D2.4 Definition of the future use cases: scope and data to build digital twins of use cases

Primary Author(s)	Tamara Djukic, Jordi Casas, Sara Pardo | Aimsun Gerdien Klunder, Kingsley Adjenughwure | TNO Fabian Russ | Institut für Kraftfahrzeuge (IKA) Yamnia Rodriguez, Núria Parera | Applus IDIADA Thomas Pallacci | University of Firenze (UNIFI)
Related Work Package	WP2
Version/Status	1.0 | Final
Issue date	30/11/2021
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.

Reviewers

Version	Date	Reviewer (Name/Organisation)	Action (Checked/Approved)
0.3	07/11/2021	András Bálint (Chalmers University of Technology)	Deliverable reviewer
0.3	07/11/2021	Fabian Rus (IKA)	Deliverable reviewer
0.3	07/11/2021	Arturo Tejada Ruiz (IKA)	WP2 leader

Document Distribution

Version	Date	Distributed to
0.4	23/11/2021	All deliverable co-authors
0.5	29/11/2021	Coordination Team
1.0	30/11/2021	Submission in the EC System
	17/03/2022	Approved by the EC

Acknowledgment

We thank all SAFE-UP project partners for supporting the work that led to this document and for their active participation in project meetings.

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Executive summary

The SAFE-UP project aims to proactively address the novel safety challenges of the future mobility systems through the development of tools and innovative safety methods that lead to improvements in road transport safety. Future mobility systems will rely on partially and fully automated vehicles to reduce traffic collisions and casualties by removing causal factors like driver distraction, fatigue or infractions and by reacting autonomously to emergency situations. On the other hand, they may introduce new collision risk factors or risky behaviours in other traffic participants. SAFE-UP's Work Package 2 will further the understanding of the impact of vehicle automation technologies on safety by leveraging newly developed behavioural traffic simulation tools. These tools will allow one to simulate specific road networks with a variable proportion of automated vehicles.

The simulation and prediction of future safety-critical scenarios requires development of a new traffic simulation environment and framework which deals with the specific challenges around road collisions. From the Grant agreement: "D2.4: Definition of the future use cases: scope and data to build digital twins of use cases", this Deliverable presents the SAFE-UP traffic simulation environment with the next generation of road users' behavioural models in the road network before and after the introduction of autonomous vehicles (AV)s. The first model simulates the human-driven vehicle with two-dimensional manoeuvres and in-lane interactions with cyclists; the second model simulates automated driving behaviour with 2D-trajectory planning controlling longitudinal and lateral movements, and the third group of models simulates he behavioural models for VRUs such as cyclists, pedestrians, and powered two wheelers (PTWs). This new generation of driving behavioural models together with new safety metrics will be systematically integrated in the Aimsun Next traffic simulation platform. The integration framework is presented in this deliverable. This framework enables harmonised simulation of the next generation of all road users' behavioural models (driver, AV, and VRU), capturing the failure of sensors, the errors of judgement that drivers and riders might take, and their distracted perception in the traffic conditions we know today and future with the presence of AVs. Furthermore, the deliverable presents the methodology and data requirements for the calibration and validation of the behavioural road users' models and traffic network model in three network scenarios. The methodology is designed to work with various data sources for the calibration and validation of the models and traffic network, to ensure a reliable simulation output.

In this deliverable, Section 2 presents an approach adopted to build the road network representation (static objects) and traffic conditions (dynamic or moving objects) that the virtual scene (digital twin) for simulation of all road users and AVs. Section 3 presents a summary of the behavioural models for all road users developed in Task 2.3 and integration framework used to create co-simulation environment of all agents. Section 4 gives a detailed integration framework description and covers all required integration features. Section 5 provides data requirements for calibration and validation of the key behavioural model parameters and the network model, to ensure a close representation of traffic conditions and road users interactions, including safety critical interactions. Finally, Section 6 provides our conclusions and recommendations.

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Abbreviation	Meaning
AV	Autonomous vehicle
CAV	Connected Automated Vehicle
CPI	Crash Potential Index
CPM	Crash Propensity Metric
D	Deliverable
DRAC	Deceleration Rate to Avoid Crash
DSS	Difference of Space distance and Stopping distance
DST	Deceleration to Safety Time
H	Headway
EAI	External Agent Interface
MADR	Maximum Available Deceleration Rate
ML	Machine Learning
microSDK	Aimsun Microscopic Simulator Behavioural Models Software Development Kit
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
TTA	Time-to-Accident
TET	Time Exposed Time-to-Collision
TIDSS	Time Integrated DSS
TIT	Time Integrated Time-to-Collision
TTC	Time-To-Collision
TTCD	Time-to-Collision with Disturbance
UD	Unsafe Density
VRU	Vulnerable road user
WP	Work Package

1. Introduction

1.1 The EU Project SAFE-UP

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

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

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

The work in Work Package (WP) 2, will further improve the understanding of the future impact of vehicle automation technologies by leveraging newly developed behavioural traffic simulation tools. These tools, currently under development by SAFE-UP's partners in Tasks (T) 2.3 and 2.4 (see Deliverable (D) 2.1, D2.2 and D2.3 for details), will allow one to simulate specific road networks with a variable proportion of vehicles equipped with automation technologies. By analysing the simulation results, one will be able to determine whether these technologies induce changes (positive or negative) in surrogate indicators of traffic safety.

1.2 Objective of this Report

This report presents an overview of the scope and data requirements to build digital twins of SAFE-UP use cases in the traffic simulation environment with new generation of road users' behavioural models required to identify future safety critical scenarios. Based on the crash data outcomes of Task 2.1 and the requirements and operation of the road users' simulation models in deliverable D2.2-2.3, the aim is to:

- To specify the input and output parameters of all simulation models in order to integrate them efficiently in one co-simulation environment, which is capable to cover all aspects of the SAFE-UP use cases and future safety critical scenarios;

- To present the integration framework of the all road users’ behavioural models prone to more human-like behaviour in terms of driving, riding, walking and cycling, prone to perception and judgment errors (unlike the behavioural models in today´s traffic simulation tools);
- To collect and present the data requirements and methodology to validate traffic simulation environment.

Eventually, the simulation environment is created in a virtual machine, an operating system (OS) that enables running one or more operating systems (computers) to run in another one in completely isolated way, that hosts platform of the Aimsun Next traffic simulation software. In this way, a single computer can host multiple operating systems, all running different OSes and applications, without affecting or interfering with each other. Aimsun Next covers microscopic aspects of the simulation, such as trajectories of all road users’ traffic, road infrastructure, safety critical events’ logs and scenarios management. The simulation integration framework, hosted on a virtual machine, integrates the sub-microscopic behaviour of automated vehicles, cyclists and pedestrians with External Agent Interfaces (EAI) and behaviour of human driver and powered two wheelers with the microSDK platform (platform for integration of multiple operating systems with no code changes). Therefore, this document also presents how those integration frameworks are coupled with each other to accomplish this task.

1.3 Report Organization

The rest of the report is organized as follows: Section 2 presents an approach adopted to build the road network representation and traffic conditions that represent a static and dynamic virtual scene (digital twin) for simulation of all road users and AVs. Next, in Section 3 we present a summary of the behavioural models for all road users developed in Task 2.3 and the integration framework used to create co-simulation environment of all agents. Section 4 gives a detailed integration framework description and covers all required integration features. Section 5 presents the data requirements for calibration and validation of the key behavioural model parameters and the network model, to ensure a close representation of traffic conditions and road users’ interactions, including safety critical interactions. The final Section 6 follows with our conclusions and recommendations.

2. Building a road network model

2.1 Background

As innovations like connected automated vehicles (CAVs) disrupt mobility as we know it, new safety challenges will keep emerging. Rather than using the traditional approach of post-collision analysis, SAFE-UP is proactively designing and analysing safety-critical scenarios in a highly automated and mixed traffic environment by integrating road crash data and future traffic conditions with new forms of safety metrics and sub-microscopic models in a traffic simulation platform. To validate the potential of these concepts, SAFE-UP will use two types of use cases (one urban and one non-urban) covering pedestrians, cyclists, PTW and cars impacting at least 64% of all current traffic fatalities, as stated in the project proposal.

In order to understand the importance and effects of the future automation technologies on safety critical scenarios estimated by WP2 in SAFE-UP, it is instructive to define baseline and future scene of mixed traffic with AVs, that will be considered and simulated in WP2, in terms of

1) Road network model
2) Future road environment scenarios: vehicle technology readiness, penetration rates and management strategies and services

2.2 Road network model

The goal of this subsection is to give the reader an insight of the different types of data required for building a road graph and network model for the microscopic simulation models developed in SAFE-UP as well as a workflow to build a road network model. A transport road graph involves developing abstract representation of transport networks that consists of sections and nodes and their attributes, and represents the first step within a building process of the network model. Within WP2, we use simulation software Aimsun Next to build the graph and network model for each use case within SAFE-UP project. Traffic simulation software enables efficient import and export of the network graphs and models from OpenDRIVE and HighResolution maps that can be used within other SAFE-UP's work packages to ensure integrated data exchange. In WP2 we have adopted and developed two compatible network representations that are different at the level of detail:

- **Network graph** from OpenDRIVE format – corresponds to a 3-dimensional abstract representation of the transport road network whose format specification contains definitions for all static objects of a road network that allow simulation of vehicles driving on roads. Its main goal is the facilitation of data exchange between different driving simulators. Unlike other file formats, the description is typically used for simulation applications. The data describes the exact road geometry, including surface properties, markings, signposting, and logical properties such as lane types

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and directions. Dynamic entities like cars, bikes, or pedestrians are not included. The basic principle is to define a network graph as a reference road geometry and then attach various attributes in the network model to meet simulation requirements of microscopic models for all road users, including AVs.

- **Network model** – corresponds to network representation used by microscopic simulation-based models developed in WP2 and can be seen as an extension of the objects and attributes to represent transport network and individual road users´ behaviour. This network representation requires more detailed data, including, traffic control plans, pedestrian crossings, signalized nodes, intersection control type, capacity, travel demand, etc.

Once the road network model representation is built in Aimsun Next, the essential challenge in building the network model becomes the calibration of the supply and demand parameters to reflect the baseline traffic conditions. Different calibration and validation requirements are expected for microscopic traffic simulation models developed in WP2 at the level of road user behavioural models (such as car-following, merging, lane-changing), as well as the road network. For more detailed overview of the calibration and validation approach developed in SAFE-UP we refer to Section 4 of this deliverable.

