Getting the human factor into traffic flow models – a new open-source design to simulate next-generation traffic operations

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1 **ABSTRACT**

2 Automated driving may lead to (much) higher road capacities combined with increased road
3 safety, driver comfort and lower costs. Although this vision may hold ground in the long run,
4 first a transitional period will take place in which increasing percentages of vehicles with many
5 different levels of automation will drive on our road networks. This transition poses a
6 fundamental scientific challenge. The models used today to simulate and predict vehicular traffic
7 are not valid to predict emergent properties of traffic flows under increasing amounts of vehicle
8 automation. For example, we have no idea how non-equipped drivers respond to other drivers
9 reading their morning papers behind the steering-wheel, nor what the consequences of these
10 interactions are on traffic safety and capacity.
11   In this paper we do not propose a new behavioural theory with which the effects of
12 increasing vehicle automation can be predicted. What we propose is an advanced open-source
13 simulation framework OpenTraficSim (OTS) that makes it possible to incrementally extend
14 microscopic models with explanatory mental models, such that new behavioural theories can be
15 tested and shared within our community. Given the societal importance of predicting the effects
16 on safety and efficiency of vehicle automation, we sincerely hope this paper will fuel the
17 discussion on how both open- and closed source simulation software can be adapted and made
18 ready for the next-generation traffic simulation models that are needed in the coming decades.
19
20 Keywords: Vehicle automation, Traffic simulation, Open-source, OpenTrafficSim

1   **INTRODUCTION**

2   The appeal of automated driving for many politicians, leaders of industry and scientists is the
3   potential of (much) higher road capacities combined with increased road safety and decreased
4   vehicle emissions.
5   There are strong arguments that support this enthusiasm. Higher capacities, that is, shorter
6   minimum time headways are indeed possible by taking human drivers out-of-the-loop. In
7   countries with well-trained drivers, high quality cars and road facilities, the average minimum
8   time headway is slightly above 1,5 seconds (implies maximum flows of 2400 veh/h). This is
9   close to average human reaction time, i.e. the time it takes the brain to process and interpret
10   visual information, and take action accordingly (brake or overtake). Clearly, technology can do
11   the job at a fraction of the time and much safer as well, as demonstrated in many field trials over
12   the past three decades *(1, 2)*. There are also additional behavioural inefficiencies that can be
13   resolved with technology, for example more effective anticipation to downstream conditions and
14   more efficient use of available traffic lanes.
15   However, vehicle automation will not take place overnight. A transitional period of at least
16   15-20 years will take place during which gradually vehicle automation will become
17   commonplace in new vehicles. Many scientists and practitioners foresee a transition through
18   five (or 6 *(3)*) different levels of automation: no automation; driver assistance; partial automation
19   (with the driver as a permanent supervisor); high automation (with conditional or partial
20   supervision by the driver); and full automation. Either case, during this transition period (a)
21   increasing percentages of drivers with (b) cars equipped with different levels of automation will
22   drive alongside "non-equipped" drivers on our road networks that (c) are (potentially) not (at all)
23   designed optimally to facilitate safe and efficient traffic operations for these mixed traffic flows.
24
25   The central scientific challenge for the traffic flow theory and simulation community is that there
26   is no unified theory of driving (or even a set of candidate theories) yet that enables us to
27   *quantitatively* predict on beforehand the effects of increasing percentages of (heterogeneous)
28   vehicle automation capabilities on either capacity or safety during this transitional period.
29   Capacity is the emergent result of the complex interactions between drivers in vehicles with
30   different (automation) capabilities (including none at all). How will for example non-equipped
31   drivers respond to drivers passing at high speeds in tight platoons reading their morning papers
32   behind the steering-wheel? It is unclear whether the effective minimum time headway would
33   actually decrease under all circumstances. Research shows for example how reaction time may
34   double in case an accident causes a queue to build up *(4, 5)*, perhaps the unfamiliar experience of
35   being overtaken by such a platoon may have the same effect.
36   The obvious reason we cannot use existing mathematical models for e.g. car-following (CF,
37   e.g. *(6-12)*) and lane changing (LC, e.g. *(13-17)*) to predict the consequences of vehicle
38   automation is that these are mostly descriptive with respect to driving behaviour, that is, they do
39   not endogenously compute behavioural responses of drivers to for example different traffic
40   conditions or different road-lay-outs. Instead, these models contain parameters (e.g. reaction
41   time, degree of politeness, risk-averseness) that are set exogenously and that are calibrated using
42   data collected under current traffic conditions. Clearly, we do not have evidence (yet) for how
43   non-equipped drivers respond to traffic conditions with say 40% "level-5 automated" vehicles,
44   nor do we have evidence for the resulting dynamics. In fact, every change in the driving
45   environment (in-vehicle assistance, road lay-out, traffic regulations, environmental conditions,
46   etc) that may cause structural changes in driving behaviour (vehicle automation is an extreme

1 example) requires at best circumstance-specific parameter calibration and validation of existing
2 microscopic models and in the worst-case the identification and estimation of completely new
3 models altogether.
4   For predicting safety consequences the situation is even more problematic. Most CF and LC
5 models used today are by design collision-free, which means that deriving surrogate safety
6 measures (e.g. time to collision) as a proxy for (un)safety from simulations is fundamentally
7 flawed. To assess whether safety is at risk, explanatory psychological constructs are needed that
8 can endogenously predict under which circumstances drivers take risks and/or make mistakes
9 that may lead to unsafe situations and ultimately accidents. However, a small but increasing
10 number of papers are published in which behavioural theories are incorporated in traffic flow
11 models. For example, Hamdar and co-authors *(18)* propose a car-following model based on
12 prospect-theory in which drivers way faster travel time against the risk of rear-end crashes, and
13 Hoogendoorn et al combine a Task-Capacity-Interface model with the IDM to predict reaction
14 time dynamics *(19)*.
15   In *(20)* Treiber and his co-authors conclude that the most probable reason that the traffic
16 flow community has stuck to simple descriptive models for so long is that *"the destabilizing*
17 *effects of reaction times and estimation errors can be compensated for by spatial and temporal*
18 *anticipations: one obtains essentially the same longitudinal dynamics, which explains the good*
19 *performance of the underlying simple models"* In other words, we did not need explanatory
20 psychological constructs to describe and predict most phenomena we observe. With the
21 transition to partial or full vehicle automation at hand, this is a luxury we can no longer afford.
22   This is particularly true since there are many phenomena in current traffic that we do not
23 fully understand, such as the capacity drop and most phenomena related to lateral movement.
24 Incorporation of psychological concepts in simulation can help in explaining such variations in
25 driver behaviour.
26
27 In this paper we do not propose a new behavioural theory with which the effects of increasing
28 vehicle automation can be predicted. What we propose is an open-source simulation framework
29 OpenTraficSim (OTS) that makes it possible to incrementally extend microscopic models with
30 explanatory mental models, such that new behavioural theories can be tested and shared within
31 our community. This framework builds on the design of microsimulation model MOTUS *(21)*
32 with which already a number of ex ante evaluations of advanced driver assistance systems have
33 been performed (e.g. *(22, 23)*). Note that OTS is designed to also facilitate macroscopic and even
34 reservoir type simulation *(24)*; in this paper we discuss micro-simulation only.
35   This paper is organised as follows. In the next section we first briefly discuss some of the
36 research challenges relevant to the transition towards (whatever degree of) vehicle automation.
37 Based hereon we derive some basic requirements for the design of a generic simulation
38 framework that can support this research. The section thereafter discusses the resulting agent-
39 based design of OpenTrafficSim and in particular the Generic Traffic Unit (GTU) concept. Next
40 we present a small experiment with a first prototype. We finish with a discussion and outlook
41 toward the further implementation of the presented framework.

