

Evaluating the Safety Impact of Connected and Autonomous Vehicles on Motorways

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1 **ABSTRACT**

2 Recent technological advancements bring the Connected and Autonomous Vehicles (CAVs)
3 era closer to reality. CAVs have the potential to vastly improve road safety by taking the human
4 driver out of the driving task. However, the evaluation of their safety impacts has been a major
5 challenge due to the lack of real-world CAV exposure data. Studies that attempt to simulate
6 CAVs by using either a single or integrating multiple simulation platforms have limitations,
7 and in most cases, consider a small element of a network (e.g. a junction) and do not perform
8 safety evaluations due to inherent complexity. This paper addresses this problem by developing
9 a decision-making CAV control algorithm in the simulation software VISSIM, using its
10 External Driver Model Application Programming Interface. More specifically, the developed
11 CAV control algorithm allows a CAV, for the first time, to have longitudinal control, search
12 adjacent vehicles, identify nearby CAVs and make lateral decisions based on a ruleset
13 associated with motorway traffic operations. A motorway corridor within M1 in England is
14 designed in VISSIM and employed to implement the CAV control algorithm. Five simulation
15 models are created, one for each weekday. The baseline models (i.e. CAV market penetration:
16 0%) are calibrated and validated using real-world minute-level inductive loop detector data and
17 also data collected from a radar-equipped vehicle. The safety evaluation of the proposed
18 algorithm is conducted using the Surrogate Safety Assessment Model (SSAM). The results
19 show that CAVs bring about compelling benefit to road safety as traffic conflicts significantly
20 reduce even at relatively low market penetration rates. Specifically, estimated traffic conflicts
21 were reduced by 12-47%, 50-80%, 82-92% and 90-94% for 25%, 50%, 75% and 100% CAV
22 penetration rates respectively. Finally, the results indicate that the presence of CAVs ensured
23 efficient traffic flow.

24 *Keywords: Connected and Autonomous Vehicles; Traffic Microsimulation; Road Safety;*
25 *Surrogate Safety Assessment Model; VISSIM; External Driver Model;*

1 1. INTRODUCTION

2 Connected and Autonomous vehicles (CAVs) will be a reality in the near future and have the
3 potential to reduce traffic congestion, road crashes and vehicle emissions (Poczter and Jankovic,
4 2014; Fagnant and Kockelman, 2015). The concept of CAVs has generated high expectations
5 regarding safety performance of future road transport systems, as 94% of crashes involve
6 human error as a contributing factor (Singh, 2015). Based on this figure, few previous studies
7 have evaluated the potential safety impact of CAVs, estimating a safety benefit of
8 approximately 90% during the fully autonomous era. However, this level of impact has not
9 been confirmed yet due to lack of data.

10 For this reason, the vast majority of automotive manufacturers have ongoing projects on CAVs
11 and field operating trials are being carried out in both motorways and urban environments (e.g.
12 Waymo project (Waymo, 2016)). These trials have proven that CAVs will introduce a spectrum
13 of unprecedented challenges and will bring a multifaceted transformation to the existing road
14 network. For instance, whether existing motorway and urban infrastructure can accommodate
15 CAVs is yet to be fully elucidated. Additionally, the communication standards and a unified
16 protocol between existing infrastructure and CAVs have not been clarified yet. Furthermore,
17 the inherent challenges arising from the interaction between human driven and CAVs during
18 the transition period are largely unknown (Reich, 2013). Moreover, the compatibility between
19 software of different CAV manufacturers is uncertain and this might affect their operations and
20 co-operative decision making at a corridor or a network level (Anderson *et al.*, 2014).

21 Despite the real-world CAV trials and the advancements in knowledge, CAV fleet data are not
22 easily obtainable. This is one of the primary reasons why existing part of literature has mainly
23 speculated the impacts of CAVs (Anderson *et al.*, 2014; Fagnant and Kockelman, 2015; Kim
24 *et al.*, 2015). More recently, research has focused on CAV simulation which may be perhaps
25 the only viable alternative method to evaluate the impact of CAVs and can provide valuable
26 initial insight into the implementation of CAVs. However, recent attempts to simulate CAVs
27 found in the literature have limitations.

28 This study advances the understanding of the impacts of CAVs by conducting a comprehensive
29 CAV safety evaluation using traffic microsimulation. For this purpose, a decision-making
30 CAV control algorithm is developed in the External Driver Model Application Programming
31 Interface (API) of PTV VISSIM traffic micro-simulation software. The proposed algorithm is
32 assigned to a specific vehicle category in the simulation software and is tested in a calibrated
33 motorway model. The corridor-level safety impact of CAVs is finally evaluated using the
34 Surrogate Safety Assessment Model (SSAM).

35 The paper is organised as follows: In the next section, existing literature on CAV simulation
36 and its differences from this study are presented. A detailed description of the road segment
37 drawn in VISSIM, the functionality of the CAV control algorithm and the calibration and
38 validation process follow next. The fourth section of the paper presents the results obtained
39 from the simulation, discusses about their contiguity to existing literature, presents this study's
40 limitations and proposes future directions for CAV simulation research. Finally, the last section
41 summarises the conclusions of the research.

42 43 2. PREVIOUS RESEARCH

44 The purpose of this literature review is to critically analyse methods that have been applied in
45 studies to derive the range and scale of the impact of CAVs with a special focus on safety. It is

1 worthwhile to point out that not all the studies reviewed evaluate the safety impact of CAVs.
2 Nonetheless, the method and data employed in each of the studies are analysed. It must be
3 emphasized that, for consistency, studies mentioning or implying both vehicle automation and
4 connectivity are considered in this section.

5 The two major approaches identified in the literature to estimate CAV impacts are, so far, based
6 either based on historical or simulated data.

7 **2.1 Studies employing historical data**

8 Recent studies have attempted to predict the potential safety impact of CAVs using historical
9 crash data (Hayes, 2011; Silberg *et al.*, 2012; Fagnant and Kockelman, 2015). Based on the
10 number of crashes that include human error as a contributing factor and under the assumption
11 that this factor will not exist in autonomous road environments, it is suggested that a 90%
12 reduction in crash rates can be achieved with the introduction of CAVs (Fagnant and
13 Kockelman, 2015). Alternatively, by comparing CAV implementation to the implementation
14 of automated technologies in aviation or rail, studies conclude that road crash rates could be
15 as low as those of aviation and rail, ultimately reaching 1% of the current figures (Hayes, 2011).
16 Although these approaches have provided a useful starting point in understanding the scale of
17 safety benefits, they are based on a series of assumptions that may limit their capability in
18 producing reliable outcomes.

