18.2584;	0;	0;	0:0:5;	7.75365;	61.8295;	165.2475;	8.8588;	61.8598;	168.8586;	8.8588;	7.75365;	0;
1;	0;	154;	Car;	3.61117;	5.6;	0.98034;	18.3565;	0;	0;	0:0:5;	9.5893;	61.8142;	163.4120;	8.8588;	61.8444;	167.0230;	8.8588;	9.5893;	0;
1;	0;	154;	Car;	3.61117;	5.7;	0.974502;	18.4539;	0;	0;	0:0:5;	11.4347;	61.7987;	161.5666;	8.8588;	61.8290;	165.1777;	8.8588;	11.4347;	0;
1;	0;	154;	Car;	3.61117;	5.8;	0.968605;	18.5508;	0;	0;	0:0:5;	13.2898;	61.7832;	159.7116;	8.8588;	61.8134;	163.3227;	8.8588;	13.2898;	0;
2;	0;	154;	Car;	3.80233;	5.8;	0;	0;	0;	0;	0:0:5;	0;	-85.8346;	26.0739;	8.8595;	-85.7891;	29.8759;	8.8366;	0;	0;
1;	0;	154;	Car;	3.61117;	5.9;	0.96265;	18.647;	0;	0;	0:0:5;	15.1545;	61.7676;	157.8470;	8.8588;	61.7978;	161.4580;	8.8588;	15.1545;	0;
2;	0;	154;	Car;	3.80233;	5.9;	1.25;	0.125;	0;	0;	0:0:5;	0.0125;	-85.8347;	26.0614;	8.8595;	-85.7892;	29.8634;	8.8367;	0.0125;	0;
1;	0;	154;	Car;	3.61117;	6.0;	0.956639;	18.7427;	0;	0;	0:0:6;	17.0287;	61.7519;	155.9728;	8.8588;	61.7822;	159.5838;	8.8588;	17.0287;	0;
2;	0;	154;	Car;	3.80233;	6.0;	1.24998;	0.249998;	0;	0;	0:0:6;	0.0374998;	-85.8350;	26.0364;	8.8597;	-85.7895;	29.8384;	8.8369;	0.0374998;	0;
1;	0;	154;	Car;	3.61117;	6.1;	0.950572;	18.8377;	0;	0;	0:0:6;	18.9125;	61.7362;	154.0891;	8.8588;	61.7664;	157.7001;	8.8588;	18.9125;	0;
2;	0;	154;	Car;	3.80233;	6.1;	1.24991;	0.374989;	0;	0;	0:0:6;	0.0749987;	-85.8355;	25.9989;	8.8599;	-85.7900;	29.8009;	8.8371;	0.0749987;	0;
1;	0;	154;	Car;	3.61117;	6.2;	0.944451;	18.9322;	0;	0;	0:0:6;	20.8057;	61.7203;	152.1959;	8.8588;	61.7505;	155.8070;	8.8588;	20.8057;	0;
2;	0;	154;	Car;	3.80233;	6.2;	1.24978;	0.499967;	0;	0;	0:0:6;	0.124995;	-85.8361;	25.9489;	8.8602;	-85.7906;	29.7509;	8.8374;	0.124995;	0;
1;	0;	154;	Car;	3.61117;	6.3;	0.938278;	19.026;	0;	0;	0:0:6;	22.7083;	61.7044;	150.2934;	8.8588;	61.7346;	153.9044;	8.8588;	22.7083;	0;
2;	0;	154;	Car;	3.80233;	6.3;	1.24959;	0.624925;	0;	0;	0:0:6;	0.187488;	-85.8368;	25.8864;	8.8606;	-85.7913;	29.6884;	8.8378;	0.187488;	0;
1;	0;	154;	Car;	3.61117;	6.4;	0.932052;	19.1192;	0;	0;	0:0:6;	24.6203;	61.6884;	148.3815;	8.8588;	61.7186;	151.9926;	8.8588;	24.6203;	0;
2;	0;	154;	Car;	3.80233;	6.4;	1.24931;	0.749857;	0;	0;	0:0:6;	0.262474;	-85.8377;	25.8114;	8.8610;	-85.7922;	29.6134;	8.8382;	0.262474;	0;
1;	0;	154;	Car;	3.61117;	6.5;	0.925776;	19.2118;	0;	0;	0:0:6;	26.5414;	61.6723;	146.4604;	8.8588;	61.7026;	150.0715;	8.8588;	26.5414;	0;
2;	0;	154;	Car;	3.80233;	6.5;	1.24895;	0.874752;	0;	0;	0:0:6;	0.349949;	-85.8388;	25.7240;	8.8616;	-85.7933;	29.5260;	8.8387;	0.349949;	0;
1;	0;	154;	Car;	3.61117;	6.6;	0.91945;	19.3037;	0;	0;	0:0:6;	28.4718;	61.6562;	144.5301;	8.8588;	61.6864;	148.1411;	8.8588;	28.4718;	0;
2;	0;	154;	Car;	3.80233;	6.6;	1.24849;	0.9996;	0;	0;	0:0:6;	0.449909;	-85.8400;	25.6240;	8.8622;	-85.7945;	29.4260;	8.8393;	0.449909;	0;
1;	0;	154;	Car;	3.61117;	6.7;	0.913077;	19.3951;	0;	0;	0:0:6;	30.4113;	61.6400;	142.5907;	8.8588;	61.6702;	146.2017;	8.8588;	30.4113;	0;
2;	0;	154;	Car;	3.80233;	6.7;	1.24791;	1.12439;	0;	0;	0:0:6;	0.562348;	-85.8413;	25.5116;	8.8628;	-85.7958;	29.3136;	8.8400;	0.562348;	0;
1;	0;	154;	Car;	3.61117;	6.8;	0.906657;	19.4857;	0;	0;	0:0:6;	32.3599;	61.6237;	140.6422;	8.8588;	61.6539;	144.2532;	8.8588;	32.3599;	0;
2;	0;	154;	Car;	3.80233;	6.8;	1.2472;	1.24911;	0;	0;	0:0:6;	0.687259;	-85.8428;	25.3867;	8.8636;	-85.7973;	29.1887;	8.8408;	0.687259;	0;
1;	0;	154;	Car;	3.61117;	6.9;	0.900192;	19.5757;	0;	0;	0:0:6;	34.3175;	61.6073;	138.6847;	8.8588;	61.6375;	142.2957;	8.8588;	34.3175;	0;
2;	0;	154;	Car;	3.80233;	6.9;	1.24634;	1.37374;	0;	0;	0:0:6;	0.824633;	-85.8444;	25.2493;	8.8644;	-85.7990;	29.0513;	8.8416;	0.824633;	0;
1;	0;	154;	Car;	3.61117;	7.0;	0.893682;	19.6651;	0;	0;	0:0:7;	36.284;	61.5908;	136.7182;	8.8588;	61.6210;	140.3293;	8.8588;	36.284;	0;
2;	0;	154;	Car;	3.80233;	7.0;	1.24532;	1.49828;	0;	0;	0:0:7;	0.974461;	-85.8462;	25.0995;	8.8653;	-85.8007;	28.9015;	8.8425;	0.974461;	0;