1   **GETTING HUMAN FACTORS IN SIMULATION MODELS**

2   **Challenges for driving behavioural research**

3   In the last decade many research groups have worked on the behavioural response to in-vehicle
4   information *(22, 25)* and automation systems *(26-29)*. And there are many open research
5   challenges.
6   Simulating drivers with level 1 or level 2 automation systems requires an understanding of
7   how and under which conditions these systems are used. It is for example highly uncertain
8   whether drivers are prepared to give up the steering wheel under those conditions where
9   improved efficiency really matters *(19)*. These conditions include dense hi-speed traffic, under
10   which the task load of drivers is already high, but during which the potential gain of vehicle
11   automation in terms of capacity are highest. Field trials of connected adaptive cruise control
12   systems show that rather the opposite is true—drivers are more likely to turn off these systems
13   under those conditions *(30)*. Moreover, many such advanced cruise control systems allow drivers
14   to configure the system to their own preferences, including the minimal time headway. There is
15   evidence that under high percentages of vehicles equipped with *cooperative* cruise control
16   drivers are willing to reduce their headway well below one second *(31)*, but the distribution of
17   those settings is wide.
18   When drivers *do* give up the steering wheel (either voluntarily or automatically as in level 3
19   automation systems) and substitute their role as driver for one as supervisor, additional problems
20   occur. In recent studies researchers conclude that drivers of automated vehicles may be
21   vulnerable to fatigue when normal vehicle control is restored *(26-28)*. It takes time for a driver to
22   re-engage with the driving task (particularly in terms of the lateral control of the vehicle) after a
23   longer period of automatic driving *(26)*. The editors of a special issue in Human Factors on
24   automation in vehicles *(32)* tentatively conclude in their editorial that we "should not assume that
25   automation can substitute seamlessly for a human driver" nor should we "assume that the driver
26   can safely accommodate the limitations of automation".
27   A related challenge is that whereas some in-car innovations will make the driving task
28   simpler (lane keeping, adaptive cruise control), other systems (advisory and information
29   systems) may well do the opposite. The reason is that these may provide many opportunities for
30   distraction that would likely increase the complexity of the driving task *(28)*.
31
32   There are also research challenges that to our knowledge have received little or no attention at
33   all, but which are fundamental in making predictions (through simulation) of partially automated
34   traffic flows. In our view the most important one concerns the response and driving behaviour of
35   unequipped (or level 1, 2) drivers under increasingly heterogeneous traffic conditions with a mix
36   of level 3-5 automation. The complexity of this challenge is nicely pointed out by Zheng *(33)* in
37   his recent review of lane changing models: "[in heavy traffic] *a typical LC decision-making*
38   *process closely involves at least two players – the lane changer and the follower in the target*
39   *lane. This is because the follower is often also required to make decisions as a result of someone*
40   *else's LC decision. Thus, at least two decision-making players and processes are involved in the*
41   *LC process in heavy traffic*". In other words, LC, much more than CF, is an interaction process
42   rather than an individual decision-making process, and a similar argument goes for gap
43   acceptance, crossing intersections, etc. These interactions that are today already poorly
44   understood may fundamentally change if one of the players is a (partially) automated vehicle. To
45   unravel this interaction process different experimental methodologies are needed than single
46   driver simulator (or instrumented vehicle) methods. Moreover, new mathematical formalisms

1   (e.g. game theory) need to be used to quantify these interactions in simulation. Much can be
2   learned here from pedestrian research (see e.g. *(34)*)
3   Clearly, these challenges require a huge amount of research in the coming years. We now
4   focus on what these challenges imply for next generation simulation models.

5   **Requirements for OpenTrafficSim (OTS)**

6   From the human factors literature we can list the relevant (at least most popular) mental
7   constructs and capacities used to explain the driving process:

8   - *Workload* is a construct that expresses the total amount of mental effort. i.e. the amount
9   of (information-processing) resources used per time unit, to meet the level of
10   performance required *(35)*. Note that workload can be considered a driver state variable
11     $WL(t)$, that dynamically evolves over time.
12   - *Task capability* is a construct that describes the driver's capabilities to perform (driving)
13   tasks. Also $TC(t)$ can be considered a driver state variable, that is determined by his /her
14   (baseline) driving skills, experience, etc., and that may evolve over time due to
15   circumstances. The relationship between task demands and capacities has been modelled
16   by *(36)* and is used in e.g. *(19)* as the task-capability interface model (TCI) of the driving
17   process.
18   - *Situational awareness* is a construct that was operationalized for air traffic simulation and
19   control by Endsley *(37)* that defines the degree in which a driver is aware of his
20   environment, and specifically those elements that are relevant for the driving task.
21   Situational awareness can also be considered a state variable $SA(t)$ that may dynamically
22   evolve over time as a function of WL, TC and many other factors. Note that different
23     $SA(t)$ variables could exist for different stimuli or threats. Awareness closely relates to …
24   - … *Subjective perception* (SP), which can be considered a separate construct. SP
25   translates the physical driving environment to what the driver subjectively makes of it.
26   - *(subjective) Task Complexity* is a construct that is often used but is not clearly defined. In
27   *(35)* complexity is interpreted as a measure for traffic conditions (denser traffic is more
28   complex), whereas in *(38)* it is considered a measure that rates the clarity of visual
29   information. Subjective task complexity or simply complexity can be understood as a
30   state-variable $STC(t)$ that rates the difficulty of the driving environment.
31
32   The key to incorporate these constructs in a modular and generic way is that they are considered
33   explanatory for the (exogenous) parameters in most microscopic traffic simulation models. In
34   their literature review Hoogendoorn et al *(39)* conclude for example that the changed role of the
35   driver from automation 1 upward may have a substantial influence on driver-workload and
36   situation awareness resulting in, for instance, *an increase in reaction time*. We use the
37   delineation in *(20)* to identify the key variables and their probable explanatory constructs:

38   - Reaction time is a function of probably all constructs (WL, TC, SA and TC)
39   - Estimation capabilities of stimuli such as speed differences, headways, etc (inputs to CF
40   and LC) are subject to SP and SA.
41   - Both temporal and spatial anticipation are manifestations of the fact that humans have
42   predictive capabilities (with of course different degrees of accuracy). These capabilities
43   can be modelled via SP, or through a dedicated "predictive mental component".
44

1   There are, of course, many additional variables relevant for CF and LC, such as those that govern
2   decision making (affected by all constructs), inertia (related to SA and SP), aggressiveness
3   (related to personal characteristics and probably also WL), etc.