2.2.1 Graph and network model development and utilization

Figure 1 illustrates the general process that has been followed for the development of the network model for the SAFE-UP use cases in simulation software Aimsun Next. Typical network model development and data utilization steps include:

1. **Identification of use case scope** – Identification of the use case's purpose, spatial extent, and appropriate modelling requirements.
2. **Selection of modelling approach and simulation model** – Identification of the modelling approach and type of simulation (microscopic/ mesoscopic/ macroscopic/ hybrid) to be used.
3. **Data collection and preparation** – Collection of data required for the development of the graph and network model. This step includes collecting data from traffic monitoring systems, conducting field data collection, reviewing base maps, retrieving information from data warehouses, or requesting data from specific agencies. It also includes checking data validity, processing and reducing data to extract specific information, and formatting data for their use in data-driven and simulation-based models.
4. **Base network model development** – Creation and coding of sections, nodes and turns representing the road network geometry, definition of the geometric characteristics of each section, node and turn, insertion of traffic control elements and public transport, specification of travel demand matrices, and setting of simulation parameters.
5. **Error checking** – Checks for coding errors that can affect the execution of data-driven and simulation-based models. Refinement of the geometry to fit technologies requirements and error-checking is an important modelling step as coding errors and geometry shape carried through calibration or delivered to SAFE-UP project partners can significantly affect results. This is an iterative process with step 4, where

parameters modelling network geometry, traffic demand, traffic control devices and driver behaviour are reviewed to ensure they provide valid and logical values.

6. **Network model calibration** – Adjustment of network and simulation model parameters to reproduce traveller behaviour and traffic performance. This involves the establishment of calibration targets, selection of appropriate calibration parameters to reproduce observed roadway capacities and route choice patterns, and calibration of model parameters so that its performance matches data from field observations.

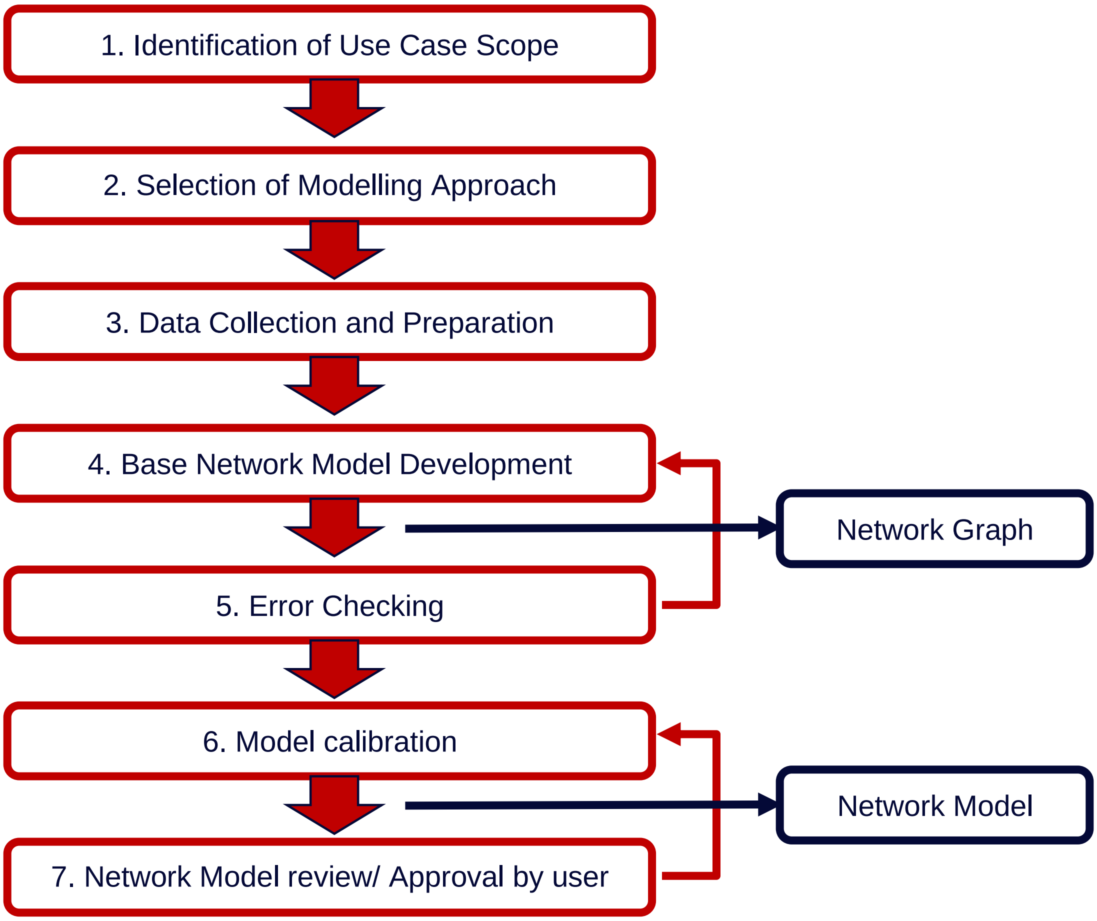

Figure 1. Workflow process for the network model development in SAFE-UP project

The transport network graph is typically an output generated after a few iterations of steps 4 (base network model development) and 5 (error checking), while the full network model requires further calibration and validation developments. Once the network graph and model development are completed, network models can be delivered to the use cases leaders for approval, before it could be used or shared with other project partners. In the SAFE-UP use cases, during this development process, the approval process will be done iteratively with the network graph development and network model calibration.

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2.2.2 Data requirements to build the graph and network model

Building a graph and network model for application in microscopic simulation models typically requires more data than other types of modelling approaches, such as macroscopic simulation models. For example, microscopic models typically require the most data due to their need to model individual road users´ behaviour in detail. Mesoscopic models may require slightly fewer data depending on the simplifications made in their driver behaviour models. Macroscopic models typically require the least amount of data, as traffic behaviour is usually only characterized by flow rates, average observed speeds, and observed link densities.

The required data to build the graph and network model for the SAFE-UP use cases, can typically be grouped into the following categories:

- **Network geometry** – Data describing various geometrical aspects of the use case area, such as the location of intersections, road widths and shapes, slopes, the number of lanes on each section, equipment used for monitoring traffic performance, etc.
- **Demand** – Data, expressed in number of trips per time unit between the various origin and destination nodes. Rules followed by travellers to select a path within a network may also be included in this category.
- **Traffic control** – Data characterizing the operation of traffic signals and ramp meters, priority schemes for transit vehicles at signalized intersections, tolls operations, etc.
- **Transit operation** – Data characterizing the operation of public transport, such as transit routes, vehicle composition, stop locations, service schedule.
- **Network traffic state and performance –** Data characterizing how traffic behaves along roadway elements, such as volumes, speeds, travel times, location of bottlenecks, etc. Data should be collected for all critical time periods being studied, e.g. AM peak, Midday peak, PM peak, planned event (e.g. concert, football match).

Table 1 lists data required for the development of graph and network model in SAFE-UP use case. Data items in bold format presented in Table 1 represent the minimum information required to build abstract transport network representation as a graph. The remaining data listed in Table 1 are used to ensure that simulated and/or predicted flows replicate observed behaviour in the network.

Table 1: Overview of data required for building use case's network models.

Data Category	Data Sub-Category	Data items
Network geometry	Road geometry elements from OpenDRIVE file	• **Road/section shape, length, curvature and slope** • **Road category** • **Number of lanes** • Purpose of lane (general traffic, HOV vehicles, managed lane, etc.) • **Allowed turnings directions at the node** • **Lane utilization: turnings from lane to lane (through lane, left-turn lane, etc.)**

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		• **Pedestrian crossings** • **Placement of traffic signs and traffic control along roadway links** • **Node/intersection layout**
	Basic Functional parameters	• **Section maximum speed** • **Section Capacity** • Section user defined costs • Turn maximum speed
	Traffic Monitoring	• **Location and type of traffic sensors**
Traffic control	Intersection control	• Type of intersection control (stop sign, yield sign, traffic signals) • Type of traffic signal control (fixed time, actuated, traffic responsive) • Signal timing plan (start time, cycle length, yellow, phases, green) • Arterial signal coordination plan (offset relative to other control plans) • Data interchange interface for actuated and adaptive control plans
	Ramp metering	• Type of ramp meter • Metering plan • Location of traffic sensors
Demand	Vehicle fleet characteristics	• **Vehicle mix** • Truck percentages and/or volumes • Vehicle occupancy
	Traffic zones	• Zone boundaries • Centroids and connectors
	Travel patterns	• **OD flow matrices** • **Network entry/exit flows, if OD matrices are not available** • **Mode shares (only if for models including transit or non-vehicle modes)**
	Freeway traffic patterns	• Freeway mainline counts • Freeway ramp volumes
	Arterial traffic patterns	• Link counts along major arterial segments • Intersection turning counts
Transit operations	Public transport data	• Transit routes (ideally GPS based, GTFS file) • Stop locations • PT Service schedules and headways (including stop-time mean and deviation) • Fleet size and composition

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		• Signal priority scheme
Network performance	Traffic state and behaviour	• **Volume, speed and occupancy data from mainline loop detector stations, on-ramps, off-ramps, tube counts** • Travel times along major arterial segments
	Bottlenecks	• Time bottleneck stations • Location and extent • Cause of bottleneck

Two major factors often drive data requirements: developing an accurate graph representation of the existing transport network elements and ensuring that simulated and/or predicted flows replicate observed behaviour. The modelling of network geometry in the graph form, can be seen as a relatively straightforward process, since this process generally focuses on the fixed and well-defined elements that can be imported from OpenDRIVE files and other GIS-based files, or from the existing network models available in traffic simulation software.

2.2.3 Specification of the graph network models in SAFE-UP

Evaluation of the AVs impact on reduction of safety critical events in the road can be evaluated in a simulation environment that supports the AVs processing functions and its sensors or actuators. For this reason, the essential requirement to create a graph network model for all road users including AVs, is to use road geometry and its elements defined in OpenDRIVE format. The road networks that are described in the OpenDRIVE file can either be synthetic or based on real data. The main purpose of OpenDRIVE format was to provide a road network description that can be fed into simulations to develop and validate ADAS and AD features. In addition, the OpenDRIVE standardised format definition and description enables exchange between different traffic simulators. In SAFE-UP, Aimsun has built an OpenDRIVE importer in the Aimsun Next, to enable import of road geometry and static road elements that represent the graph model consistent for all road users in the same road conditions. More details on the integration of all road users models and AV model in Aimsun Next are provided in Section 3 of this Deliverable.

In the SAFE-UP project, we have created a repository of the graph models for simulation of future safety critical scenarios, where OpenDRIVE files together with equivalent road representation in Aimsun Next will be stored and exchanged throughout the project. From the safety assessment concept of SAFE-UP, the initial graph model must fulfil the following requirements:

1. Road layout from urban and peri-urban road environment
2. Availability of at least one cross intersection, T-intersection and roundabout, signalised intersection, two way and multilane road segments, as these are the key infrastructure elements where majority of traffic crashes happen today, as identified in Task 2.1 and reported in Deliverable 2.6.