19 **2.2 Studies applying CAV simulation**

20 Research has focused on CAV simulation during the past few years. Based on the approach of
21 CAV simulation, the studies can be categorized into two groups. The first approach includes
22 studies that use custom-built simulation frameworks (Figueiredo *et al.*, 2009; Noort, Arem and
23 Park, 2010; O'Hara *et al.*, 2012; Pereira and Rossetti, 2012). These studies aim to achieve
24 detailed CAV simulation by creating an integrated multi-level simulation platform, which in
25 most cases include traffic, sensor (robotics) and network simulators. Simulation software used
26 in these studies includes VISSIM, SUMO and Mas T2erLab for traffic simulation, USARSIM,
27 MDDVS PreScan for robotics simulation and NS2 or NS3 for network simulation. The
28 complexity and the unique design of these proposed simulation frameworks makes the results
29 difficult to interpret, less reliable and the comparison challenging (Li *et al.*, 2013). Additionally,
30 although these studies could simulate CAVs accurately, they had high computational needs, a
31 fact that limited the scale of the conducted experiments significantly, compared to simpler
32 simulation applications.

33 The alternative approach includes studies that use a traffic micro-simulation software and its
34 extensions (e.g. API or COM interface). This method usually introduces simplifications, such
35 as an indirect simulation of vehicle sensors or vehicle communication. This kind of
36 simplifications, however, has a small effect on the calculation of the network- or corridor-level
37 impact of CAVs as the functionality of sensors can be indirectly programmed sufficiently. Most
38 of the studies adopting this method manage to develop large scale experiments and produced
39 significant results. This category of studies comprises of differences in the definition of CAVs'
40 operational characteristics and therefore their outcomes are not necessarily comparable.

41 Roncoli *et al.* (2015) used AIMSUN to model vehicle automation and vehicle to infrastructure
42 (V2I) communication in a motorway with ramp metering and variable speed limit setting. Their
43 study relied on a Traffic Management Centre (TMC) for lane changing decisions. However,
44 this is only a partial representation of CAV control behaviour, as although CAVs might be able

1 to follow suggestions from a centralised TMC in the future, the major challenge relates to their
2 ability to sense their surroundings and make independent decisions accordingly.

3 Furthermore, Park et al. (2012) used PARAMICS to evaluate the impact of vehicle automation
4 on ramp management through an algorithm that proposed advisory lane changes upstream of
5 ramp merging areas of the motorway. The study could suggest advisory lane changes on ramp
6 areas and could therefore reduce only merging-related conflicts.

7 Finally, there is a series of studies that used VISSIM to simulate CAVs. Li et al. (2013) used
8 the External Driver Model API of VISSIM to model autonomous intersection control. They
9 transferred the VISSIM generated vehicle trajectories data into the SSAM software to estimate
10 the number of generated conflicts. The autonomous intersection control proved to be highly
11 effective producing only one traffic conflict in 1,800 seconds of simulation. However, this
12 method is designed specifically for intersections and is not transferrable to a network or
13 corridor level.

14 ATKINS (2016) used VISSIM's COM interface in order to evaluate the impact of CAVs in
15 urban and motorway networks with respect to the efficiency of traffic flow. Despite using a
16 wide range of CAV market penetration rates, time headways between vehicles and CAV-
17 orientated parameters, CAV decisions were ultimately made through the default driver model
18 of VISSIM. Similarly, Stanek et al. (2018) changed the default Wiedemann 99 driving model
19 parameters in VISSIM in order to simulate connected and autonomous driving behaviour
20 according to values found in the literature. The alteration of the default driver model parameters
21 of VISSIM (e.g. CC1; safety distance to the preceding vehicle) however, cannot be directly
22 connected to or imply full vehicle automation and connectivity. Also, a possible use of this
23 method for safety evaluation could show inaccurately increased simulated traffic conflicts due
24 to the stricter headway safety parameters of VISSIM. Jeong et al (2017) also used VISSIM's
25 COM interface. They proposed a CAV algorithm that controlled the longitudinal movement of
26 CAVs during the simulation based on surrounding traffic conditions. Their proposed algorithm
27 showed encouraging network and individual-level safety results and provided useful insights.
28 However, it inevitably included assumptions regarding the longitudinal control of the CAV and
29 did not include a lateral control algorithm.

30 **2.3 Use of Traffic Simulation for Safety Evaluation**

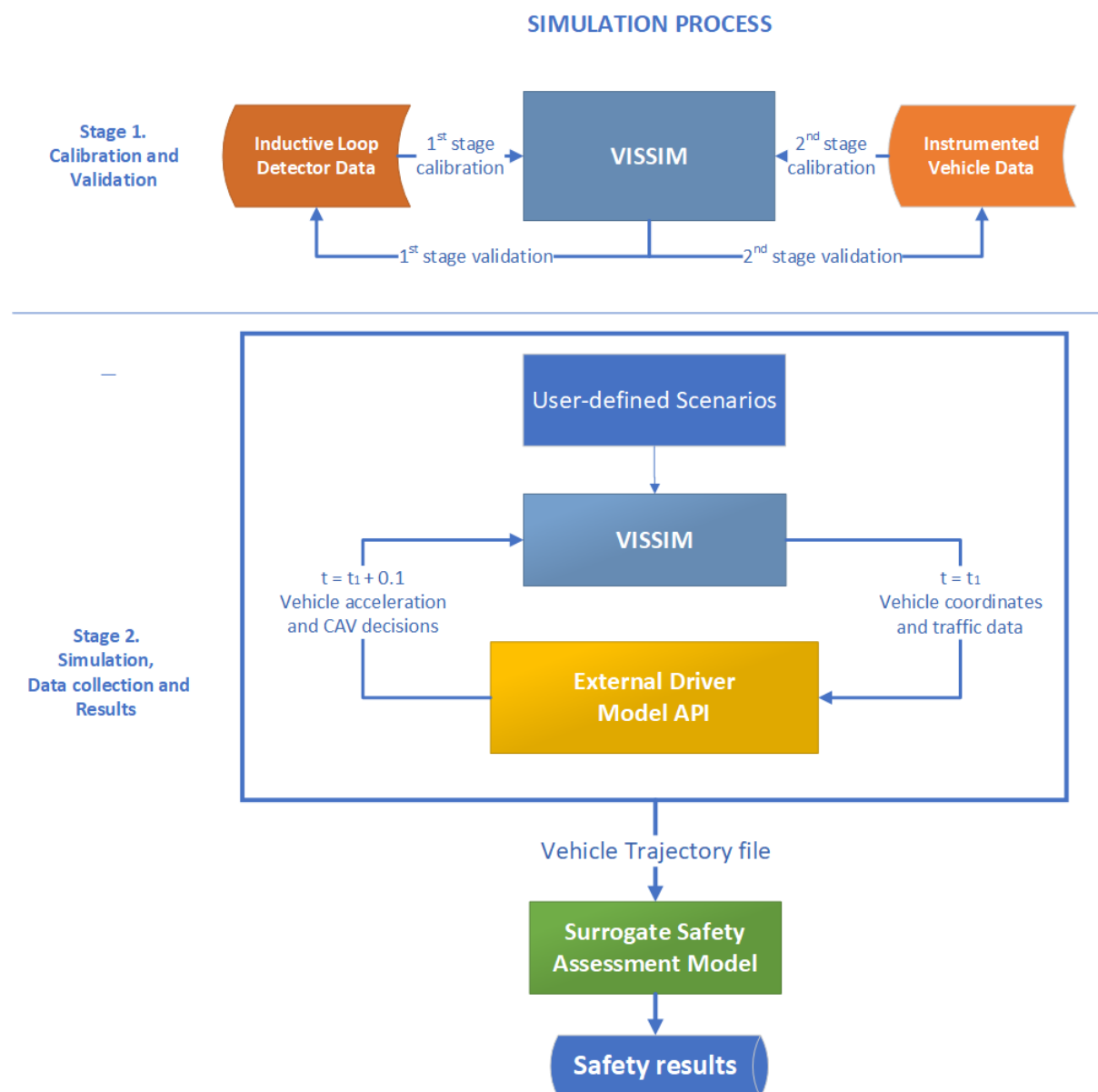
31 The use of traffic micro-simulation for safety evaluation has been questioned about its ability
32 to reproduce real-world traffic conditions reliably (Tarko, 2005; Saunier et al, 2007). However,
33 studies are supporting the use of microsimulation for safety evaluation purposes (Fan *et al.*,
34 2013; Huang *et al.*, 2013; Essa and Sayed, 2015; Shahdah, Saccomanno and Persaud, 2015).
35 These studies use traffic micro-simulation for safety evaluation through the SSAM, developed
36 by the Federal Highway Administration (FHWA) and manage to obtain promising results
37 through safety oriented two-stage calibration methods. ; For example, Fan *et al.*, (2013) used
38 traffic conflicts as a measure of safety to calibrate their simulation network. They concluded
39 that conflicts calculated through SSAM are similar to those measured in the field using
40 traditional traffic conflicts techniques. This two-stage calibration method can improve the
41 representativeness of the simulated data; however, it is sensitive to observation error as the
42 characterisation of vehicle conflicts may be subjective. A two-stage calibration is applied in
43 this paper as well and is described in the following section.