4   **MODULAR AGENT-BASED DESIGN FOR MICROSCOPIC TRAFFIC SIMULATION**

5   **Overall structure of the OTS simulation process**

6   To facilitate simulation of these mental processes (with implementations of the appropriate
7   psychological models) we propose the simulation process schematically outlined in FIGURE 1.
8   In this scheme, GTU stands for generic traffic unit (a person or vehicle) and will be explained
9   further below. So-called on-GTU-Units (OGU's) represent technologies that either enhance the
10 vehicle (e.g. vehicle automation) or assist the driver (e.g. route navigation, information systems).
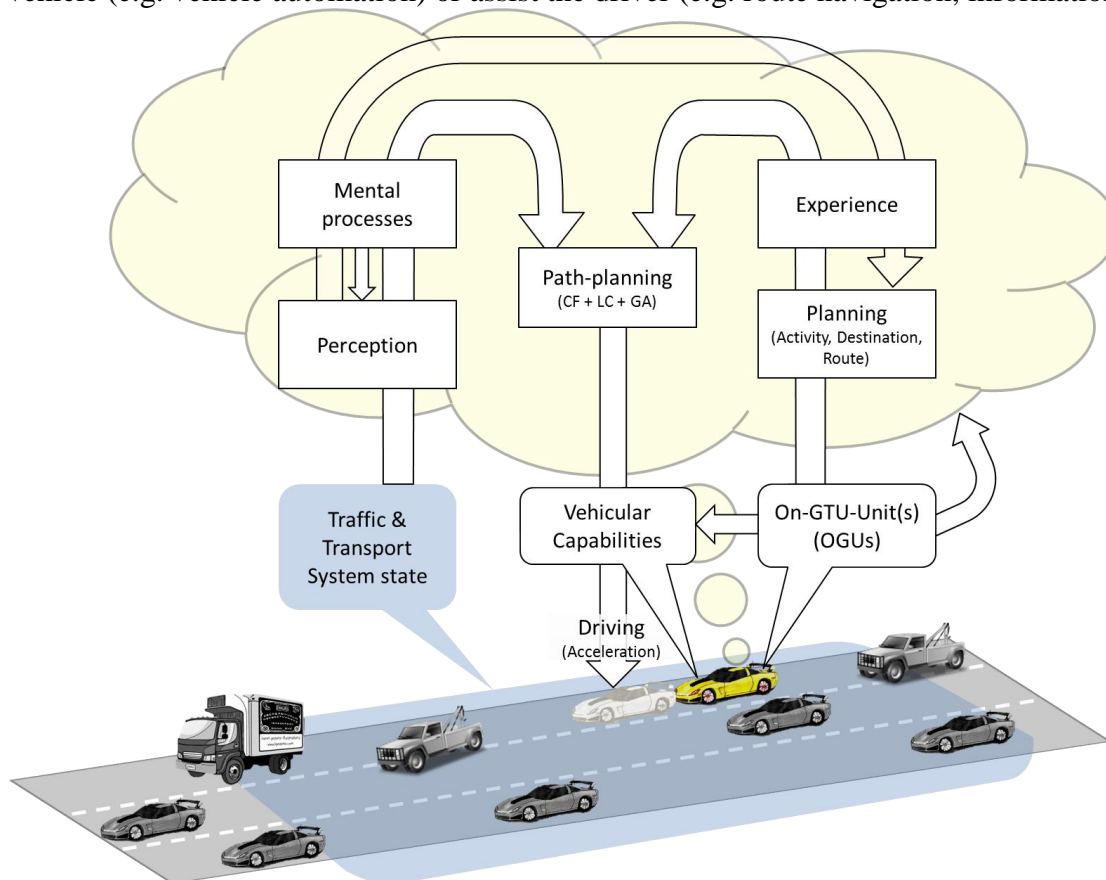
11
12 **FIGURE 1 Schematic representation of the microscopic driving process in OpenTrafficSim (OTS).**

13 Below a (simplified) "algorithm" for a single simulation step:
14   Step 1.   The simulation environment provides each driver with the prevailing system state
15   (the infrastructure, controllers, positions, speeds of drivers in the vicinity, etc.)
16   Step 2.   If Perception is activated the state may be altered as a result of e.g. (limited) visual
17   capacities. A driver assistance system (OGU) may on the other hand enhance
18   perception.
19   Step 3.   Mental constructs—if instantiated—are updated. This may further degrade or
20   enhance subjective perception and likewise affect some or all driving parameters
21   (reaction time, sensitivity, etc).

Step 4.   The fundamental difference of OTS with other simulation environments is in the update (re-evaluation) scheduling of driving behaviors (CF, LC, GA, etc). This scheduling is not the product of the (arbitrary) choice for a numerical time step, but a process that is explicitly modeled (e.g. *(40)* it is shown that action points have a wide distribution and are themselves a function of the (traffic) circumstances and possibly many other factors). On the basis of a plan (route / destination) and the drivers Experience (if instantiated) the driver computes a continuous (possibly 2 or 3D) path over the infrastructure for the next n time units using whatever models for CF, LC, GA are implemented. The schedule interval n can be as short (e.g. one time step) or long (20 seconds) as needed and can be modeled as a function of circumstances. To compute such a path, the driver needs to make assumptions (predictions!) about drivers around him. In the example in the second part of the paper this point is further explained. With computing this path come intentions (flashing lights, next time instant the driver wants to re-evaluate, etc). A driver assistance system (OGU) may change or override this path. Note that re-evaluation of this path will occur either at the intended re-evaluation interval or as soon as circumstances dictate.

Step 5.   If physical models for the driving task have been instantiated, these execute the driving intentions resulting in activities of e.g. the drivers body, clutch, pedals, transmission, engine, resulting in an actual physical movement (if any)

Step 6.   The DSOL (see further below) simulation environment executes during the interval n the movement resulting from the computed path, unless circumstances require re-evaluation before the simulation of the path is finished.

The Generic Travel Unit (GTU) and other OTS classes

The core objects in OTS simulations are so-called generic travel units (GTUs). The GTU class hierarchy has two major branches: Person and Vehicle. In many aspects, these classes are one another's mirrors. A Person has perceptive capabilities, so does a Vehicle (given it has sensors, etc); a Person has Mental capabilities, a vehicle has Computing capabilities; etc. FIGURE 2 schematizes the GTU in relation with some of the other main classes.

The key message is that with this GTU design (FIGURE 2) and the simulation process organised as in FIGURE 1 OTS offers maximum flexibility for micro-simulation:

- In the simplest scenario, Perception simply copies the system state (e.g. list of vehicles, network, etc); both Mental and Experience are dummy objects and Vehicle just contains parameters (length, max acceleration, etc) resulting in a "normal" microsimulation.
- Every Person can drive any type of Vehicle according to any (combination of) models for both planning and driving, either very simple, or highly complex.
- All Vehicle automation or Person information systems are modelled through On-GTU-Units (OGUs) that may affect all Person or Vehicle objects, parameters and methods.

Finally, this design and the underlying DSOL simulation engine (see next section) allows also for true multi-modal simulation, that is, a simulation in which multiple modes plan and move *in the same (virtual) environment*.