Following these criteria, the following digital maps of the synthetic and real-world networks were collected and imported in Aimsun Next, as a basis to test integration of the models and importer of OpenDRIVE files:

1. Synthetic network example: from CARLA simulator – to test integration of all the road agents and AVs, their behavioural interactions, Town 7 was selected for testing.
2. Real life road segment in OpenDRIVE: Vendrell, Spain. – combination of urban and peri-urban network
3. Real life road in OpenDRIVE: Friedrichshafen, Germany – covers the corridor in urban area of the Friedrichshafen.

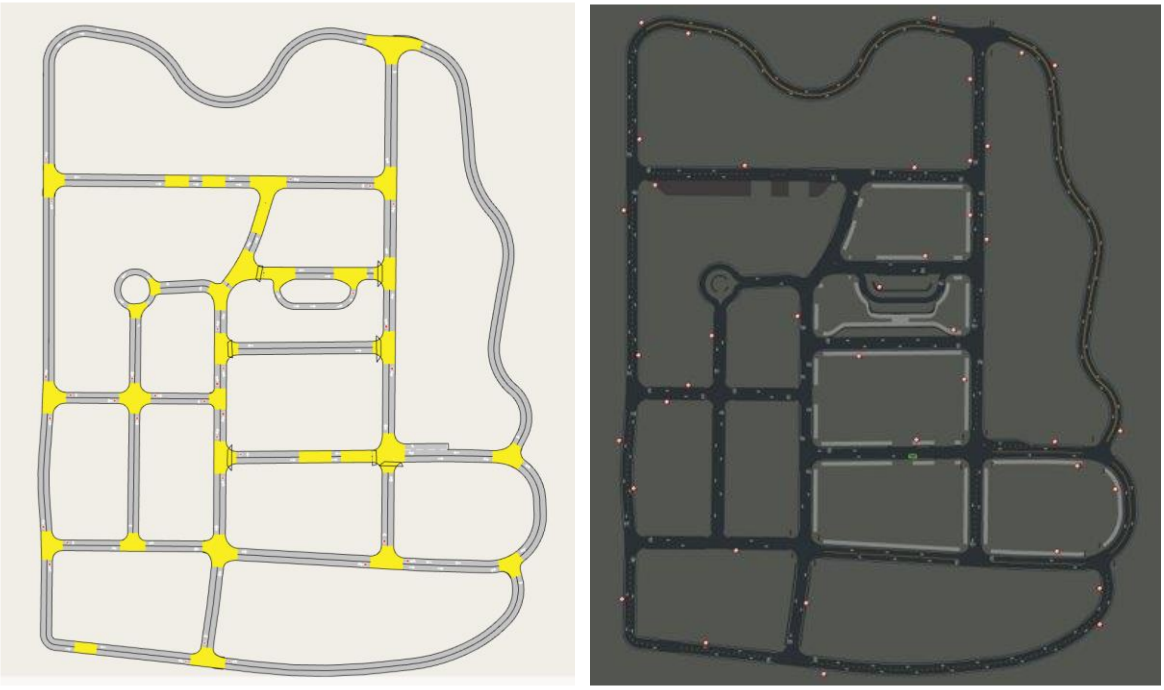

Figure 2. Town 7 from CARLA simulator imported in Aimsun Next and in OpenDRIVE format

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Figure 3. Real life road in Vendrell, Spain available in Aimsun Next and in OpenDRIVE format

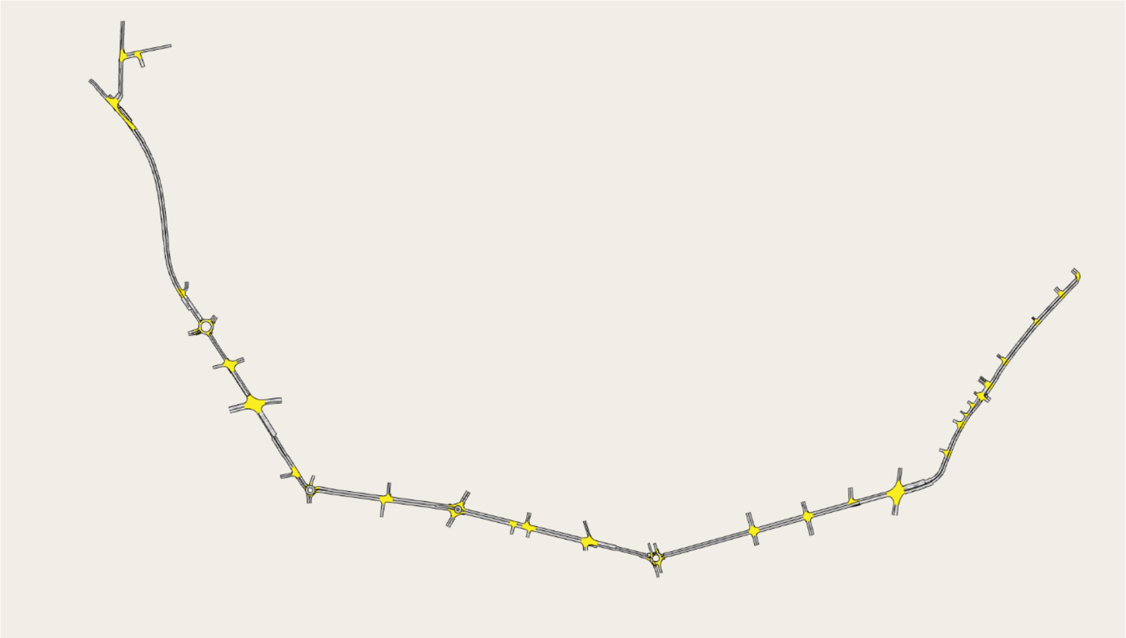

Figure 4. Real life road in Friedrichshafen, Germany available in Aimsun Next and in OpenDRIVE format

2.3 Future road environment conditions

The aim of the future road conditions modelling is to provide an idea of the changes to key safety parameters that may arise when road user interacts with AV and to define the boundaries within which potential changes to the interactions of the road users under a number of local traffic conditions may be envisaged. This is considered more informative than selecting specific data on e.g., fleet compositions, penetration rates, etc, for pre-determined years which would necessarily contain both an element of uncertainty and a limited range of applicability.

In WP2, the following road conditions, management strategies and behavioural assumptions and management strategies will be considered:

- Urban road environment and peri-urban road network;
- Traffic conditions during a peak hour and off-peak hour during the daylight. The night conditions are excluded from the analysis, as behavioural models of road users do not cover this feature;
- No cooperative maneuvers will be considered
- Simulation will consider driver perception, such as a reaction time and whether they feel assertive or tired (by calibrating the parameters of the human behavioural model)

Depending on the outcomes of the discussions to be held in WP5, further traffic conditions and scenarios are going to be implemented to scale the simulation of future safety critical scenarios.

3. Road user models

One of the SAFE-UP project objectives is to identify potentially new safety critical situations that can serve as a basis to develop the future safety concepts required in the emerging mobility scenarios with AVs. The WP2 is looking at how AVs will change the situation on our roads by analysing how road users we know today will interact with AVs, and how safety-critical these interactions will be, by simulating future road scenarios that include automated vehicles.

The use of traffic micro-simulation techniques for analysing transport systems and traffic networks is rapidly growing. These techniques may be applied whenever a dynamic and detailed representation of the system is required. Applications range from forecasting interventions on the road infrastructure, to the assessment of advanced traffic management and information provision systems, and the verification of technologies and systems to increase safety, capacity, and environmental performance, such as advanced driver assistance systems (ADAS) and cooperative systems.

So far, great efforts and resources have been devoted to the model development and several commercial micro-simulation software products are now available and extensively used in both professional practice and research, such as SUMO, Aimsun Next, Vissim, Paramics, TransModeler.

AV modelling challenge in traffic simulation

In order to understand the importance of the simulation results produced by WP2 in SAFE-UP, it is instructive to briefly review work that has been undertaken elsewhere, both into AVs, CAVs and interaction with all street level actors, using simulation methodologies. The topic has been investigated using different software for several decades and has typically been undertaken through making a range of simple approximations and changes to pre-existing driving behaviour to replicate how automated vehicles are likely to behave at a very simple level (Makridis, 2018) (Ge, 2018) (Calvert S. C., 2017) (Mena-Oreja, 2018) (Milanes, 2014). These include making changes to car-following distances, faster reaction times to surrounding vehicles, and ‘error free’ driving scenarios, with the ‘new’ vehicles exhibiting ‘ideal’ or ‘perfect’ behaviour.

While AVs and other vehicles are being designed to replace human driving, and in some cases replicate it as closely as possible, their operation, and hence the way in which they are modelled, is very different. For example, simulation models replicate longitudinal vehicle dynamics through simple heuristics, based on behavioural paradigms such as keeping a safe distance subject to a reaction time, which are implemented in Aimsun Next through the 'Gipps equation', controlling vehicle acceleration according to speed, following distance and other factors (Gipps, 1986). Similarly, when seeking to replicate lateral vehicle movement, a range of gap acceptance criteria are typically set out based on the ability of drivers to perceive and understand the risk posed by adjacent vehicles. These decision-making processes clearly vary from driver to driver, and indeed from day to day or even hour to hour, and stochastic processes are introduced into the models to allow for this.

It is clear however that this is not the case for an AV, where its behaviour is definitively set by its manufacturer and will not vary through time, or from unit to unit at the level (from the aspect) of the human driver heterogeneity. While accounting for this lack of variability is straightforward, identifying the control processes used is not, and while many automotive OEMs and Tier 1 suppliers have tested and operated AVs, the underlying logic behind vehicle operation, being of extreme commercial value, is not public domain. Those that are, in the main are R&D formulations, and although these are based on sound logic, there is no way of telling the degree of similarity that these may (or may not) have with those of the automotive OEMs.

Road users´ behaviour modelling challenge in traffic simulation

There are, however, a small number of research publications and experiments on impact of AVs in mixed traffic that have been performed in the interaction of more realistic human driver models, two-wheelers and VRU. The simulation and prediction of future safety-critical scenarios requires development of a new modelling framework which deals with the specific challenges around road crashes. Up until now, driving and riding behaviour in vehicles and vulnerable road users (VRUs) has been led to model a traffic phenomenon, such as queues, spillbacks, and simulation of crashes is bounded by these behavioural models' definition – i.e., traffic simulations have been collision free. All current behavioural models for driving behaviour (in commercial and academic traffic simulation products) are, by design (e.g., (Newell, 2002) (Laval J. L., 2010)) or within reasonable parameter bounds (e.g., (Gazis, 1961) (Kerner, 2006), collision-free, and thus fundamentally limited to capture all safety critical interactions or crash effects. Second, most behavioural models in traffic simulation are anisotropic, that is, they capture drivers' reaction to what happens in front of them only. The challenge is thus to develop models that are isotropic, resulting in "stable-but-every-now-and-then-unsafe" interactions that can potentially result in collisions. All road users' behaviour is more complex task that requires modelling for safety critical interactions simulations. For example, longitudinal driving (speed choice, acceleration) is typically an operational task with a substantial amount of "automated" (subconscious) cognitive processing; lateral movement involves tactical behaviours that require more (conscious) cognitive effort: conditional decision-making (do I want/need to change lanes); assessing the conditions (are there safe gaps?); computing the appropriate response (starting a lane change manoeuvre or deciding against it); and implementing and monitoring this decision (Michon, 1985) (Schakel W. K., 2012) (Farah, 2010).