44 In summary, it is difficult to reliably predict the safety impact of this disruptive paradigm shift
45 on existing transport systems as CAVs are not yet present in traffic streams. There is a need to

1 develop a CAV control algorithm that can simulate CAVs containing as few assumptions as
 2 possible and implement it in an integrated roadway environment to examine the safety impact.
 3 This paper takes a step towards this direction by developing an integrated algorithm in VISSIM,
 4 in order to evaluate the corridor-level safety impact of CAVs.

5 3. METHOD

6 The evaluation of the safety impacts of CAVs in this paper, is conducted on a motorway
 7 segment designed in VISSIM. CAVs are represented using an external CAV driver model API
 8 written in C++ programming language. The external driver model was assigned to a specific
 9 vehicle type in VISSIM. This section describes the design of the motorway model, its
 10 calibration and validation, explains the functionality of the proposed CAV control algorithm
 11 and the interaction between VISSIM and SSAM. The overall architecture of the proposed
 12 simulation framework is presented in Figure 1.



13

14 **Figure 1 Architecture of the CAV microsimulation framework**

3.1 The Microsimulation Platform

After conducting a critical evaluation of most available traffic micro-simulation packages and taking into account the advantages and disadvantages of all available traffic simulators (Pereira and Rossetti, 2012), the widely-used traffic micro-simulation software package PTV VISSIM 9.0 combined with its External Driver Model Application Programming Interface (API) was chosen for this study. A three-lane motorway section (M1 Junctions 19-21, located between Leicester and Rugby in the United Kingdom) was chosen as a test-bed. Initially, by using an aerial photograph, both directions of the road segment were drawn. Lane width and the length of links, merging and diverging areas were drawn according to the aerial photograph. The merging and diverging areas were designed following guidelines from literature specialising in motorway merge areas (e.g. Fan *et al.*, 2013; Whaley, 2016). The total length of the mainline corridor designed was 44.27 km, contained eight on and off-ramps in total and six vehicle input points (see Figure 2). The model designed, did not contain the roundabout at Junction 20.

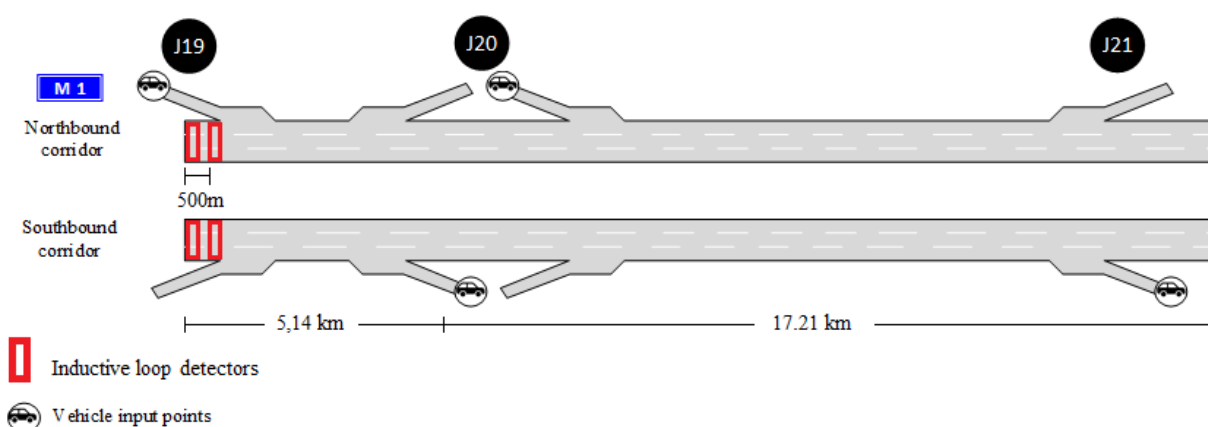


Figure 2 Outline of the simulated motorway segment

Driver Behaviour

Vehicle movement in VISSIM is determined by other vehicles' movement and surrounding infrastructure. The driver and the vehicle are considered as one entity and can be assumed to be in one of the four driving modes – free driving, approaching, braking and following. The default human driver behaviour is represented using the Wiedemann 99 or Wiedemann 74 psycho-social model (PTV AG, 2015). A calibrated Wiedemann 99 driving model was used to simulate human driving behaviour in this paper, since it was recommended by VISSIM for interurban traffic and contained more adjustable driving behaviour parameters which could contribute to a more accurate safety-orientated calibration of the baseline model. A list of the aforementioned parameters is presented in Table 1.