- The Mover class of a Person can also be used to model pedestrians, cyclists, motordrivers, barge or plain pilots, and conversely, the Vehicle class can represent any type of car, tram, train, vessel, etc.

1 A central prerequisite for this is that the simulation engine is able to deal with objects that run on
2 different clocks (are updated with their own time step).
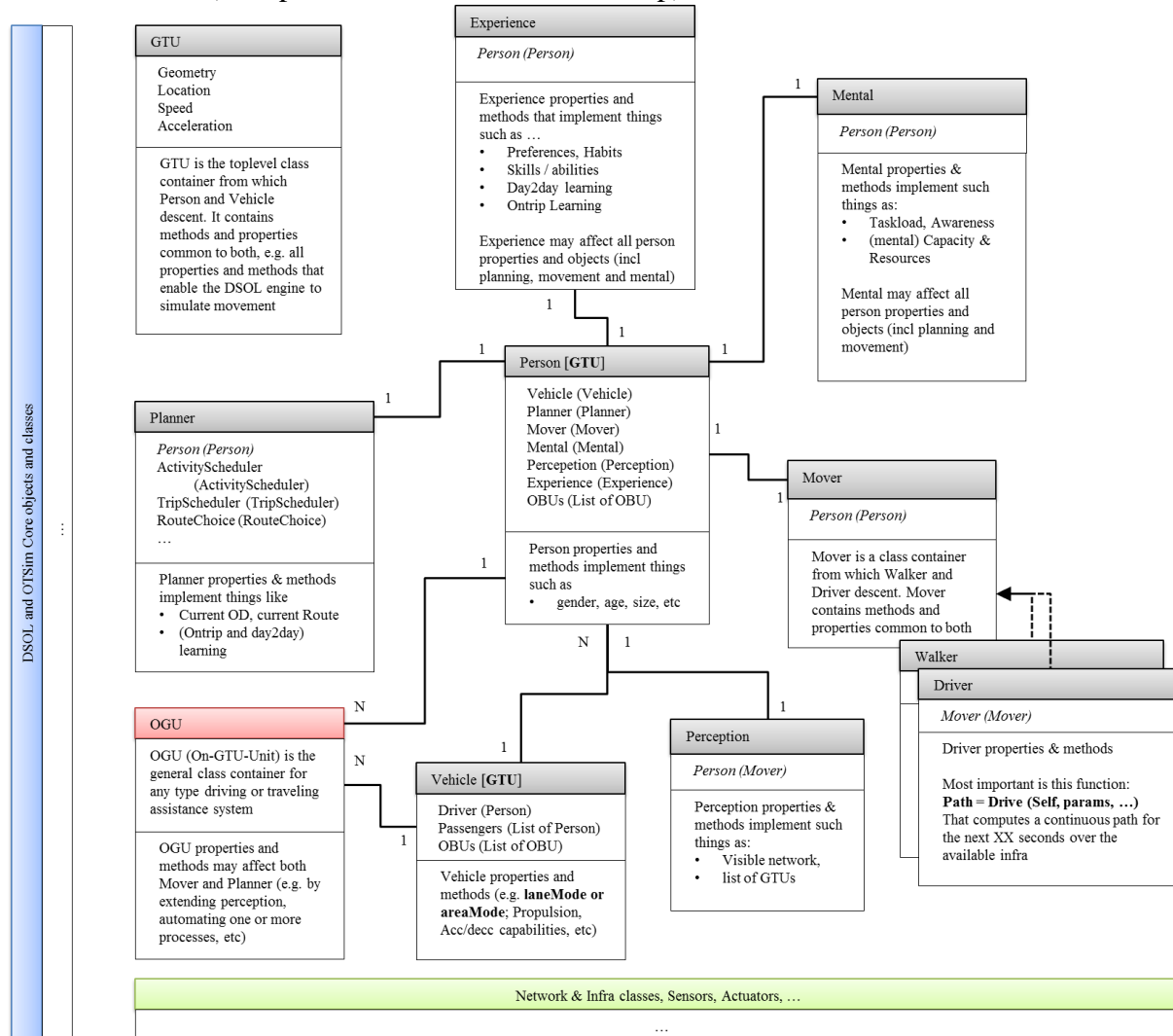
3
4 **FIGURE 2: Pseudo-UML schema for the Generic Travel Unit - the core simulation object in OTS**

5 **OTS PHILOSOPHY AND SOFTWARE DESIGN**

6 OTS has been built on top of the open source simulation package DSOL, Distributed Simulation
7 Object Library *(41, 42)*. DSOL is a Java-based, object oriented, multi-paradigm simulation
8 environment that prepares for distributed and parallel execution of the simulation model. DSOL
9 is a general purpose simulation environment that adheres to the best practices in the simulation
10 field, such as strict separation between simulator and model *(43)*, strict notions of time and state
11 *(44)*, state-of-the are random number generators *(45, 46)*, probability distribution functions *(47)*,
12 and a clear structure for experiments and run control conditions *(48)*. The fact that DSOL is
13 object oriented makes it easy *(49)* to extend the available simulation objects in the library such as
14 simulators, experiments and statistics, into traffic specific building blocks for OTS, while still
15 being able to use all other simulation objects that have not been specialized for use in a traffic
16 environment. The use of Java has several key advantages over other programming languages: the
17 availability of a very large ecosystem of open source libraries, the ability to compile into stand-

1 alone programs that can run on any computer with a Java Runtime Environment installed, and
2 platform independence (e.g., Windows, Mac and Linux),.
3
4 DSOL is a multi-paradigm simulation platform. running event scheduling simulations (DEVS –
5 Discrete EVent Systems Specification), time stepped models (DTSS – Discrete Time Systems
6 Specification), or differential equation (DESS – Differential Equation Systems Specification);
7 for more information, see *(43, 50)*. Combinations are also possible, and extensions such as cell-
8 based models and agents have been built as well *(51)*. Multi-formalism offers many advantages
9 for our OTS library:

10 • Time-stepped models can be used when the system state is evaluated at constant intervals
11   can be easily implemented using the DTSS formalism;
12 • The event mechanism of DEVS is easy to use for scheduling traffic lights, arrivals of
13   vehicles in the system, and models where the state is recalculated at scheduled time
14   instants rather than at constant intervals;
15 • Differential equations can be included as DESS (sub)models, e.g., for calculating non-
16   linear acceleration and braking behavior, which is usually relatively easy to represent as a
17   set of differential equations;
18 • Agent-based models can be used to specify the behavior and believes, desires and
19   intentions *(52)* of traffic users such as car drivers or pedestrians. Each traffic user can
20   now plan their own paths based on observations and schedule state changes using the
21   event scheduling mechanism of DSOL.
22
23 One of the most time-consuming tasks in making large-scale simulation models for traffic is the
24 construction of the network models, e.g., by importing GIS files, databases, or CAD drawings.
25 OTS builds on earlier projects with DSOL where models can very quickly be instantiated using
26 components *(53, 54)*. For these so-called automated model generation methods *(55, 56)* it is very
27 important to develop solid meta-models to ensure syntactic, semantic, and pragmatic correctness
28 of the generated simulation model *(57)*.
29   Finally, a strict unit system has been implemented in OpenTrafficSim for scalars, vectors,
30 and matrices, allowing the Java compiler to check the correctness of formulas and to convert
31 values between units. When a scalar that expresses a length is divided by a scalar that expresses a
32 time, the resulting scalar can only be allocated to a scalar has 'speed' as its unit. This speed can
33 now be displayed in m/s, m/h, or mi/h, totally dependent on the wishes of the user. Units are
34 internally stored is SI units, so a length of 500 nautical miles can be divided by a fortnight,
35 leading to an average speed expressed in km/h. The fact that the compiler checks for errors and
36 the internal representation is always in SI units enables programmers to catch many coding errors
37 *at compilation time* (instead of during runs).