In the SAFE-UP project, the next generation of road users' behavioural models in traffic will be developed to bridge the gap between the fields of traffic flow theory, simulation, traffic safety, and human factors in decision making. To do this, four types of models are being developed to incorporate decision making process of road participants, in planning, decision making and execution prone to make judgment mistakes. The first is advanced, human-driven, two-dimensional vehicle manoeuvres and in-lane interactions with cyclists; the second is behavioural model of pedestrians, the third is behavioural model of cyclists, and fourth, behavioural model of powered two wheelers (PTWs). all prone. The modelling assumptions for all these models are summarised in the following sub-sections for completeness and detailed further in the internal project Deliverables: 2.2 and 2.3.

3.1 AV model

The automated vehicle model integrated in the simulator is developed by Applus+ IDIADA. This is not a simple mathematical model but has been built from the company's CAVRide demonstrator. Applus+ IDIADA has aligned its development and validation expertise to engineer a level 4 autonomous car that meets the necessary functional requirements to safely operate whilst keeping overall car performance. The full description of the AV model is included in Deliverable 2.3.

Several software components of the CAVRide make the automated vehicle model, meaning the production software (that is, the software that runs on the real platform) the one that also runs on the simulator. This has great advantages: on the one hand, the simulation corresponds to reality in a reliable way; on the other hand, the software that goes on board of the vehicle is being tested in complex scenarios, which would be very expensive to reproduce in reality.

The main components that form the model are:

- **Prediction**: the vehicle can interpret the traffic environment and predict other vehicles' actions.
- **Planning and decision maker**: behavioural and trajectory planning modules calculate the optimal trajectory for the current situation considering the predictions of the vehicles involved and the traffic signs.
- **High-level control**: algorithm which generates effective commands to move the vehicle according to the current trajectory.

The biggest simplification of the model is the vehicle dynamics. The dynamic behaviour of vehicles can be analysed with various approaches. This can be as straightforward as a simple spring mass system to a large degree of complexity using drivetrain, braking, suspension, steering, distribution of mass, aerodynamics, and tyre models. However, since the objective of the simulation is to have an analysis of the traffic behaviour, it is not necessary to reproduce the vehicle dynamics in detail. It also has the advantage of requiring less computational load.

The sensing devices (such as LIDARs, radars, cameras, etc.) are replaced by filters which limit or modify the true characteristics of the road users that are being simulated. For example, rain degrades the automated vehicle's ability to sense its surroundings. This fact can be simulated by decreasing the range in which the simulation objects are reported to the automated vehicle model. In turn, the model, having a restricted view of the environment, could make different decisions than in favourable environmental conditions where it would have more information about the environment.

Figure 5 shows a snapshot of the AV model execution during a Aimsun Next traffic simulation. On the left side, the Aimsun Next program simulates the standard vehicles at an intersection. On the right side, the automated vehicle model is receiving the surrounding traffic (purple boxes), calculating the trajectory for that current situation (dotted curve) and executing the control commands to update the vehicle state. The colour of the trajectory dots indicates the desired speed at those points from blue (maximum allowed speed) to red (zero speed).

We expect most of the implications of autonomous driving to be very positive, reducing the number of road fatalities and the number of incidents. However, new future safety-critical scenarios due to the introduction of the automated vehicle may happen. The early identification of problems in simulation will help us to improve the state of the art of autonomous driving by eliminating these new critical situations before they occur in reality. That is why reliable simulations including the automated vehicle are essential to evaluate its effects on traffic flow.

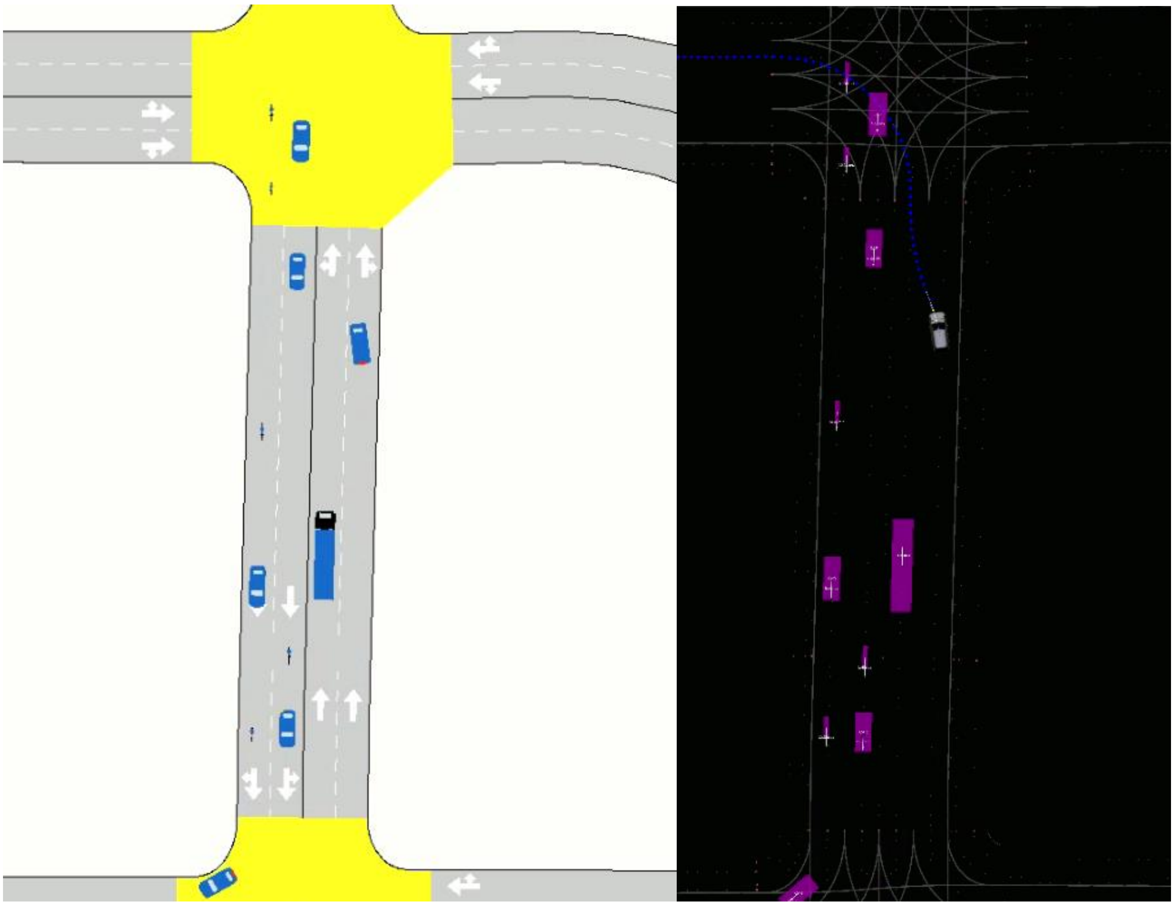

Figure 5. Snapshot of a traffic simulation at an intersection. The vehicle in grey colour is controlled and run by automated vehicle model.

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3.2 Human driver model

The goal of the Human Driver model is that it is a realistic human driver model in a mixed traffic environment such that we will be better able to model and assess traffic safety in a mixed traffic environment (including automated vehicles) using simulation. With realistic we mean that it will not be a perfect model (as normally in most microsimulation models), but that comparable errors are made as by human drivers, such that the frequency of dangerous situations will also be comparable with the real world. This will make it easier to use traffic simulation for safety evaluation of both human-driven and automated vehicles and get more realistic estimates on number of critical (or challenging) driving situations, near-crashes and possibly simulating actual crashes.

Most of the current driver models for microsimulation are collision-free, because they assume a perfect driver that does not make mistakes (Schakel, Knoop, & van Arem, 2012) (Calvert, Schakel, & van Lint, 2020). This is however not the case in reality as humans are prone to errors and it is those errors that most often lead to crashes (Van Lint & Calvert, 2018) . It is clear that incorporating variables that reflect actual human factors like perception errors, distraction, workload, fatigue in driver models will lead to more realistic models (Saifuzzaman & Zheng, 2014). Research has shown that variables like reaction time and perception errors can be used to incorporate such human factors into driver models, making it possible to have a non-collision free model (Van Lint & Calvert, 2018). In addition, it is known from literature that human factors like age, gender can affect driver behavior (Saifuzzaman & Zheng, 2014).

Based on the descriptions above, the most important requirements for the model are defined:

- The model should incorporate human factors like perception errors, reaction time, distraction.
- The model should be suitable for capturing critical driving situations, near-crashes and possibly actual crashes.

The most important boundary conditions are that it is a lane-based model, and lateral movements within a lane are not modelled. This model is validated for motorway driving. It can also be applied on other road types in microsimulation (such as urban or provincial roads), though the model is lane-based (which is not always the case in reality in urban traffic) and the behavior is not validated for those road types. In addition, the human driver model does not include the possibility for bidirectional overtaking.

A first basic version of the Human Driver Model is available, described in Deliverable 2.2 Enhanced Human Driver Behavioural Microsimulation Model.

The model consists of two layers, a layer with three collision-free models (car-following, lane change decision and gap acceptance models) and a driver perception error module. Details of these models are described in Deliverable 2.2.

Based on the requirements described in Deliverable 2.2., the following properties will be included in the final human driver model:

Table 2: Model Property Description

Model Property	Description
1. **Handles collision-free traffic.**	The lane change decision, car-following and gap-acceptance models are collision-free. These models have been tested in previous research and have shown to work well in various traffic conditions (Schakel, Knoop, & van Arem, 2012) . Therefore, they can be used for studies focused on the effect on traffic flow and throughput.
2. Interaction with other road users in mixed traffic.	The final model can recognize and interact with other road users such as automated vehicles, pedestrians, cyclists, and powered-two-wheelers, if they are present on a link on the route of the human driven vehicle within a certain perception range (e.g., not on the sidewalk).
3. **Incorporates human factors in driver behavior**.	The driver perception error module has human factors properties like perception errors, distraction, and driver characteristics like age, gender and experience. First, the module returns a perceived distance and perceived speed difference which is calculated based on the perception error of the driver. The driver can under-estimate or over-estimate distances and speed differences. In addition, the driver perception module has a task-capacity model which depends on driver characteristics like age, gender and experience. For example, the more experienced a driver, the higher, its task capacity. Finally, the model returns an estimate of the reaction time of the driver based on the situation awareness. The higher the situation awareness, the shorter the reaction time.
4. Handles non-collision-free traffic and critical traffic interactions.	The model can capture critical driving situations, near-crashes and possibly actual crashes. The human driver model is not collision-free and drivers can make mistakes in estimating distances and speeds. They can also have delayed reaction time due to high workload. This can lead to potentially dangerous situations in car-following and lane change situations and even crashes in the simulation.