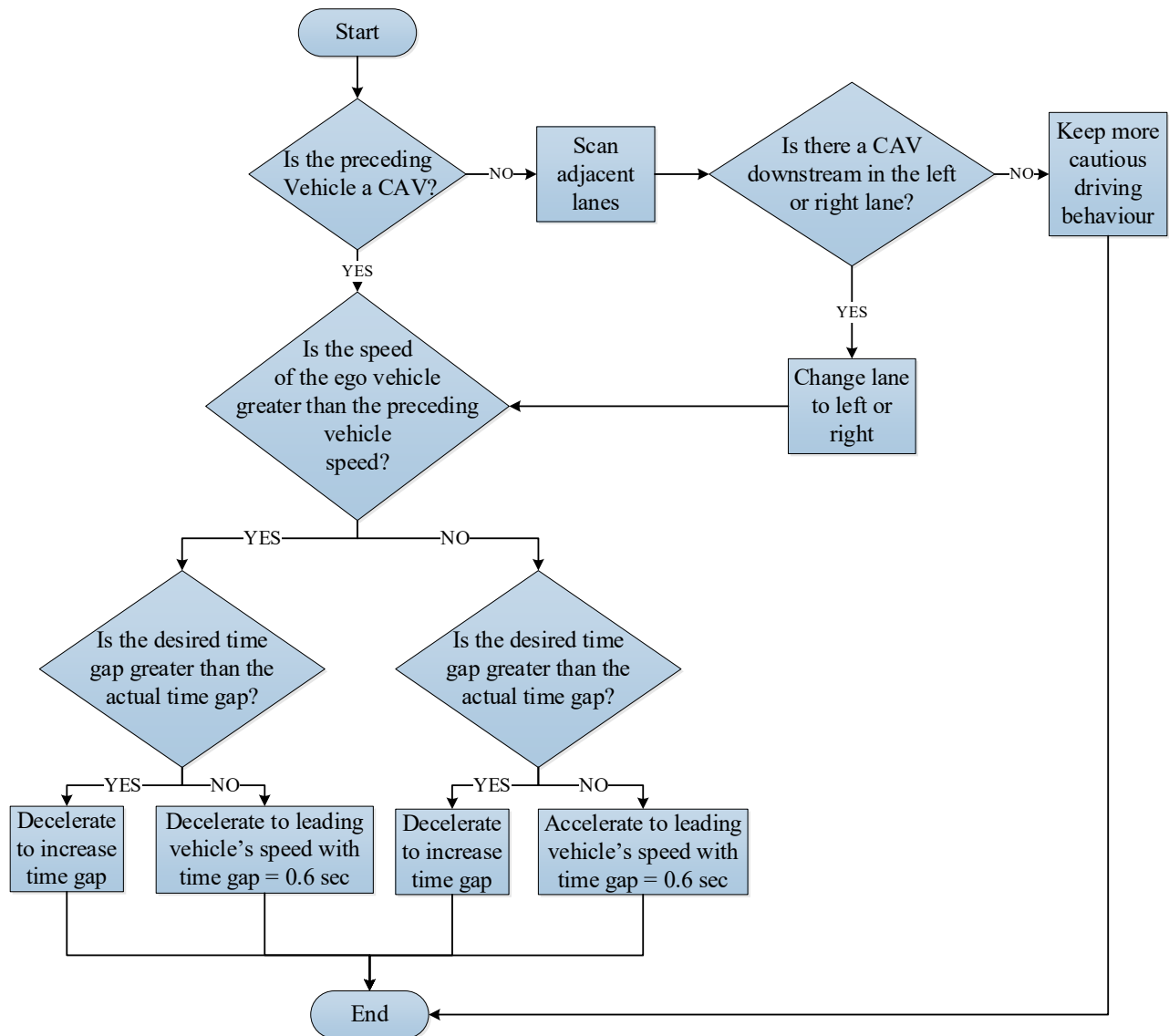
Table 1 Adjustable driving behaviour parameters in PTV VISSIM 9.0

Parameter	Unit	Description
CC0	m	Standstill distance: the average desired standstill distance between two vehicles. It has no variation.
CC1	s	Time headway: is the time (in seconds) that a driver wants to keep.

CC2	m	'Following' variation: restricts the longitudinal oscillation or how much more distance than the desired safety distance a driver allows before he intentionally moves closer to the car in front.
CC3	s	Threshold for entering car following mode in VISSIM: controls the start of the deceleration process, i.e. when a driver recognizes a preceding slower vehicle.
CC4	m/s	'Following' thresholds: control the speed differences during the 'Following' state. Smaller values result in a more sensitive reaction of drivers to accelerations or decelerations of the preceding car
CC5	m/s	
CC6	1/(m*s)	Speed dependency of oscillation: influence of distance on speed oscillation while in following process.
CC7	m/s ²	Oscillation acceleration: actual acceleration during the oscillation process.
CC8	m/s ²	Standstill acceleration: desired acceleration when starting from standstill
CC9	m/s ²	Acceleration at 80 km/h: desired acceleration at 80 km/h

1

2 For CAV simulation, the External Driver Model API of VISSIM allows the user to integrate
3 an external application in the simulation. For this study, a user-defined driving behaviour was
4 developed using C++ programming language and a compatible dynamic link library (dll)
5 compiler, Microsoft Visual Studio. The driving behaviour dll, replaced the internal driving
6 behaviour with CAV driving behaviour and was assigned only to the CAV-type vehicles in
7 VISSIM. VISSIM passes the state of a vehicle and its surroundings to the external application
8 and the dll computes the behaviour of the vehicle for the next time step. The flowchart of the
9 proposed CAV control algorithm is shown in Figure 3 and is described in the following
10 paragraphs.



1

2 **Figure 3 Flowchart of the proposed CAV control algorithm.**

3

4 *Longitudinal Movement*

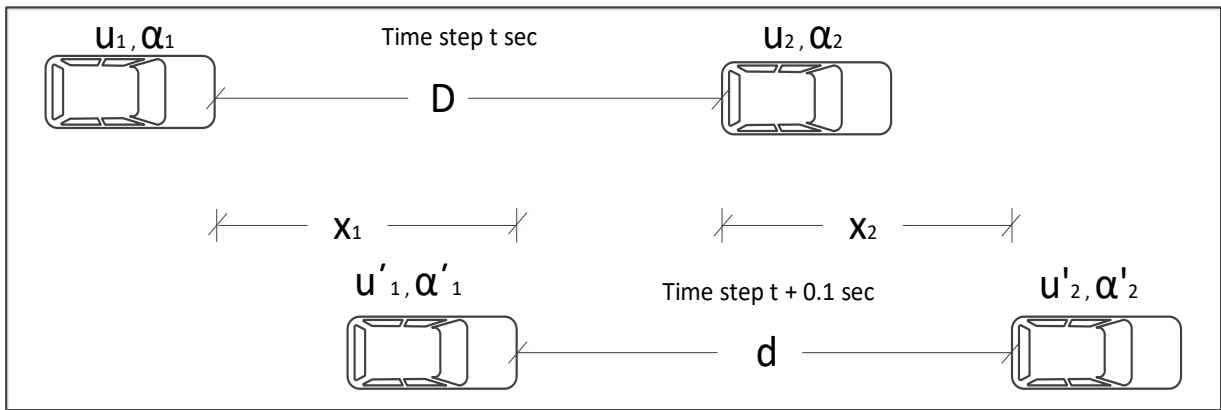
5 This study assumes that CAVs are able to drive closer to their preceding vehicles compared to
6 human drivers, ultimately forming vehicle platoons with other CAVs. The accepted car-
7 following time-gap chosen for this study was 0.6 seconds, which is in-line with relevant
8 literature (e.g. (ATKINS, 2016; Stanek *et al.*, 2018)). This time-gap is achieved by calculating
9 the acceleration or deceleration of each of the dll controlled vehicles, for each simulation time
10 step, as follows: the acceleration or deceleration (a) of a vehicle in VISSIM during each time
11 step is defined in equation (1):