AN ILLUSTRATIVE EXPERIMENT

39 In this section we present a small experiment. Note that we do not propose or implement a new
40 mental model; we adjust parameters of driving behaviour (reaction time and desired speed) to
41 demonstrate why integration of human factors into simulation is crucially important for
42 *predicting* emerging effects on both traffic efficiency and safety caused by changes in the driving
43 environment.

1   **Test case description**

2   We investigate the 'viewers jam' phenomenon. Such traffic jams arise at the location of an
3   incident on the other direction of the freeway. While drivers pay attention to the incident, their
4   driver behaviour deteriorates as speeds tend to drop and reaction times increase *(58)*. We
5   simulate this finding on a 5km single-lane road stretch, with an incident at 3km. We assume that
6   driver distraction grows linearly from zero to a maximum value over 600m up to 300m upstream
7   of the incident, while staying at its maximum over 300m upstream of the incident, see FIGURE
8   3(a). In the initial state we have 300 vehicles at their desired speed and desired headway, with
9   the first vehicle at $x = 0$. Simulations are of 1000s with a numerical time step $\Delta t = 0.25$s.
10   Car-following behaviour is simulated with the IDM+ model *(59)*, the discrete equation for
11   acceleration of a single vehicle is given in equation (1). The following parameters are used: $b_0 =$
12   0.75m/s^2, and the default desired speed v_0 is set at 120km/h. Other values are taken from *(60)*:
13   maximum acceleration $a_{max} = 1.25$m/s^2, maximum comfortable deceleration $b = 2.09$m/s^2,
14   stopping distance $s_0 = 3$m, and desired headway $T = 1.2$s. We also use vehicle length $l = 4$m.
15   Finally, s is the net headway while Δv is the approaching rate to the leading vehicle.
16   Note that reaction time T_r is incorporated in a similar way as in the HDM *(20)*. The input to
17   equation (1) is delayed; but drivers do *anticipate* each time step Δt in the period $[t-T_r, t)$ to
18   compensate for T_r by assuming constant acceleration of both the ego vehicle and the leader.

19

$$a(t) = a_{max} \cdot \min\left(\max\left(1 - \left(\frac{v(t)}{v_0}\right)^4, \frac{-b_0}{a_{max}} \right), 1 - \left(\frac{s^*(t)}{s(t)}\right)^2 \right)$$

20   (1)

$$s^*(t) = s_0 + v(t) \cdot T + \frac{v(t) \cdot \Delta v}{2\sqrt{a_{max} \cdot b}}$$

21
22   Driver distraction is integrated in two ways, We assume that desired speed drops and
23   secondly that reaction time increases. The level of distraction d for driver i at time t is given in
24   equation (2) in line with FIGURE 3(a). There are differences between drivers for d^0, which is the
25   level to which a drivers' behaviour is affected. For each driver it is a fixed random value taken
26   from a uniform distribution between 0 and 1.
27

28
$$d_i(t) = d_i^0 \cdot \begin{cases} 0, & x_i(t) < x_1 \text{ or } x_i(t) > x_3 \\ \dfrac{x_i(t) - x_1}{x_2 - x_1}, & x_i(t) \geq x_1 \text{ and } x_i(t) < x_2 \\ 1, & x_i(t) \geq x_2 \text{ and } x_i(t) \leq x_3 \end{cases}$$
                                                                                                        (2)

29
30   The change in desired speed is given in equation (3) (driver and time step index omitted for
31   clarity), where v_0^{def} is the default desired speed of 120km/h, and Δv_0 is the maximum change for
32   a fully distracted and most affected ($d^0 = 1$) driver. $\Delta v_0 \leq 0$ is changed between scenarios.
33

34
$$v_0 = v_0^{def} + d \cdot \Delta v_0$$ (3)

35

1   The change in reaction time T_r is done in a similar way, according to equation (4). Here, T_r^{def}
2   is the default reaction time of 0.5s, whereas ΔT_r is the maximum change for a fully distracted and
3   most affected driver. $\Delta T_r \geq 0$ is changed between scenarios.
4

5    $$T_r = T_r^{def} + d \cdot \Delta T_r \qquad (4)$$

6   **Test scenarios and performance indicators**
7   We define 12 scenarios to assess the effects of Δv_0 and ΔT_r on the resulting traffic operations.
8   For 6 we have $\Delta v_0 = \{0, -10, -20, -30, -40, -50\}$km/h with $\Delta T_r = 1$s, and for the remaining 6 we
9   have $\Delta v_0 = -50$km/h with $\Delta T_r = \{0, 0.25, 0.5, 0.75, 1.25, 1.5\}$s. Note that $\Delta T_r = 1$s is missing in
10   this array as it is part of the first 6 scenarios. For each scenario 30 runs are used as d^0 is a
11   random.
12   A number of indicators is derived to assess traffic efficiency and safety. The overall
13   efficiency is measured by the average outflow (the production) expressed in equation (5) where
14   t_1 is the time when the 1st vehicle crosses the downstream end and t_{300} is the time when the last
15   vehicle crosses the downstream end.
16

17   $$q = \frac{299}{t_{300} - t_1} \qquad (5)$$

18

19   For large values of T_r collisions may occur which we allow. A collision occurs in case a
20   specific vehicle has a negative net headway for a consecutive number of time steps (note that
21   headways < 0 are truncated to 0 in equation (1) to prevent simulation artefacts). Since we allow
22   collisions, we also compute time-to-collision (TTC) (6):
23

24 $$TTC = \begin{cases} 0, & s < 0 \\ \dfrac{s}{\Delta v}, & s \geq 0 \end{cases} \qquad (6)$$

25   **Results**
26   The influence of Δv_0 and ΔT_r on downstream flow is shown in FIGURE 3(b-c). For $\Delta v_0 = 0$km/h
27   there are no disturbances at all and temporal anticipation is completely able to compensate for
28   the reaction times as high as 1.5s in total. For $\Delta v_0 = 10$km/h we see a strong drop as disturbances
29   now occur. Together with $T_r^{def} = 0.5$s and $\Delta T_r = 1$s, mild disturbances thus produce a strongly
30   deteriorated traffic efficiency. For larger values of Δv_0 efficiency drops slowly as disturbances
31   are slightly larger. Interestingly, even for $\Delta v_0 = -50$km/h, values of ΔT_r up to 0.75 seem to have
32   little influence on efficiency with downstream flow being about 2250veh/h. Apparently,
33   temporal anticipation is relatively accurate for reaction times up to 1.25s in total. For large
34   values of ΔT_r we do see seriously deteriorated traffic flow efficiency.
35   FIGURE 3(d-e) show the influence of ΔT_r on the number of collisions and TTC between 0s
36   and 4s, i.e. critical values. Both indicators show a similar effect, larger reaction times deteriorate
37   safety. For $\Delta T_r = 1.25$s we get 1.1 collisions on average, while $\Delta T_r = 1.5$s produces 5 collisions
38   on average. TTC values between 0s and 4s are also frequent for these values of ΔT_r. For $\Delta T_r =$
39   0.75s and $\Delta T_r = 1$s TTC values between 0s and 4s also occur, but not often.
40   The influence of Δv_0 on the number of collisions is not present, as with $\Delta T_r = 1$s being used
41   within these scenarios, no collisions are produced at all. The influence of Δv_0 on TTC is present,