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	It is well-known in literature that most crashes are caused by driver errors (Saifuzzaman & Zheng, 2014). In our model we focus on perception errors, which can lead to other type of errors. Therefore, appropriate modelling of perception errors can be used for realistic estimates on number of critical driving situations, near-crashes and possibly actual crashes. This makes it suitable for traffic safety studies.

3.3 Pedestrian model

In addition to the vehicle types predominantly represented on the highways, i.e., cars and trucks, road users from the Vulnerable Road Users (VRU) group are also represented in simulations of the urban areas. In addition to motorcyclists and cyclists, VRUs also include pedestrians. This group is characterized by a particularly high risk of injury due to their lower protection against external forces. Furthermore, no capability test is required for pedestrians to participate in road traffic, so knowledge of the rules of the road cannot always be assumed.

A pedestrian model is developed by the Institute for Automotive Engineering (ika) at RWTH Aachen University. We assume that a pedestrian participates in the traffic as soon as its route intersects with a traffic lane. This happens not only at controlled crossings with traffic lights or crosswalks, but also at any other locations. The uniqueness of each individual plays a role here, as individual parameters influence the decision-making process. After the route has been chosen, each person decides individually on the basis of the detected road users, their perceived speeds, the distances, and their experiences whether and how to cross the road.

Thus, two main issues play a role in pedestrian model development:

- Identification of the potential conflict partners and analysis of the conflict zone
- Influence of the subjective perception in the crossing decision

Figure 6 shows the schematic structure of the pedestrian behavioral model. As soon as the simulation software indicates a crossing request of a pedestrian, that means that the pedestrian's route crosses a driving lane, the behavior model is activated. First, the pedestrian needs to check his or her own position relative to the road. We distinguish whether we are still on our start position, have not crossed the middle of the first lane yet or have already crossed the middle of the first lane.

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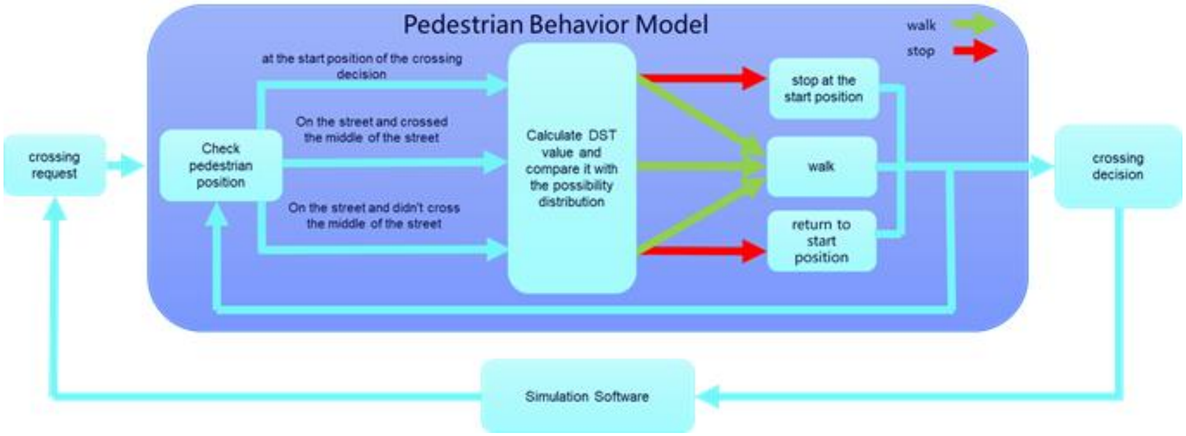
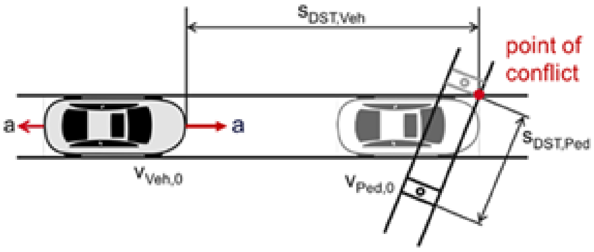


Figure 6. Pedestrian Behaviour Model

Using existing environmental data from the simulation of all relevant conflict partners, we analyze the conflict zone and calculate the “Deceleration to Safety Time” (DST). The DST indicates how high the deceleration of a vehicle must be in order to reach the conflict zone only after the pedestrian has just left it (Köller, 2017) (C. Hupfer, 1997) (Kotte & Pütz, 2018).

The is calculated as follows in Figure 7:



$$DST_0 = a = \frac{2 * \left(s_{DST,Veh} - v_{Veh,0} * \frac{s_{DST,Ped}}{v_{Ped,0}}\right)}{\left(\frac{s_{DST,Ped}}{v_{Ped,0}}\right)^2} \left[\frac{m}{s^2}\right]$$

DST < 0: vehicle needs to decelerate
DST > 0: vehicle needs to accelerate

Figure 7. Calculation and parameters for the determination of DST0

To incorporate the subjective perception of a pedestrian into the crossing decision, the probability for a crossing decision is determined for different DSTs.

For this purpose, a virtual reality pedestrian simulator is designed, built, and developed in terms of software and hardware (Figure 8).

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Figure 8. Functional overview of the virtual reality pedestrian simulator

In the pedestrian simulator the subject wears virtual reality glasses and has trackers attached to the body at each relevant joint. For the movement in the virtual world, the test person walks on the spot. This has the advantage that the subject performs a "natural" walking motion and the distance walked in the simulation is independent of the space available in the reality. The positions, angles and distances of the tracked signals are then calculated in a pedestrian kinematics model and displayed as a movement in the simulation.

A subject study will then evaluate the individual crossing decisions. For this purpose, subjects are asked to cross the road, whereby vehicles are initialized with different DSTs. The result of the study will show us a dependence between the crossing probability of a subject depending on the DST.

On the basis of the calculated DST and the evaluated study data for the crossing probability, the pedestrian behavior model decides whether the pedestrian stops, crosses the road or turns back.

3.4 Cycling model

Like the pedestrian behaviour model, the bicycle behaviour model is also developed by ika. Bicycle riding behavior is much more agile and unstable in its lateral motion compared to motor vehicle dynamics. Observing the surrounding lateral and rear traffic is relatively difficult on a bicycle. Thus, in reality, the lateral driving behavior of the cyclist shows a much higher misbehaviour and potential danger in road traffic than the longitudinal. The developed model refers, in terms of complexity, only to the implementation of a realistic lateral driving behavior of a cyclist and describes the lateral displacement to the reference line.

The lateral driving behavior of a cyclist depends on many different factors of a driving scenario. On the one hand, it changes depending on the road layout, straight/curve, and the number and type of surrounding vehicles. The experience of a cyclist also plays a significant role, for example, interaction with a truck immediately signals an increased danger potential to a cyclist. In addition, the type of cyclist plays an important role, because a schoolchild, a racing cyclist or a "normal cyclist" show significant differences in their lateral guidance in addition to the different speeds (Twisk, 2018) (Feenstra, 2010) (Oehl, 2019).

To be able to realistically determine these person-dependent lateral driving parameters for a representation of the entire society, it is necessary to conduct a study with test persons. The performance of real driving tests is not suitable due to the bad reproducibility and the lack of safety-relevant scenarios. The use of a simulator provides an efficient tool for determining the necessary parameters.

For this purpose, a virtual reality bicycle simulator is being designed, developed, and built by the ika as part of the project (Figure 9).

Hardware setup:

The simulator consists of a commercially available bicycle, so that almost every test person should be familiar with the simulator's controls right away. To represent the longitudinal motion behavior of the bicycle, the rear wheel is rotationally mounted. This allows the cyclist to use the pedals freely and the roller trainer on the wheel can be used to represent driving resistances. In addition, the steering angle is measured on the steering wheel and the front wheel is returned to its original position via a return plate. For a realistic braking feeling, the front brake was converted to the rear wheel so that both brake pedals can be operated, and a disc brake and a rim brake are active on the rear wheel. To enhance the immersion, there is a wind generator in front of the bike simulator that generates a wind current depending on the bike speed. For the visual simulation, the test person wears virtual reality glasses, which are used according to the same principle as for pedestrians described in section 3.3.

Software setup:

The software setup consists of detecting the driving inputs/positions, the simulation software, and the virtual bicycle dynamics model.

Steering angle, wheel speed and head position are continuously tracked and sent to the virtual bicycle dynamics model. With an additional localization software, the corresponding information from the virtual environment (e.g., elevation data, roughness values, ...) can be matched with the position of the bicycle. All data is fed into a longitudinal, lateral, and vertical single-track model, so that the new driving state of the bicycle can be calculated. This new state is then sent to the simulation software so that the new positioning can take place in the virtual world and be displayed by the virtual reality glasses.

Figure 9. Virtual reality bicycle simulator

Based on study data from the bicycle simulator, a realistic lateral cyclist model will be developed and validated. The behavioral model can basically be divided into three main behavioral characteristics:

- „Lateral wobble“:

A real cyclist does not follow a perfect reference line in a lane but has a periodic fluctuation in its lateral definition range based on lateral center of gravity displacement and road roughness/unevenness. This is defined here as "lateral wobble" and is superimposed over any movement of the cyclist. Depending on the type/category of cyclist, the lateral sway varies in frequency and amplitude.

- Curve behaviour:

The curve behavior of a cyclist is largely determined by his or her speed, yaw behavior and steering angle. In addition, external factors such as the road layout and the friction coefficients play a role. Thus, different types/categories of cyclists show situations where curves are being cut or driven out of the curve.

- Behavioral interaction with potential conflict partners:

To describe the behavioral interaction between a cyclist and potential conflict partners, they first need to be identified. For this purpose, all potential conflict partners in the surroundings of the cyclist are checked on the basis of the relative distance and the relative speed. To be able to make a clear behavioral decision based on the situation awareness, only the interaction with one conflict partner is examined at a time. The relevant conflict partner is always the one that represents the highest potential danger due to its relative parameters.

For example, cyclists behave very dynamically during overtaking maneuvers because their vehicle width is much smaller than that of other road users. The first step is to check whether a potential overtaking maneuver exists. Should an overtaking maneuver be identified, the lane-independent lateral movement of a cyclist follows.

If a cyclist is overtaken by another road user, the cyclist shows a tendency towards cautious and restrained riding behavior due to their higher risk of injury. What is more important here is when and how a cyclist notices the overtaking maneuver from the side/rear. As soon as the danger/the overtaking maneuver has been recognized, the cyclist moves laterally to the road boundary to increase the distance to the collision partner.