$$a = \frac{\Delta v}{\Delta t} \quad (1)$$

1

2 where Δv is the difference between current speed and target speed and Δt is the time step of the
 3 simulation, in this case 0.1 sec. Assuming that the dll controlled vehicle is not following
 4 the preceding vehicle with the desired time gap (d) - a situation which is graphically described
 5 in Figure 4- the distance travelled by both cars (x_1, x_2) and the time gap during time step t and
 6 time step $t + 0.1$ can be defined by equations (2)(3) and (4)

7



8

9 **Figure 4 Desired and actual distance diagram for ego vehicle acceleration / deceleration**
 10 **calculation**

$$x_1 = u_1 * t + \frac{1}{2} * a_1 * t^2 \quad (2)$$

11

$$x_2 = u_2 * t + \frac{1}{2} * a_2 * t^2 \quad (3)$$

12

$$d = x_2 + D - x_1 \quad (4)$$

13 By subtracting equation (2) from equation (3) and taking into account that the target final
 14 speed of the dll-controlled vehicle is the speed of the preceding vehicle, equation (5) and
 15 subsequently (6) are calculated, assuming that the initial speed of the preceding vehicle u_2 ,
 16 and the speed of the vehicle at the back, u_1 are not equal. In equation (6), a'_1 represents the
 17 acceleration of the CAV in order to achieve the desired time gap.

$$t = \frac{2 * (x_2 - x_1)}{u_2 - u_1} \quad (5)$$

18

$$a_1' = \frac{(u_2 - u_1)^2}{2 * (x_2 - x_1)} \quad (6)$$

1

2 The dll-controlled vehicle continuously adjusts its acceleration according to equation (6). It
 3 must be noted that the aforementioned acceleration/deceleration calculation only starts when
 4 the preceding vehicle in the same lane as the dll-controlled vehicle is a CAV vehicle.

5 *Lateral Movement*

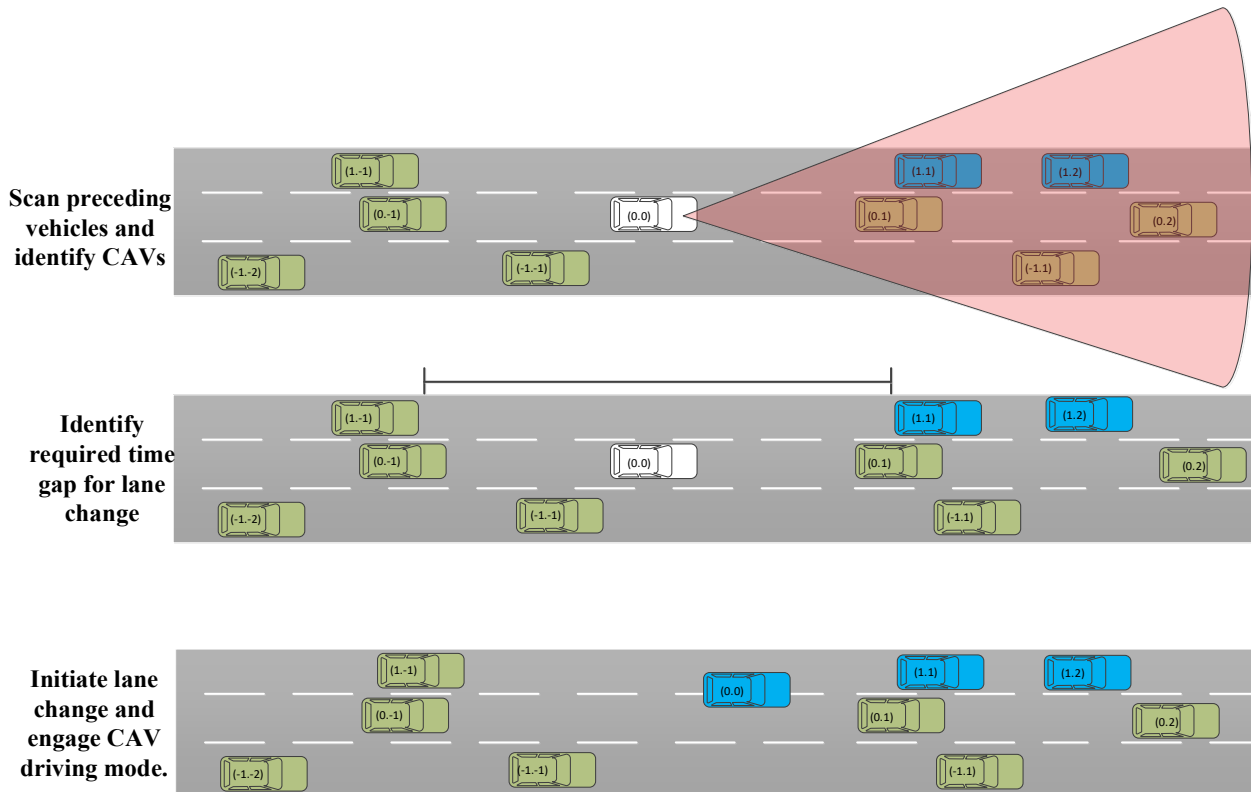
6 This study hypothesises that when travelling on a motorway, CAVs will try to identify nearby
 7 CAVs in order to form a vehicle platoon (Haas and Friedrich, 2017; Gong and Du, 2018). If
 8 the preceding vehicle of the dll controlled vehicle is not a CAV, it searches adjacent lanes for
 9 nearby downstream CAV vehicles (see

10 Figure 3). The searching process was designed to resemble real-world sensor behaviour. In
 11 order to simulate sensor range in CAV vehicles, the radius that CAV vehicles could search for
 12 other CAV vehicles was set to 200 meters in the C++ code, a value which was in-line with the
 13 range of a typical radar used in CAVs. During each time step, VISSIM creates a matrix
 14 containing the relative coordinates of the dll controlled vehicle with respect to nearby vehicles.
 15 The position of each nearby vehicle in the matrix depends on its relative simulation position to
 16 the dll-controlled vehicle and is described by two indexes: index1, index2. Index1 represents
 17 the lane that the nearby vehicle runs on; a value of zero means the nearby vehicle is in the same
 18 lane as the dll-controlled vehicle, a value of +1 and -1 means the nearby vehicle runs on the
 19 first lane on the left or right accordingly. Index 2 represents the relative longitudinal position
 20 compared to the dll-controlled vehicle; a value of +1 and -1 means the nearby vehicle is the
 21 next vehicle downstream and upstream accordingly whereas +2 or -2 means the nearby vehicle
 22 is the second next downstream or upstream accordingly. Consequently, that means that the
 23 maximum number of vehicles that can be tracked by the dll-controlled vehicle in a three-lane
 24 motorway is twelve and vehicles that are more than two vehicles away from the dll-controlled
 25 vehicle are not tracked.