1   with smaller values of Δv_0 reducing the infrequent number of low TTC values at $\Delta T_r = 1s$ even
2   further, namely already from 143.57 at -50km/h to 26.43 at -40km/h. The strength of the
3   disturbances thus affects safety.
4   FIGURE 3(f) finally shows the spatial distribution of small values of TTC up to 8s for one
5   scenario, with $\Delta v_0 = -50km/h$ and $\Delta T_r = 1.25s$. From the distribution we can see that because of
6   the temporal anticipation, traffic remains relatively safe away from the incident. Near the
7   incident, very critical TTC values occur, and for this scenario even 1.1 collisions occurred on
8   average. In the range of 1000m till 2500m TTC values between 2s and 8s occur. This is because
9   of moving jams that move upstream. These moving jams show strong decelerations because the
10   large reaction times at the incident create very strong decelerations.

(a)

(b)   (d)

(c)   (e)

(f)
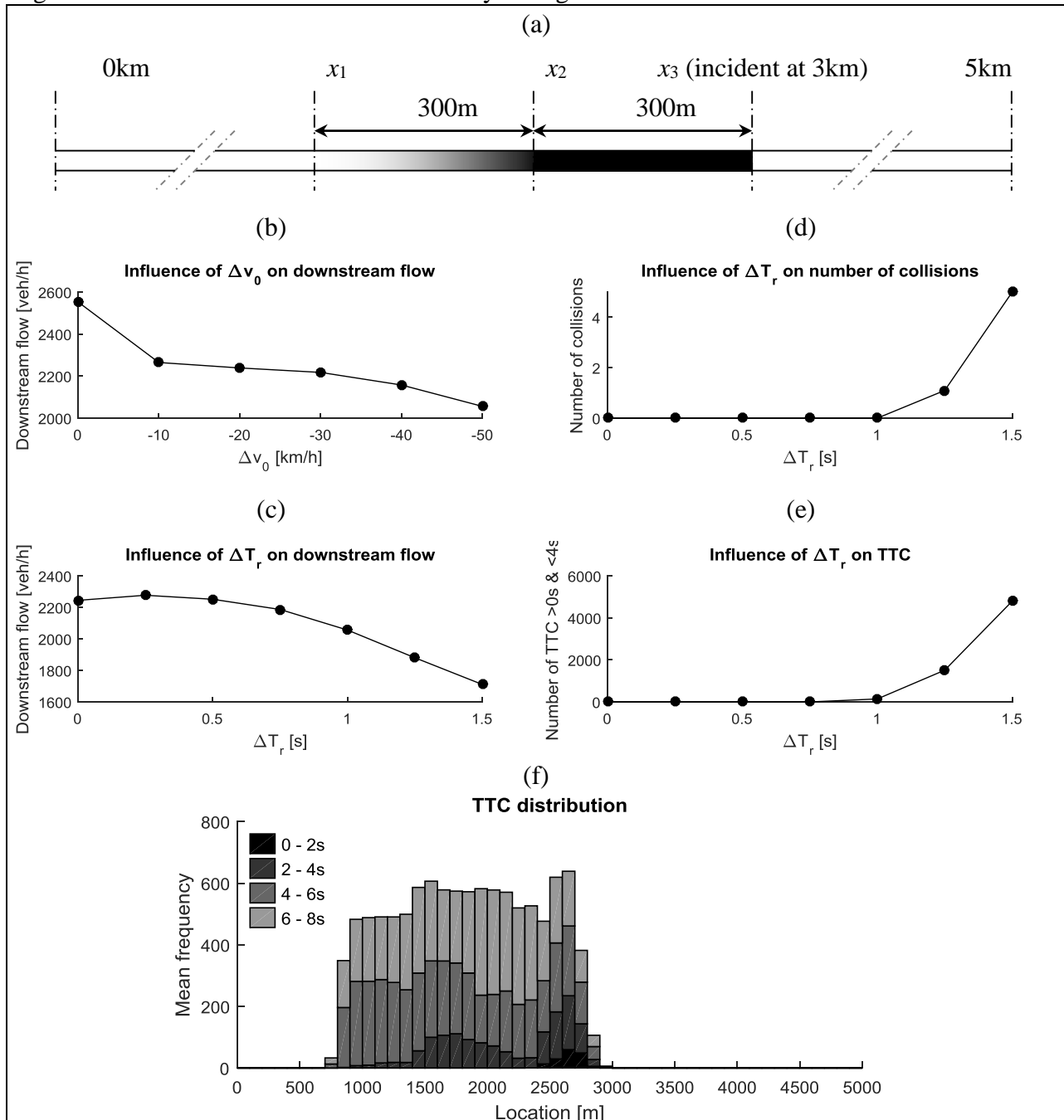
1 **FIGURE 3: Experiment layout (a) and main results (b-f)**

2 **Discussion**

3 What this experiment illustrates is that by simulating the findings in *(58)* (a speed reduction and
4 reaction time increase caused by an incident on the other carriageway) using a regular car
5 following model, possibly counter intuitive results may occur. The results indicate that increased
6 reaction time does not necessarily create unsafe traffic, at least not if the assumption of Treiber
7 and co-workers *(20)* holds that temporal anticipation of drivers is usually able to compensate the
8 reaction time sufficiently. Put simply, drivers have quite effective predictive abilities and *(20)*
9 provide fairly convincing arguments for it. The question is under which conditions this remains
10 the case and which determinants govern these predictive abilities.
11   However, if we introduce larger distractions our results indicate that both efficiency and
12 safety deteriorate. In that case in our simulation even collisions occur for particular values of
13 ΔT_r. In reality, secondary collisions certainly do take place (also in opposite driving directions).
14 Nonetheless, the question again is which (critical) factors govern the probability of accidents
15 under a variety of conditions. Clearly, if we would be able to endogenously compute reaction
16 time and sensitivity to stimuli using validated mental models, this opens up the possibility to
17 actually predict both safety and efficiency effects through simulation under conditions for which
18 current models are not valid (yet). These evaluations would further improve if we are able to
19 understand better how drivers are able to make predictions, and under which conditions these
20 may deteriorate.