3.5 Powered Two-wheeler model

The Powered Two-Wheeler (PTW) model, developed by UniFi, aims to reproduce riders' behaviour in mixed traffic conditions using an innovative approach. This kind of scenarios are interesting because of their complexity and because they can reproduce common urban scenes (W. C. Lin, Wong, Li, & Tseng, 2016). However, analysing mixed traffic steams can be effective only if models are able to catch intrinsic characteristics of this type of flow. Often, riders' models are developed from drivers' ones, as in (Lee, Polak, & Bell, 2009; Lenorzer et al., 2015), and the existing tools not often represent behaviour of PTWs in traffic in a proper way (Lee & Wong, 2016). Indeed, car drivers' behaviour is usually lane-based, whereas PTW riders' one is not. The presented model is developed specifically for motorcyclists and is based on Artificial Intelligence algorithms to be as realistic and flexible as possible. Its structure is defined to make developer able to add and model new manoeuvres without compromising or changing the model itself. It is designed to manage a single agent in microscopic traffic simulators (agent-based approach). For the time being, it can only handle longitudinal dynamics, especially braking because of their relevance in safety-critical conditions (Davoodi & Hamid, 2013). Moreover, in safety-critical scenarios, emergency braking is the evasive manoeuvre most required by riders and it is also the most difficult to learn (Huertas-Leyva, Nugent, Savino, Pierini, et al., 2019). However, the model can comprehend every kind of manoeuvres. The agent considers both decision-making and manoeuvre execution processes. Indeed, the model is divided in two kinds of modules as reported in Figure 10, i.e., the Manoeuvre Selection Module (MSM) and the Manoeuvre Planning and Execution Module (MPEM).

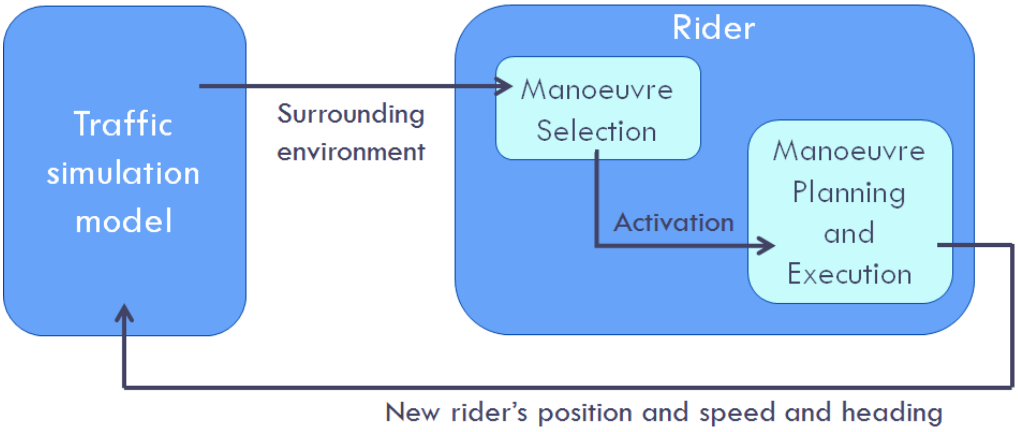

Figure 10. Structure of the PTW Model.

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MSM contains the decision-making process that defines which manoeuvres should be executed at the current time step. This decision is made according to the surrounding environment, collected through the agent's field of view. In particular, the agent makes its decision according to information about infrastructure, road markings, signals, and surrounding users. No perception errors are considered so far. According to this information the agent decides whether to keep performing the previous manoeuvre or to start a new one. The output of this module is an activation signal that activate the proper MPEM. Indeed, each manoeuvre is planned and executed by a specific MPEM. On the other hand, there is just one MSM that can activate each manoeuvre. The model can plan and execute just one manoeuvre per time step. If two manoeuvres can be activated at the same time, they will be combined (if possible) and the new manoeuvre will be the resulting combination. However, if the combination is not possible, just one manoeuvre will be activated according to a priority scale. The MPEM comprehended two sub-modules: Planning and Execution.

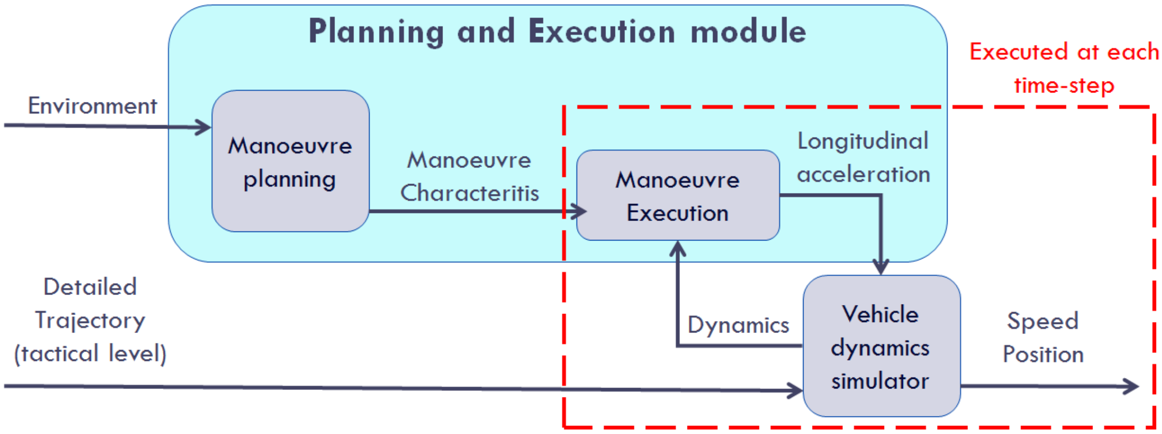

Figure 11. Manoeuvre Planning and Execution Module (MPEM).

The Planning one is called just at the beginning of the manoeuvre and defines its main characteristics, e.g., mean and maximum decelerations are defined for the braking. This information represents rider's intentions and are used by the Execution sub-module that is run at each time step. So, the model considers a difference between what the rider intends to do and what he or she actually does. The Execution sub-module takes in account the vehicle dynamics through an external software, as in Mullakkal-Babu et al., (2020). It is important to note that the execution sub-module has a deep network (i.e. a long short term memory neural network) that make it able to define the longitudinal acceleration for the current time-step, that is given to the vehicle dynamics simulator as input. The output of the MPEM is the agent's updated speed and position obtained performing the mauver and following a reference trajectory.

In conclusion, the PTW model is based on the following algorithm (steps executed at each time step):

- The agent checks if the current boundary conditions lead to the end of the previous manoeuvre,

- The agent checks if the current boundary conditions lead to the beginning of a new manoeuvre (ending the previous one),
- If a new manoeuvre is chosen, it is planned,
- The manoeuvre is executed at the current time step.

4. Simulation integration framework

4.1 Architecture

The integration of all behavioural models is based on two types of technologies available in Aimsun Next, each with a different purpose:

- External Agent Interface (EAI) – allows the user to simulate in Aimsun Next microscopic simulation externally controlled vehicles, for example, a human driver in a simulator, an autonomous vehicle controller, or an experimental control system being tested in a simulation environment, and
- Aimsun Microscopic Simulator Behavioural Models Software Development Kit (microSDK) allows the user to replace Aimsun Next microscopic models (car-following, lane-changing, etc.) with his own behavioural models, programmed in C++.

The system integration architecture is summarised in the Figure 12, where Aimsun Next platform is running in one computer with all behavioural models integrated using MicroSDK for Human driver and PWT model as part of a dynamic library, while behavioural models, for AV, cycling and pedestrian are integrated using the EAI and they can run in different computers using TCP/IP communication.

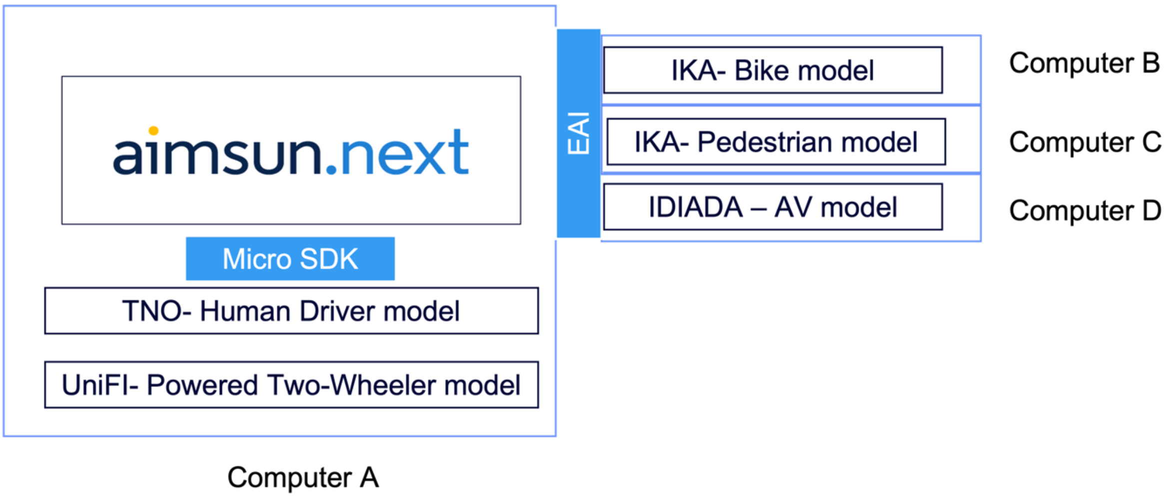

Figure 12: System architecture of the integration of models with Aimsun Next technologies

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4.2 Interface specification

4.2.1 External Agent Interface for integration in Aimsun Next

EAI can introduce externally controlled road users models into an Aimsun Next microscopic simulation. Such external road users can be guided by the actions of, for example, a human driver in a simulator, an autonomous vehicle controller, or an experimental control system being tested in a simulation environment.

The data exchanged via the EAI are based on geographic locations expressed as x- and y-coordinates rather than the simulated representation of the traffic network expressed via lanes and turns. It uses any coordinate system that is required with the EAI connection model. This means that the external control logic does not need detailed knowledge of how Aimsun Next models the traffic network – it can continue to use its own network model. Data exchange relies solely on there being a shared system of common coordinates.

External vehicles are positioned on the traffic network within the simulation. The other vehicles in the simulation – the ones controlled and updated by Aimsun Next – will then react to the presence of external vehicles by following them, collaborating with their lane-change manoeuvres, and including them in their assessment of gaps at junctions in the same way as they react to other 'internal' vehicles in the simulation.

As an option, the external application can take control of any vehicles generated by Aimsun Next, in which case Aimsun Next stops updating them, meaning they must be updated by the external application. The external application may also return vehicle ownership to Aimsun Next, in which case Aimsun Next begins to update them again.

The EAI is based on a client–server architecture in which Aimsun Next is the server, responsible for managing traffic signals and the other vehicles and pedestrians in the simulation. The client is the external controller, or simulator, which receives information about the dynamic objects in the simulation and responds with the updated positions and headings of the externally controlled vehicles.