26 Nearby vehicle data that could be made available to the dll-controlled vehicle included
 27 acceleration and deceleration, speed, distance, vehicle ID, lane angle, dimensions, and lane
 28 changing values, similar to the data gathered from a radar sensor. Adjacent CAVs could be
 29 identified from the dll-controlled vehicle due to a user-defined attribute programmed in the
 30 C++ code.

31 If the first preceding vehicle in the same lane of the dll-controlled vehicle was not a CAV and
 32 another CAV was identified as a first preceding vehicle in an adjacent lane –starting from left
 33 to right-, a lane changing manoeuvre was initiated through the control algorithm, if the
 34 predefined time gap was found and the direction of the lane change was set. The required time
 35 gap that was set for the purpose of this study was 0.6 seconds from the vehicle upstream and
 36 downstream in the target lane. The lane changing parameters such as lane angle and number of
 37 target lane, are controlled entirely by VISSIM (PTV AG, 2010). Once the lane changing
 38 manoeuvre has been completed, the dll controlled vehicle engages CAV car-following
 39 behaviour. The step by step formulation of the vehicle platoons is schematically shown in
 40 Figure 5 . Human driven vehicles are shown in green colour while the dll controlled vehicle
 41 (CAVs) is shown in white. The dll controlled vehicle searches its preceding vehicles and
 42 identifies a CAV (shown in blue colour) in the lane on its left. Since a CAV is identified in an

- 1 adjacent lane, the ego-vehicle then proceeds to search for a satisfactory gap for lane change.
- 2 After detecting the required gap, it initiates a lane change and joins the platoon.



3

4 **Figure 5 Step-by-step platoon formulation through the proposed CAV control algorithm**

5

6 *Vehicle Connectivity*

7 Vehicle connectivity, in the form of network simulation (e.g. vehicular ad-hoc networks),
 8 cannot be directly achieved using only a traffic simulation package. However, according to the
 9 developed CAV behaviour, the range that CAVs could search in order to identify other CAVs,
 10 and obtain accurate acceleration/deceleration, speed measurements was programmed to be 200
 11 meters.

12 It must be emphasized that this section presented an indirect simulation of the CAV subsystems
 13 (sensing, perception, planning and control) and behaviour, with reasonable assumptions. More
 14 specifically, the sensing subsystem was indirectly represented with the ability of the algorithm
 15 to collect nearby vehicles' data up to a range of 200 meters, while the perception subsystem
 16 was represented in the algorithm with the equations that transformed the raw data gathered,
 17 into useful variables that are used in the acceleration/deceleration calculation equations. The
 18 planning subsystem in this study was responsible for making the lateral-decision making
 19 decisions. Finally, the control subsystem was represented by the equations calculating the
 20 acceleration or deceleration of the CAV.

21

22

1 **3.2 VISSIM and SSAM integration**

2 In order to evaluate the safety impact of CAVs, the Surrogate Safety Assessment Model
 3 (SSAM) is used in this study. SSAM is a tool developed and validated by the Federal Highway
 4 Administration of the U.S. Department of Transportation that utilises several algorithms to
 5 identify traffic conflicts from vehicle trajectory files (Gettman et al., 2008). VISSIM can output
 6 the vehicle trajectory file at the end of each simulation run by clicking the corresponding option
 7 in the VISSIM graphical user interface. The trajectory file includes data about the trajectory of
 8 all vehicles that appeared in the simulation. SSAM processes one simulation time step at a time
 9 and checks for traffic conflicts using predefined Time to Collision (TTC) and Post
 10 Encroachment Time (PET) threshold values. The default value for TTC is 1.5 seconds and for
 11 PET 5 seconds. While processing the vehicle trajectory files, SSAM projects the vehicles'
 12 future positions (next few simulation timesteps) if they are to keep the same speed and remain
 13 on the same path, for up to the duration of the predefined TTC value. If a vehicle overlap is
 14 identified in this way, this pair of vehicles is recorded in the SSAM output file. For more
 15 information on the identification of conflicts in SSAM, readers can refer to Gettman et al.,
 16 (2008).

17 Along with the identification of the conflicting vehicles, SSAM provides data about the conflict
 18 itself such as the conflict type (i.e. rear-end, lane change or crossing), the simulation time when
 19 the minimum TTC value is observed, the coordinates of the location of the conflict, conflict
 20 angle and speed and acceleration values of the conflicting vehicles before and after the conflict.
 21 Finally, the latest version of SSAM (3.0) can provide heatmaps showing the concentration of
 22 conflicts along the simulated motorway segment.

24 **3.3 Data Collection, Calibration and Validation of the Microsimulation Model**

25 *Data Collection*

26 The data used for calibration and validation come from two sources. The first one is historical,
 27 minute level, inductive loop detector traffic measurements between January 2016 and January
 28 2018. The dataset comprised of 21,900 observations per inductive loop detector resulting in a
 29 total of 127 million observations. The data was split into a calibration (January 2016-
 30 December 2016) and a validation dataset (January 2017-January 2018). Additionally, using
 31 this data, the vehicle fleet composition was calculated and used as input for VISSIM. More
 32 specifically, the heavy goods vehicles percentage from Monday to Friday was 20.02%, 21.47%,
 33 23.04%, 22.26% and 20.92% accordingly. The second source of data is traffic measurements
 34 collected by a Loughborough University's instrumented vehicle. The vehicle is equipped with
 35 a Continental ARS308-2 long range radar, a PointGrey Grasshopper 3 (GS3-U3-41C6C-C)
 36 camera, a Ublox NEO-M8L GPS, a Mobileye device and data are communicated through
 37 different devices using a CANbus. Real world trips between Junctions 19 and 21 were
 38 conducted between April 2017 and December 2017 with a total duration of 156 minutes with
 39 140,400 observations. The data were divided equally into a calibration and a validation dataset.
 40 The data gathered from the trips were cleansed and fused together using Matlab.