21 **CONCLUSION AND OUTLOOK**

22 In this paper we discussed why it is imperative for the traffic flow simulation and theory
23 community to start serious collaborations with our peers in the human factors and social
24 psychology fields:
25 • Most of the microscopic models used today are in principle not predictively valid to
26   evaluate ex ante the effects of vehicle automation, because they lack explanatory models
27   for the dynamics of critical parameters of human drivers such as reaction time and
28   sensitivity to stimuli.
29 • It is possible to simulate traffic using findings from HF studies (we gave a small
30   example) and do what-if analyses, but one must be very modest in drawing conclusions
31   because of the many assumptions involved (in this case the idea that drivers have pretty
32   strong anticipatory abilities) and the limited knowledge we have with respect to the
33   circumstances under which these are still valid.
34
35 We also presented a modular agent-based design for the open-source simulation suite
36 OpenTrafficSim (OTS) that provides the objects and classes to integrate Human Factors
37 gradually (as research efforts progress) into regular micro simulation modelling. OTS is built on
38 state-of-the-art open-source simulation libraries and offers much additional functionality related
39 to visualisation and network handling. Clearly, we have just started and in the past 1½ years it
40 has been a two-steps-forward-one-step-back process. But, with support from industry now
41 progress is accelerating!
42   Given the societal importance of predicting the effects on safety and efficiency of vehicle
43 automation, we sincerely hope this paper will fuel the discussion on how both open- and closed

1 source simulation software can be adapted and made ready for the next-generation traffic
2 simulation models that are needed in the coming decades.

3 **ACKNOWLEDGMENT**

7 **REFERENCES**

8   1.   Angel Sotelo, M., J.W.C. van Lint, U. Nunes, L.B. Vlacic, and M. Chowdhury,
9   *Introduction to the Special Issue on Emergent Cooperative Technologies in Intelligent*
10   *Transportation Systems.* Ieee Transactions on Intelligent Transportation Systems, 2012.
11   **13**(1): p. 1-5.
12 2.   Van Arem, B., C.J.v. Driel, and R. Visser., *The impact of cooperative adaptive cruise*
13   *control on traffic-flow characteristics.* Intelligent Transportation Systems, IEEE
14   Transactions on, 2006. **7**(4): p. 429-436.
15 3.   SAE, *J3016: Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle*
16   *Automated Driving Systems*. 2014.
17 4.   Hoogendoorn, R.G., S.P. Hoogendoorn, K.A. Brookhuis, and W. Daamen, *Adaptation*
18   *Longitudinal Driving Behavior, Mental Workload, and Psycho-Spacing Models in Fog.*
19   Transportation Research Record: Journal of the Transportation Research Board, 2011.
20   **2249**: p. 20-28.
21 5.   Hoogendoorn, R.G., S. Hoogendoorn, K.A. Brookhuis, and W. Daamen. *Anticipation and*
22   *Hysteresis: Parameter Value Changes and Model Performance in Simple and*
23   *Multianticipative Car-Following Models*. in *Transportation Research Board 90th Annual*
24   *Meeting*. 2011. Washington, D.C.: The National Academies.
25 6.   van Wageningen-Kessels, F., H. van Lint, K. Vuik, and S. Hoogendoorn, *Genealogy of*
26   *traffic flow models.* EURO Journal on Transportation and Logistics, 2014: p. 1-29.
27 7.   Newell, G.F., *A Simplified Car-Following Theory: A Lower Order Model.* Transportation
28   Research Part B, 2002. **36**(3): p. 195-205.
29 8.   Treiber, M., A. Hennecke, and D. Helbing, *Congested Traffic States in Empirical*
30   *Observations and Microscopic Simulations.* Physical Review E, 2000. **62**(2): p. 1805--
31   1824.
32 9.   Bando, M., K. Hasebe, K. Nakanishi, and A. Nakayama, *Analysis of optimal velocity*
33   *model with explicit delay.* Physical Review Letters E, 1998. **58**(5): p. 5429–5435.
34 10.   Wiedemann, R., *Simulation des Strassenverkehrsflusses*. 1974, Traffic Engineering,
35   University of Karlsruhe: Kalsruhe.
36 11.   Gazis, D.C., R. Herman, and R.W. Rothery, *Nonlinear follow-the-leader models of traffic*
37   *flow*. Operations Research, 1961. **9**(4): p. 545–567.
38 12.   Pipes, L., *An operational analysis of traffic dynamics.* Journal of applied physics, 1953.
39   **24**(3): p. 274–281.
40 13.   Wei, H., E. Meyer, J. Lee, and C. Feng, *Characterizing and modeling observed lane-*
41   *changing behaviour.* Transportation Research Record: Journal of the Transportation
42   Research Board, 2000. **1710**: p. 104-113.

14.   Cohen, S.L., *Application of relaxation procedure for lane changing in microscopic simulation models.* Transportation Research Record: Journal of the Transportation Research Board, 2004. **1883**: p. 50–58.

15.   Laval, J.A. and C.F.Daganzo, *Lane-changing in traffic streams.* Transportation Research Part B, 2006. **40**: p. 251-264.

16.   Kesting, A., M. Treiber, and D. Helbing, *General lane-changing model MOBIL for car-following models.* Transportation Research Record: Journal of the Transportation Research Board, 2007. **1999**: p. 86-94.

17.   Choudhury, C.F., *Modeling driving decisions with latent plans*. 2008, Massachusetts Institute of Technology.

18.   Hamdar, S.H., H.S. Mahmassani, and M. Treiber, *From behavioral psychology to acceleration modeling: Calibration, validation, and exploration of drivers' cognitive and safety parameters in a risk-taking environment.* Transportation Research Part B: Methodological, 2015. **78**: p. 32-53.

19.   Hoogendoorn, R.G., B. Van Arem, S.P. Hoogendoorn, and K.A. Brookhuis, *Applying the task-capability-interface model to the intelligent driver model in relation to complexity.*, in *92nd Transportation Research Board Annual Meeting*, N. Academies, Editor. 2013: Washington D.C.

20.   Treiber, M., A. Kesting, and D. Helbing, *Delays, inaccuracies and anticipation in microscopic traffic models.* Physica A: Statistical Mechanics and its Applications, 2006. **360**(1): p. $71 - 88$.

21.   Schakel, W., B. van Arem, H. van Lint, G. Tamminga, and IEEE, *A Modular Approach for Exchangeable Driving Task Models in a Microscopic Simulation Framework*, in *2013 16th International Ieee Conference on Intelligent Transportation Systems - (Itsc)*. 2013. p. 565-571.

22.   Wang, M., W. Daamen, S. Hoogendoorn, and B. Van Arem, *Connected variable speed limits control and vehicle acceleration control to resolve moving jams*, in *Transportation Research Board Annual Meeting*. 2015, The National Academies: Washington DC.

23.   Schakel, W.J. and B. Van Arem, *Improving traffic flow efficiency by in-car advice on lane, speed, and Headway.* IEEE Transactions on Intelligent Transportation Systems, 2014. **15**(4): p. 1597-1606.

24.   Tamminga, G., M. Miska, E. Santos, H. van Lint, A. Nakasone, H. Prendinger, and S. Hoogendoorn, *Design of Open Source Framework for Traffic and Travel Simulation.* Transportation Research Record, 2012(2291): p. 44-52.