The EAI provides the PROTO file which must be used to program the interface using a software library derived directly from this file on the host system and using the client's preferred programming language. This language must be supported by Google protocol buffers[1].

The underlying communication mechanism is based on TCP/IP with data serialized using Google protocol buffers: a platform-independent, highly efficient communications library. The simulation and controller can sit on the same, or different, computing platforms

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[1] https://developers.google.com/protocol-buffers

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connected by a network. This enables the external application to be developed in any programming language, without the need for in-depth knowledge of Aimsun Next.

The serialized data must be sent through a TCP/IP socket. First, the size of the serialized message as a 32-bit integer is sent in network order. Second, the serialized message itself is sent. The frequency of this communication is the same as the simulation step, which can be set as low as 10Hz (0.1s).

4.2.2 MicroSDK for integration in Aimsun Next

The Aimsun Next Platform makes extensive use of the plug-in concept, allowing external components to be loaded to extend the functionalities of the application using dynamic libraries. The Micro SDK is best suited when user have to implement a logic to update continuously the position and speed of individual vehicles or road user depending on the road users around. The advantage of microSDK is that the user can implement only the subset of behavioural models that he wishes to override, and for the rest, Aimsun will automatically deploy the default models.

For example, the Aimsun Next microSDK provides two C++ classes for coding, for the vehicle and the simulation models used to replace the vehicle and vehicle behaviour, and includes the functions required to register the new behaviour model to replace the current Aimsun Next microsimulation model. During the simulation, the microsimulation model updates each vehicle using the specified model.

4.2.3 Test simulation scenario

To test the integration of all road users’ behavioural models with AV simulator in the Aimsun Next, a synthetic road environment shown in Figure 2 will be used. The digital map consists of a synthetic urban road segment that covers urban setting provided by an OpenDrive file from the CARLA simulator and serves as the test-ground for the simulation scenario. The simulation scenario will consist of different road segments and road users in order to keep testing and debugging of the boundary conditions during the development process. In the configuration of the testing scenario in Aimsun Next, five road users´ categories and their respective demands are defined.

Further details on the test simulation scenario, including demonstration of the integration, will be reported in Deliverable 2.7.

5. Data requirements for calibration and validation of the models

Once the graph network representation is built, the essential challenge in building the network model becomes the calibration of all the supply and demand parameters in order to reflect the real traffic phenomena. Model calibration involves adjusting model parameters and inputs to improve the traffic network model's ability to replicate real traffic conditions. Model validation is the process for verification of the model outputs. Validation can be defined as a process in which a calibrated model is tested using a different set of existing traffic data to determine if the calibration parameters are applicable to other conditions. It is closely related to the model calibration task. The importance of validation (and difference from calibration) is that it provides the user confidence that the responses to changes in the transportation system that are observed in the simulation model are representative of those that would have been found in the real system. Thus, a model may be calibrated so that it replicates current traffic measurements but, only a valid model will be able to accurately predict the effects of changes in the current system. Calibrated traffic network model requires origin destination (OD) flows or traffic states in the network as inputs that need to be calibrated. Similarly, in the supply side, road capacities are among the parameters that need to be calibrated, and these are easily in the order of thousands.

For SAFE-UP, the calibration and validation should be focused on aspects that are needed for safety evaluation. The model can be regarded of sufficient quality when realistic conflicts occur in the simulation, with a realistic frequency. For such calibration, the variables of interest include the distribution of safety metrics such as TTC, the frequency of hard-braking events, and the correlation of the number of observed conflicts in simulation with the number of actual recorded crashes in that location.

To have a realistic joint model calibration for various traffic participants, the separate models should be calibrated and validated first. After that, a common calibration and validation of the integrated models will then be performed. This ensures that issues related to individual models are first resolved and the calibrated parameters for those individual models can serve as a good starting point for the joint calibration.

5.1 Network model calibration and validation approach

In general, models used in microscopic traffic simulations are calibrated for traffic efficiency variables like speeds, flow, and travel time. However, for SAFE-UP, the focus is on safety evaluation. This means that a different calibration approach which is suitable for traffic safety evaluation needs to be followed. Based on a literature review of methods for safety calibration, the calibration methodology proposed by Cunto (2008) and Papadoulis et al (2019) was chosen. The calibration procedure is described in the figure below.

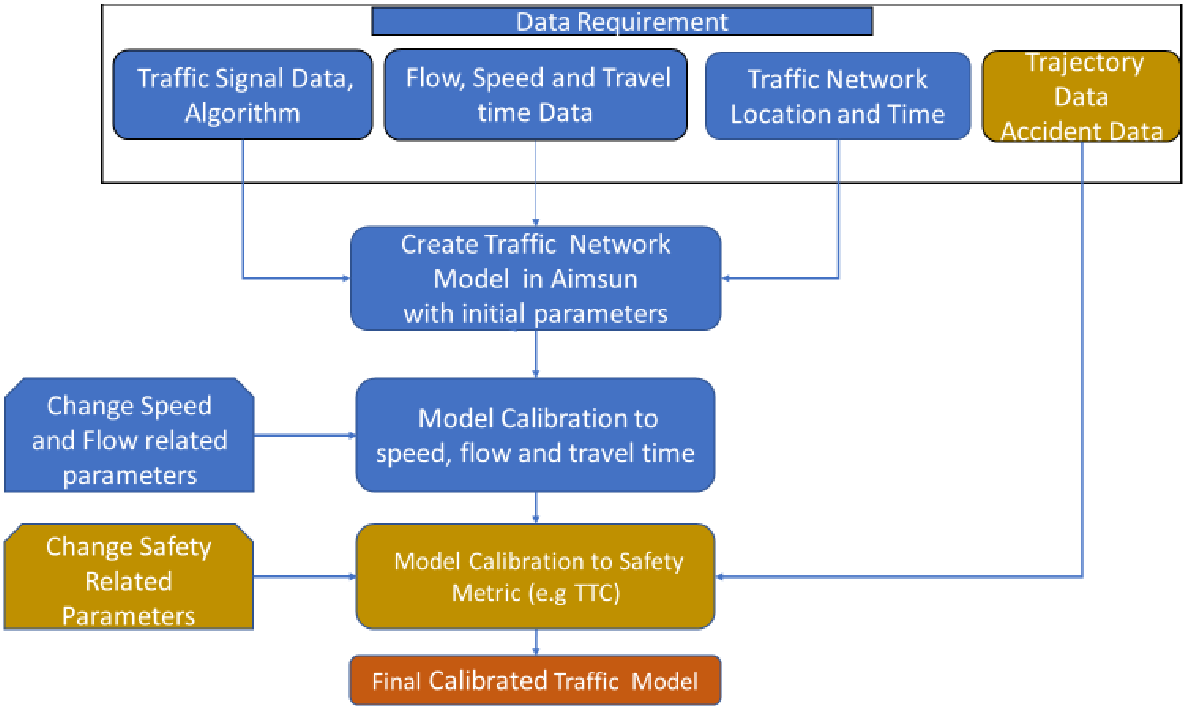

Figure 13: Human Driver Model Calibration Procedure

Step 1: Data Requirement and Collection

The data required for calibration is of different types and they preferably need to be collected from a specified network location (stretch of highway, intersection) and time period (peak, off-peak, other time of the day). These include:

- Macroscopic traffic data: Macroscopic traffic data include traffic flow, speed, and travel time data. These data can be obtained from loop detectors placed at the location of interest. This data is useful for calibration of model to traffic flow variables like travel time, speed, and flows.
- Trajectory data: Trajectory data are usually obtained from field test based on video monitoring or from naturalistic driving field experiments. This contains detailed information about vehicle positions, speeds, accelerations at discrete time intervals. This type of data is useful for traffic safety calibration where detailed modelling of driver behavior is required.
- Traffic management data: The next type of data required is traffic management data. This includes traffic control data (control type and algorithms, signal timings and plans for fixed control) This data is usually obtainable from traffic management/road authorities.
- Crash data: The last type of data required is crash data. This data contains information of the number of accidents that occur in that specific location over a

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period of time. The information can also include the type of accident and the severity. This data is usually obtained from traffic management/road authorities or other specific sources (like country-wide accident data-base).

Step 2: Creating a digital twin of a traffic network

This step involves recreating the network of interest in a simulation environment. For SAFE-UP, the chosen simulation environment is Aimsun Next. The complete network includes all relevant network elements such as road stretches, on-ramp, off-ramps, traffic intersections (signalized and unsignalized), pedestrian crossings, cyclist paths. The appropriate traffic demand for all traffic participants is also added to the network. The simulation period (usually a few hours) and the simulation resolution (usually 10Hz) are also defined in the network. Finally, initial parameters of the human driver models are defined.

Step 3: Model Calibration to Traffic Efficiency

After the network is set-up, the calibration procedure starts. The model is first calibrated to traffic flow parameters such as speeds, flow, and travel time. The process involves adjusting model parameters such that the simulated flows, speeds, and travel times in the digital network matches the observed flows, speeds, and travel time from loop detectors.

Table 3: Examples of variables measured during efficiency calibration

Variables measured	Description	Unit
Speed (Average)	Average speed measured at specific detector locations	Km/h or m/s
Average flow	Average flow measure at specific detector locations	Vehicles/h
Travel time	Average travel time between specific locations	Minutes
Speed Distribution	Distribution of speed for all drivers over the entire network or selected area.	
Travel Time Distribution	Distribution of travel time for all drivers for specific measurement points.	

For the variables above, a performance metric is defined such that the calibration procedure stops when the threshold for the performance metric is met. The following measures will be used to ensure a good network model calibration and validation: Root Mean Square Normalized Error (RMSNE), Correlation coefficient (R-squared), and the GEH statistic. These performance measures represent the most common goodness-of-fit measures in traffic engineering and transport planning practice, where values a coefficient of correlation of 0.85 is considered acceptable for model calibration. For example, for comparing flows, the GEH Statistics (a formula used in traffic engineering named after Geoffrey E. Havers) is usually used as performance metric and GEH<5 is considered acceptable for a well-calibrated model (Papadoulis et al, 2019). Most of the typical values are given in this table below and can be found in (Schakel, Knoop, & van Arem, 2012).

Table 4: Examples of parameters to adjust during efficiency calibration

Parameters	Description	unit	Typical Value
Desired Speed	The desired free flow speed of the driver	Km/h or m/s	80-85 km/h for trucks 100-130 km/h for cars
Desired Time Headway	The desired headway in seconds that the driver wishes to keep	seconds	1.2 s
Look ahead distance	How far the driver can look ahead	Metres (or number of vehicles)	200-300 m
Stand still distance	Distance between stopped vehicles	metres	3-4 m

Step 4: Model Calibration to Traffic Safety

After the model is calibrated for traffic efficiency, the next step is calibrating the model for traffic safety. For this calibration, at least one of the trajectory data and the crash data is needed. The goal of the calibration is to adjust model parameters such that the network has a realistic frequency of crashes or number of conflicts.