Example of the *.fzp file.

Output: the maximum PDRF value for each vehicle pair based on the input file. The saved output format file is *.mat.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.



	1	2	3	4	5	6
1	2	3	15.4000	0.0649	2.7170e...	176.2700
2	2	5	18.8000	7.0376e-...	2.4559e...	0.0017
3	2	15	47.9000	0.0017	3.9543e...	66.2165
4	2	16	50.5000	0.0555	1.6847e...	935.7325
5	3	2	16.1000	0.0026	0.7358	0.0019
6	3	5	20.8000	0.0720	3.7488e...	270.0847
7	3	6	58.9000	0.0101	2.7397e...	277.2637
8	4	8	26.7000	0.0270	282.4276	7.6133
9	5	6	25.1000	0.0575	1.8775e...	107.9539
10	5	10	28.8000	1.5184e-...	2.4601e...	0.0037
11	6	5	25.9000	3.2730e-...	4.4679	0.0015
12	6	10	31.3000	0.0693	3.2675e...	226.3390
13	6	12	34.5000	5.2725e-...	3.3088e...	0.0017
14	6	8	47.3000	0.0171	3.3350e...	571.8304
15	6	18	115.8000	0.0079	152.6281	1.1990

Name	Value
nb_cal	52648
nb_cars	256
PDRF_list	898x6 double
run_time	'292.95'
vehicle_pair_set	898x2 double

Example of the *.mat file.