25.   Donmez, B., L.N. Boyle, and J.D. Lee, *Safety implications of providing real-time feedback to distracted drivers.* Accident Analysis & Prevention, 2007. **39**(3): p. 581-590.

26.   Merat, N., A.H. Jamson, F.F.C.H. Lai, M. Daly, and O.M.J. Carsten, *Transition to manual: Driver behaviour when resuming control from a highly automated vehicle.* Transportation Research Part F: Traffic Psychology and Behaviour, 2014. **26**(PART A): p. 1-9.

27.   Neubauer, C., G. Matthews, L. Langheim, and D. Saxby, *Fatigue and voluntary utilization of automation in simulated driving.* Human Factors, 2012. **54**(5): p. 734-746.

28.   Merat, N., A.H. Jamson, F.C.H. Lai, and O. Carsten, *Highly automated driving, secondary task performance, and driver state.* Human Factors, 2012. **54**(5): p. 762-771.

29.   Saffarian, M. and R. Happee, *Supporting drivers in car following: A step towards cooperative driving*, in *Intelligent Vehicles Symposium (IV), 2011 IEEE*. 2011. p. 939--944.

30.   Hoedemaker, M. and K.A. Brookhuis, *Behavioral Adaptation to Driving with and Adaptive Cruise Control (ACC).* Transportation Research Part F: Traffic Psychology and Behaviour, 1998. **1**: p. 95-106.

31.   Nowakowski, C., J. O'Connell, S.E. Shladover, and D. Cody, *Cooperative Adaptive Cruise Control: Driver Acceptance of Following Gap Settings Less than One Second*, in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 2010. p. 2033-2037.

32.   Merat, N. and J.D. Lee, *Preface to the special section on human factors and automation in vehicles: Designing highly automated vehicles with the driver in mind.* Human Factors, 2012. **54**(5): p. 681-686.

33.   Zheng, Z., *Recent developments and research needs in modeling lane changing.* Transportation Research Part B: Methodological, 2014. **60**: p. 16-32.

34.   Duives, D.C., W. Daamen, and S.P. Hoogendoorn, *State-of-the-art crowd motion simulation models.* Transportation Research Part C: Emerging Technologies, 2013. **37**: p. 193-209.

35.   Teh, E., S. Jamson, O. Carsten, and H. Jamson, *Temporal fluctuations in driving demand: The effect of traffic complexity on subjective measures of workload and driving performance.* Transportation Research Part F: Traffic Psychology and Behaviour, 2014. **22**(0): p. 207-217.

36.   Fuller, R., *Towards a general theory of driver behaviour.* Accident Analysis \& Prevention, 2005. **37**(3): p. 461--472.

37.   Endsley, M.R., *Toward a theory of situation awareness in dynamic systems.* Human Factors, 1995. **37**(1): p. 32-64.

38.   Edquist, J., C.M. Rudin-Brown, and M.G. Lenné, *The effects of on-street parking and road environment visual complexity on travel speed and reaction time.* Accident Analysis and Prevention, 2012. **45**: p. 759– 765.

39.   Hoogendoorn, R., B. van Arem, and S. Hoogendoorn, *Automated Driving, Traffic Flow Efficiency, and Human Factors: Literature Review.* Transportation Research Record: Journal of the Transportation Research Board, 2014(2422): p. pp 113–120.

40.   Hoogendoorn, S., R.G. Hoogendoorn, and W. Daamen, *Wiedemann Revisited: New Trajectory Filtering Technique and Its Implications for Car-Following Modeling.* Transportation Research Record: Journal of the Transportation Research Board, 2011. **2260**: p. 152-162.

41.   Jacobs, P.H., N.A. Lang, and A. Verbraeck. *D-SOL; a distributed Java based discrete event simulation architecture*. in *Proceedings of the 34th Winter simulation conference*. 2002: IEEE.

42.   Jacobs, P.H., *The DSOL simulation suite*. 2005, Delft University of Technology: Delft, The Netherlands.

43.   Zeigler, B.P., H. Praehofer, and T.G. Kim, *Theory of modeling and simulation: integrating discrete event and continuous complex dynamic systems*. 2000: Academic Press.

44.   Nance, R.E., *The time and state relationships in simulation modeling.* Communications of the ACM, 1981. **24**(4): p. 173-179.

45. L'Ecuyer, P., *Efficient and portable combined random number generators.* Communications of the ACM, 1988. **31**(6): p. 742-751.

46. L'Ecuyer, P., R. Simard, E.J. Chen, and W.D. Kelton, *An object-oriented random-number package with many long streams and substreams.* Operations research, 2002. **50**(6): p. 1073-1075.

47. Law, A.M. and W.D. Kelton, *Simulation modeling and analysis.* 2000: McGraw Hill Boston.

48. Robinson, S., *Simulation: the practice of model development and use.* 2014: Palgrave Macmillan.

49. Joines, J.A. and S.D. Roberts, *Fundamentals of object-oriented simulation*, in *Proceedings of the 30th Winter simulation conference.* 1998, IEEE Computer Society Press: Washington, D.C., USA. p. 141-150.

50. Wainer, G.A., *Discrete-event modeling and simulation: a practitioner's approach.* 2009: CRC Press.

51. Zhang, M., M. Seck, and A. Verbraeck. *A DEVS-based M&S Method for Large-scale Multi-agent Systems.* in *Proceedings of the 2013 Summer Computer Simulation Conference.* 2013: Society for Modeling & Simulation International.

52. Rao, A.S. and M.P. Georgeff. *BDI agents: From theory to practice.* in *ICMAS.* 1995.

53. Verbraeck, A. *Component-based distributed simulations: the way forward?* in *Proceedings of the eighteenth workshop on Parallel and distributed simulation.* 2004: ACM.

54. Atkinson, C. and T. Kühne, *Model-driven development: a metamodeling foundation.* Software, IEEE, 2003. **20**(5): p. 36-41.

55. Huang, Y., *Automated Simulation Model Generation.* 2013, TU Delft, Delft University of Technology.

56. Huang, Y., M.D. Seck, and A. Verbraeck. *From data to simulation models: Component-based model generation with a data-driven approach.* in *Proceedings of the Winter Simulation Conference.* 2011: Winter Simulation Conference.

57. Çetinkaya, D., A. Verbraeck, and M.D. Seck, *Model Continuity in Discrete Event Simulation: A Framework for Model-Driven Development of Simulation Models.* ACM Transactions on Modeling and Computer Simulation (TOMACS), 2015. **25**(3): p. 1-17.

58. Hoogendoorn, R., S. Hoogendoorn, K. Brookhuis, and W. Daamen, *Psychological elements in car-following models: Mental workload in case of incidents in the other driving lane.* Procedia Engineering, 2010. **3**: p. 87-99.

59. Schakel, W.J., B.v. Arem, and B. Netten, *Effects of Cooperative Adaptive Cruise Control on Traffic Flow Stability*, in *Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems.* 2010. p. 759-764.

60. Schakel, W., V. Knoop, and B. van Arem, *Integrated Lane Change Model with Relaxation and Synchronization.* Transportation Research Record: Journal of the Transportation Research Board, 2012. **2316**(-1): p. 47-57.