Table 5: Example of measured variables during safety calibration

Measured variable	Description
Average or Distribution of a Safety metric	Choose a safety metric and estimate the average of distribution of that metric. For example, the distribution of TTC
Frequency of events like hard braking,	Define threshold for hard braking and count how many times braking exceeds the threshold.
Number of identified conflicts based on safety metrics	Define a conflict using thresholds of base metrics and count the number of times when the threshold is exceeded.

Correlation of conflict with the number of crashes	Using crash data, estimate correlation of number of crashes with the number of observed conflicts in simulation. For the definition and estimation of conflicts, Surrogate Safety Assessment Module (SSAM) or other models with the definition of a conflict can be used.

For the variables above, a performance metric is defined such that the calibration procedure stops when the threshold for the performance metric is met. A commonly used performance metric for comparing distributions is the Kullback–Leibler divergence metric. For correlation of crashes and conflicts, the Spearman's rank correlation coefficient can be used (a well-known nonparametric measure of rank correlation). It assesses how well the relationship between two variables can be described.

Final Model Validation

After the safety calibration process is done, then the resulting model is considered the final model. This model then needs to be validated. The model can be validated in various ways.

First by visual inspection. This involves checking for very unrealistic behaviors. Secondly, by looking at the congestion patterns and the location of congestion. In addition, the speed, flow, and travel time measurements should still be reasonably close to the observed values from loop detectors. The calibration of model to safety should not totally change the efficiency of the traffic network.

Finally, the model can be validated by applying the model to a different location with similar traffic network geometry and traffic conditions (Cunto, 2008). Ideally, the model should have comparable performance for such locations (assuming that the driving behavior does not differ significantly from the location used for initial calibration).

5.2 Calibration and validation of the AV model

The behavioural model for AVs is connected to the Aimsun Next program by the External Agent Interface. In this manner, an existing microsimulation is enhanced with the aim of analysing future mobility systems.

The EAI is designed to introduce externally controlled vehicles into an Aimsun Next microscopic simulation and have external vehicles guided by the actions of, for example, a human driver in a simulator, an autonomous vehicle controller, or by an experimental control system being tested in a simulation environment.

Analysing the behavioural model for AVs and the Aimsun Next program, some specifications or requirements are identified to perform a correct integration of both systems.

- An Open Drive map file should be shared in each simulation. The Open Drive format version should be 1.4.
- The behavioural model for AVs updates the position and heading of the externally controlled vehicles.
- The behavioural model receives information about the dynamic objects in the simulation.
- The frequency of the communication is the same as the simulation step, which can be set as low as 10Hz (0.1s).
- The static traffic signs like stops or yields should be defined in the Open Drive map file.
- The ID of any traffic signals must also be shared between the simulation and controller. Therefore, the database used for the traffic signal definition should be shared. Currently, the behavioural model for AVs uses the Spanish regulation BOE-A-2003-23514.

The data exchanged via the EAI is based on geographic locations expressed as x- and y-coordinates (coordinate system is selected based on integration model requirements) rather than being based on the simulation representation of the traffic network expressed as lanes and turns. This feature enables the external control logic to be independent of the detailed road geometry in Aimsun Next; it can continue to use its own network model. Data exchange relies solely on a shared common coordinate system.

Regarding the calibration of the AV model, it does not depend on the simulator or the scenario. The AV model has to face any situation by following the driving rules. Therefore, the calibration of the model is intrinsic. This is that the calibration depends on the characteristics that are required in the AV model itself. Depending on the values of the calibration parameters, the AV model can have a aggressive behavior in the execution of the planned trajectory, calculate trajectories of different geometry or make decisions at different instants of time. The calibration of the model is explained concisely in the deliverable 2.3.

Finally, the model can be validated in two steps. A first visual inspection makes it possible to analyse whether the vehicle's behaviour and decision-making is as expected with respect to the situation it faces at each instant of time. The second step is the most important. The correct functioning of the model will be validated by the analysis of the simulations. This analysis must provide among other things that the model does not generate avoidable collisions or risk situations.

5.3 Calibration and validation of the human driver model

For the calibration and validation of the human driver model, the approach as described in paragraph 5.1 will be followed also for the human driver model. During the calibration procedure, several parameters specific for the human driver need to be adjusted. Some of such parameters are presented in the table below. The models (IDM+, LMRS and Perception Model) and parameters are described in deliverable D2.2 Enhanced Human Driver behavioural microsimulation model. Most of the typical values are given in the table below and can be found in (Schakel, Knoop, & van Arem, 2012) and (Calvert, Schakel, & van Lint, 2020).

Table 6: Examples of parameters to adjust during safety calibration

Parameter	Model	Description	unit	Typical value
Comfortable acceleration/deceleration	IDM+	Comfortable acceleration/deceleration of a driver	m/s^2	1.25 (acceleration) 2.09 (deceleration)
Dfree	LMRS	Desired threshold for free lane		0.25
Dcoop	LMRS	Desired threshold for cooperative lane change		0.75
Dsync	LMRS	Desired threshold for synchronized lane change		0.5
Average Reaction Time	Perception Model	The average reaction time of the driver during	seconds	1.0
Minimum Reaction Time	Perception Model	The reaction time of the driver during maximum situation awareness	seconds	0.5
Maximum Reaction Time	Perception Model	The reaction time of the driver during minimum situation awareness	seconds	2.0
Perception mixture	Perception Model	Parameter which regulates percentage of drivers who over or underestimate distances and speed differences		50% overestimate and 50% underestimate
Critical Task Saturation	Perception Model	Task saturation above which situation awareness starts to decrease		95% of capacity

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

5.4 Calibration and validation of the pedestrian and cyclist model

The IKA's external cyclist and pedestrian behaviour models are connected to Aimsun Next by the EAI. The models are separate algorithms that can communicate with a simulation software via a defined Protocol Buffers interface. They work independently of any hardware or software, only the interface must contain all necessary information about the agents and the infrastructure data.

For the calibration of the pedestrian and cyclist models, the virtual reality simulators developed in SAFE-UP will be used. Therefore, studies are conducted with test persons who need to perform behavioural decisions under given conditions that are relevant for parameter settings. The simulators provide us the possibility to replay exactly defined scenarios in a reproducible way and thus to study the behaviour for a large number of test persons in exactly the same situation. Due to the own development of the hardware and software of the simulators, any amount of data can be generated for the calibration of the behaviour models.

In the study, the subjects will be asked to make various crossing decisions by using the pedestrian simulator. This will involve varying the infrastructure elements and the DSTs of the potential collision partners. Based on the study evaluation, there is a correlation between the objective data (the DST) and the subjective crossing probability that calibrates the behavioural model.

Specific scenarios in the bicycle simulator are prepared for the study. Special attention will be paid to the lateral driving behaviour of the subjects in these situations. Depending on the driver type (racing, normal, unexperienced), driving on a straight road segment, driving in a curve, and interaction with other road users will be investigated. The determined driver type dependent lateral behaviour parameters are used to calibrate the model parameters.

The validation of the models takes place in two steps. First, the calibrated model is checked for correct execution. For this purpose, the entire study data from the studies in the virtual reality simulators are split. A part is used for calibration and the other for validation. The calibrated behavioural model is exposed to certain selected situations and the behavioural decisions are compared with the reference data. Based on the study data, defined behavioural decisions of the models can be predicted clearly. Safety-relevant scenarios are thus represented in Aimsun Next and the corresponding behavioural decisions of the models are investigated by modifying the model parameters.

5.5 Calibration and validation of the powered two-wheeler model

The PTW model developed in the SAFE-UP has been coded in Matlab, and integrated in the traffic simulation Aimsun Next through MicroSDK. The PTW model simulates PTW riding maneuvers in Matlab and sends a message, containing the updated speed and position, to

Aimsun Next. Thus, a dynamic library (i.e., a dll) is provided to the software which allows the connection between the two environments that run on two different computers. The simulation platform can exchange information with the PTW model using a TCP/IP communication protocol.

The model will be completely calibrated using naturalistic driving data owned by UniFi and providing the model with the boundary conditions collected within the data. The calibration is in progress, and it is performed reproducing real maneuver and comparing the simulated response with the real one in terms of speed variation. The validation will be performed by reproducing some scenarios collected with the real PTW and comparing some variables – especially speed and acceleration. To do it, the following data are required:

- Road infrastructure. The map in Aimsun Next shall include a road infrastructure with the same general features as the ones contained in the naturalistic data, especially in terms of curvature, number of lanes, number of sections connected by each node and signals;
- Traffic Demand. The simulated traffic flow shall be comparable with the one that is observable reviewing the data;
- Type of road users. Users in the virtual environment shall be the same kind of road users who the real rider interacted with, while he was collecting data.

The calibration and the validation will be done in two steps: first in Matlab, giving the needed information to the PTW model in a static way. Then making simulation inside Aimsun Next. This two-step strategy allows developers to have a first calibration as fast as possible. Then, simulating the PTW riders' behavior in Aimsun Next, a detailed calibration can be reached by comparing the simulation outputs (e.g. PTW trajectories) with the real observations. It is important to note that the PTW model in Matlab is calibrated. Next step in the calibration process is to generate simulation outputs from Aimsun Next and benchmark with the real observations.

Concerning the validation, it will be organized in a very similar way. Basically, the model will be validated through simulations in Aimsun Next defined as the ones used for calibration. The main difference is that new manoeuvres will be simulated and new data set for validation will be used.

The variables that will be compared with data will be:

- Speed and acceleration curves;
- Distance from the reference users at the beginning of the simulated manoeuvres;
- Boundary conditions at the end of the simulated manoeuvres.

In this way, both the decision-making process and the execution of manoeuvres can be evaluated and validated.

6. Conclusions

The SAFE-UP traffic simulation environment with road network model and integration framework of all the road users' models is presented in this deliverable. It enables harmonised simulation of the next generation of all road users' behavioural models (driver, AV, and VRU), capturing the failure of sensors, risks those drivers and riders might take, their errors of judgement, and distraction in the current and future mixed traffic conditions. All aspects required to properly simulate safety critical events before and after introduction of AVs are covered by SAFE-UP traffic simulation environment, from simulation of road users' behaviour, including their perception and interaction, traffic simulation, road infrastructure, and traffic management plans. In addition, the traffic simulation environment is prepared to work with the real-life use cases, through application of road infrastructure and road users' behavioural data collected in the real world for the models' calibration and validation, and contribution to more reliable estimation of safety critical interactions in today´s and future road evolving conditions.

The SAFE-UP traffic simulation environment will be developed and extended continuously during the project. Depending on the outcomes of Task 2.2. and 2.3 further test scenarios are going to be implemented which may require extensions on the interface between models and Aimsun Next simulation platform, or even improvements of the integrated simulation models. Furthermore, final decisions on the setup of the traffic simulation and the testing scenarios for future safety critical events identification and impact assessment will be done in the frame of WP5.

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

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