41 *Calibration and Validation Strategy*

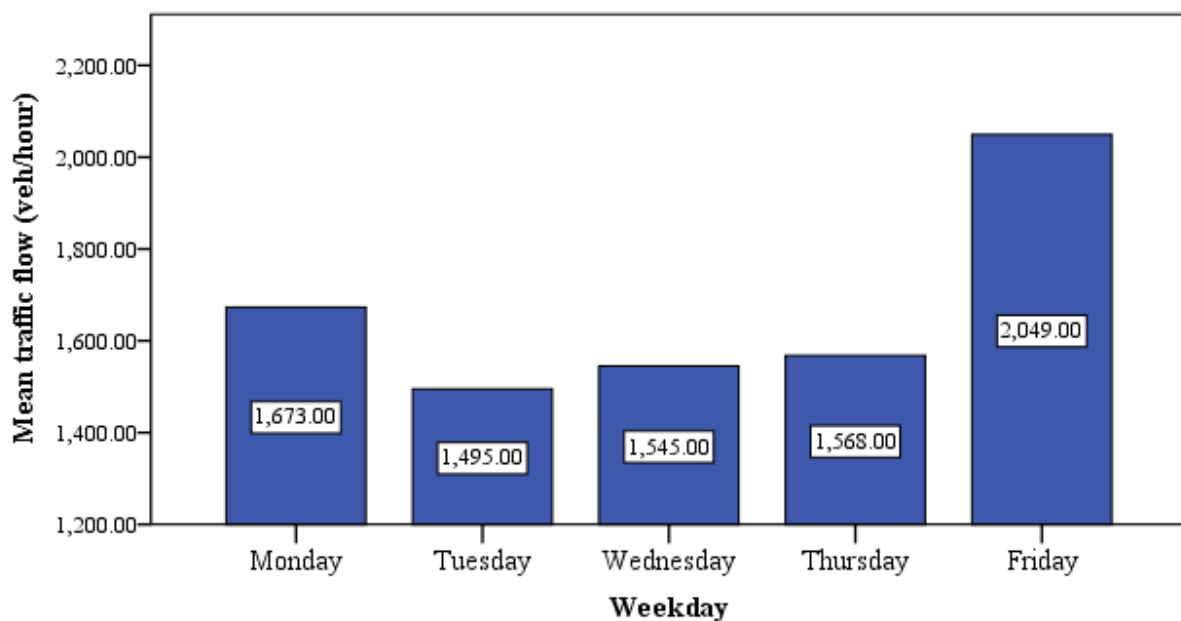
42 After taking into account previous safety simulation studies (Fan *et al.*, 2013; Huang *et al.*,
 43 2013), a two-stage calibration approach was followed. The models developed, were calibrated
 44 for the times of the real-world trips; between 11:00 and 12:00 a.m. The number of simulations

1 needed in order to achieve a 95% confidence interval level for the simulation output was
 2 calculated using Equation (7) (Shahdah, Saccomanno and Persaud, 2015). In this equation, N
 3 equals the required number of simulation runs, σ equals the sample standard deviation of the
 4 simulation output, t is the student's t-statistic for two-sided error of a $\alpha/2$ with $N - 1$ degrees
 5 of freedom and E equals the allowed error range. The result showed that 15 simulation runs
 6 were sufficient and were conducted for each calibration and validation stage.

$$N = \left(\frac{t_{(1-\frac{\alpha}{2}), N-1} * \sigma}{E} \right)^2 \quad (7)$$

7 i) First-stage calibration of VISSIM simulation model

8 Initially, historical inductive loop detector data from the calibration dataset (minute by minute
 9 traffic flow, speed and headway distribution) were used as input for the simulation models.
 10 Data coming from the real-world inductive loop detectors were input at the corresponding
 11 simulation vehicle input point. In order to evaluate the performance of the proposed CAV
 12 algorithm under different traffic conditions, five simulation models were created, one for each
 13 weekday; Monday, Tuesday, Wednesday, Thursday and Friday. The average traffic flow values
 14 for the mainline corridor in each direction are presented in Figure 6.



15
 16 **Figure 6 Average traffic flow per direction per weekday for the simulated time of the day**

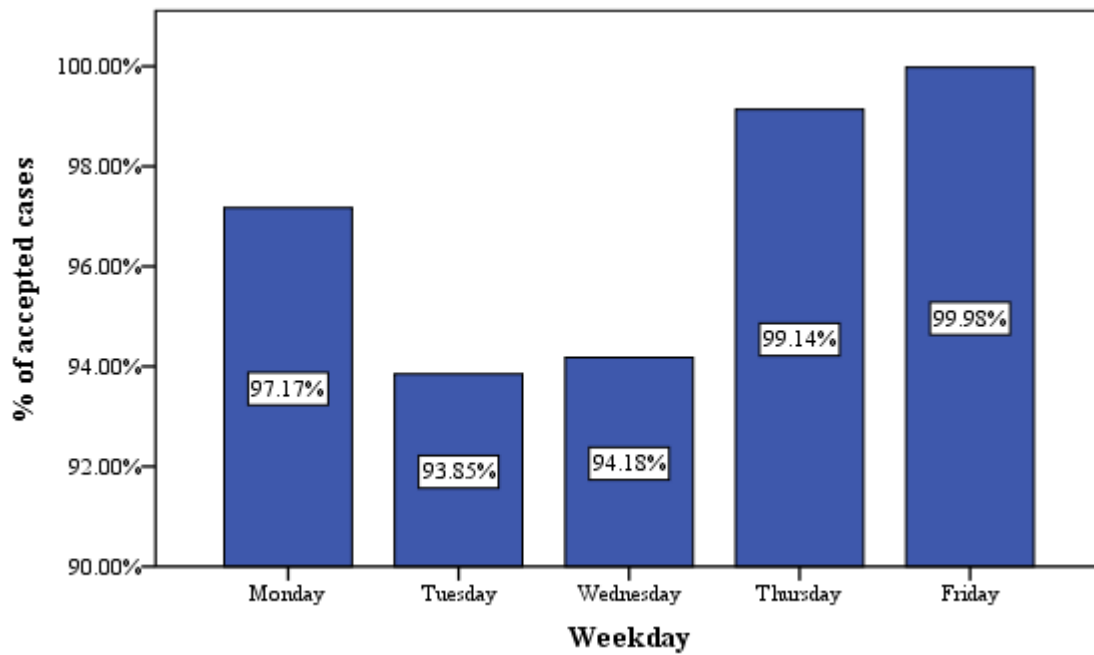
17

18 The first stage of the calibration was conducted to ensure that basic traffic parameters such as
 19 traffic volume, speed and travel time are accurately reproduced in the simulation. Following
 20 guidelines provided by FHWA (Dowling et al, 2004), the measures of performance chosen
 21 were travel time and traffic flow observed in the field versus the one produced in the simulation
 22 models. For travel time calibration, simulated values should be $\pm 15\%$ of the observed values
 23 for more than 85% of the simulated cases. The travel time calibration results showed that the
 24 simulation model accurately represented the observed values and the results are presented in
 25 Figure 8. On the other hand, in order to calibrate traffic volume values, the GEH statistic is

1 used. The *GEH* statistic is presented in equation (8) where *E* stands for the simulated traffic
 2 volume and *V* is the observed values. In order for the calibration to be successful, the *GEH*
 3 statistic should be less than 5 for 85% of the cases. The results of the calibration are presented
 4 in Figure 8 and show that the simulation produces realistic traffic flow values. All the results
 5 were validated using the validation dataset.