How to use

step 1: locate to the directory including the python program and the input file

step 2: run the following python command (either a or b) in the terminal

a. Python PDRF_fzp_process.py (

   (With default input&output files: ‘vehicles_hd_normal.fzp’, ‘results_output.mat’)

b. Python PDRF_fzp_process.py *.fzp *.mat

   (With specific *.fzp input file and *.mat output file)

PDRF_analysis.m

Purpose: to illustrate the safety metric results. The .m file is self-explained and easy to understand.

<u>Included functions in PDRF_fzp_process.py:</u>

get_PDRF(): the main function to calculate the DPRF value for each vehicle pair at each time step

prob_dense_fun(): the probability density function used to calculate the collision probability

reachable_sur(): to calculate the reachable space of the surrounding vehicle

frame_trans_gloabl_to_body(): coordinate transfer function

frame_trans_body_to_global(): coordinate transfer function

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement 861570.

Example of the results

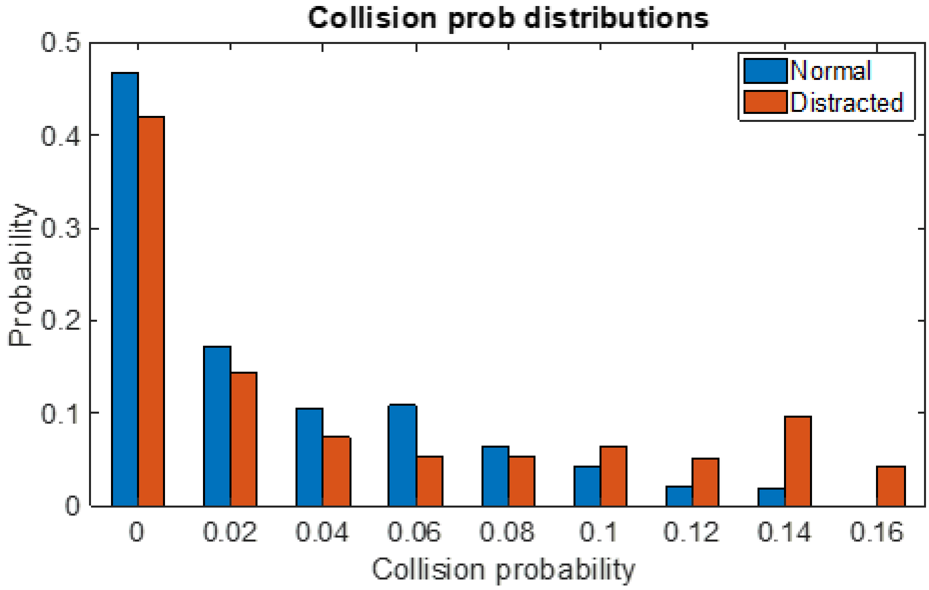


Figure 1. CP distributions over two datasets.

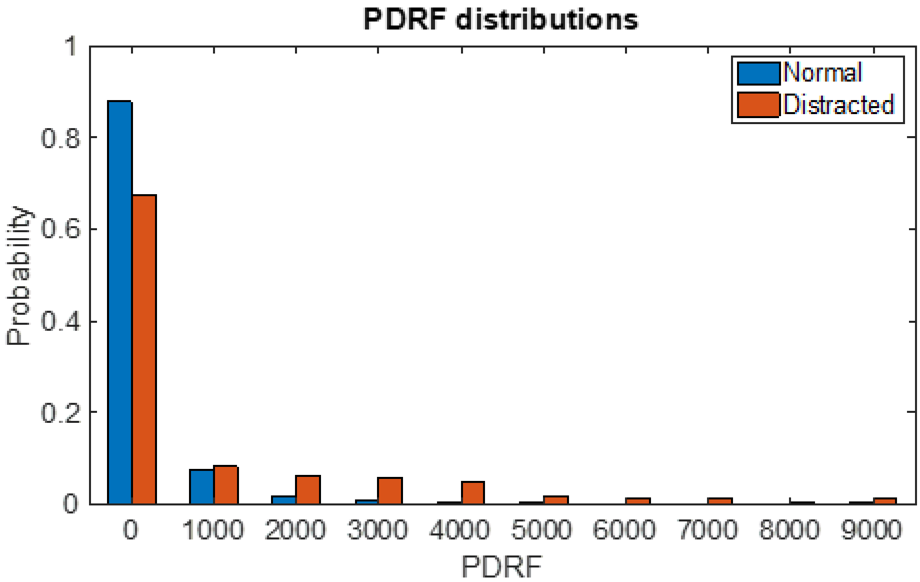


Figure 2. Safety metric PDRF distributions over two datasets.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement 861570.