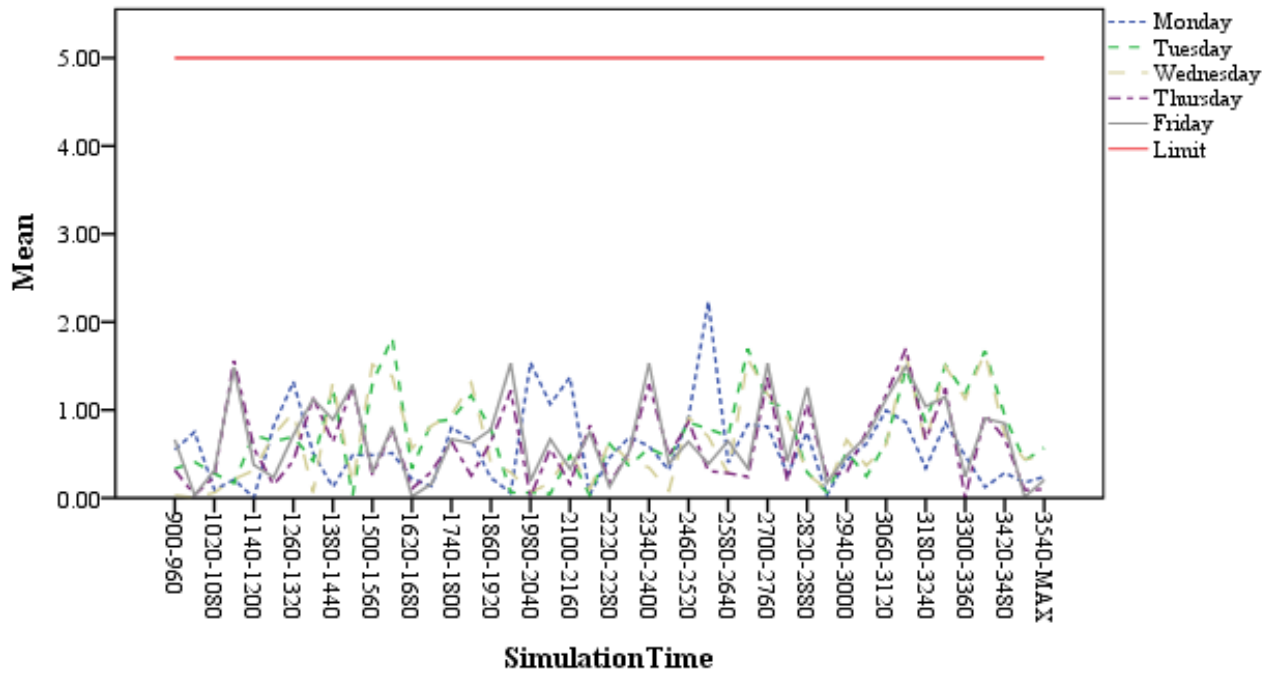
$$GEH = \sqrt{\frac{(E - V)^2}{\frac{E + V}{2}}} \quad (8)$$

6



7

8 **Figure 7 Travel time calibration results**



1

2 **Figure 8 Traffic volume calibration results**

3

4 ii) Second-stage calibration of VISSIM simulation model

5 Subsequently, the second stage of the calibration ensured that the measure of safety was
 6 accurately simulated. The measure of safety chosen for this study was the Time To Collision
 7 (TTC) distribution. A TTC distribution was calculated from data gathered through
 8 Loughborough University's instrumented vehicle was compared with TTC distributions
 9 calculated from vehicles in VISSIM.

10 The instrumented vehicle data were used to extract TTC to the preceding vehicle in the same
 11 lane during the trips. The preceding vehicle was identified from the radar data since it had a
 12 small (less than 1.75m) lateral displacement to the ego-vehicle and had the smallest
 13 longitudinal displacement. Consequently, the distance and the relative velocity to the preceding
 14 vehicle were used in order to calculate the TTC surrogate safety measure, using its original
 15 definition which is presented in equation (9), where ΔX is the gap between the ego-vehicle and
 16 its preceding vehicle and ΔS is the difference of ego speed minus the speed of the preceding
 17 vehicle. The TTC distribution calculated from the calibration dataset set was used to calibrate
 18 the simulation model and the rest of the data was used for validation.

19

$$TTC = \begin{cases} \frac{x_l - x_f - L_l}{v_l - v_f} & , \text{if } v_f > v_l \\ \infty & \text{if } v_f \leq v_l \end{cases} \quad (9)$$

20 Since VISSIM does not provide TTC distributions by default, the TTC distribution for the
 21 simulation vehicles was calculated through an external code written in the External Driver
 22 Model API. The two distributions were compared using the non-parametric Mann-Whitney U

1 test. Following guidelines from relevant literature (Habtemichael and Picado-Santos, 2013;
 2 Rahman and Abdel-Aty, 2018) and after testing all relevant car-following (CC0, CC2, CC3)
 3 and lane changing (Safety Distance Reduction Factor) parameter changes and several attempts,
 4 the change of the parameter CC3 (see Table 1) from -8, which was the default value, to -5
 5 provided the best p-value for the Mann-Whitney test. With this change, the Mann-Whitney
 6 tests indicated that the two distributions were not significantly different (Significance values
 7 0.875, 0.716, 0.611, 0.127 and 0.917 for Monday, Tuesday, Wednesday Thursday and Friday
 8 models accordingly). The results were validated using the validation data set.
 9

10 It must be noted that the simulation model was calibrated and validated only for the human-
 11 driven vehicles (0% CAV market penetration rate), due to lack of CAV data. Once CAV data
 12 become available, a CAV calibration and validation could be achieved. However, calibrating
 13 the human driven model is critical, as it provides a solid foundation for the simulation models.
 14 Additionally, the human behaviour during the transition era will determine the reaction to
 15 CAVs and affect the safety impact of CAVs significantly.

16

17 4. FINDINGS AND DISCUSSION

18 The reduction of conflicts due to CAVs was evaluated using VISSIM and SSAM as described
 19 in the method section of the paper. In VISSIM, five different CAV market penetration scenarios
 20 were tested; 0%, 25%, 50%, 75%, 100%. For each market penetration scenario and different
 21 simulation model (Monday-Friday), 15 simulation runs were performed with different random
 22 seeds. Each simulation run lasted 3,600 simulation seconds with 800 simulation seconds warm
 23 up period to allow the motorway segment to be fully occupied. It must be noted that as CAV
 24 market penetration rate increased, the computational time for each simulation run increased.
 25 For instance, a simulation run for the 0% market penetration rate scenario took approximately
 26 30 minutes to finish while a simulation run for the 100% market penetration rate scenario took
 27 45 minutes on average. The vehicle trajectory files produced by VISSIM were subsequently
 28 transferred to SSAM to identify traffic conflicts using TTC and Post Encroachment Time (PET)
 29 as surrogate safety measures.

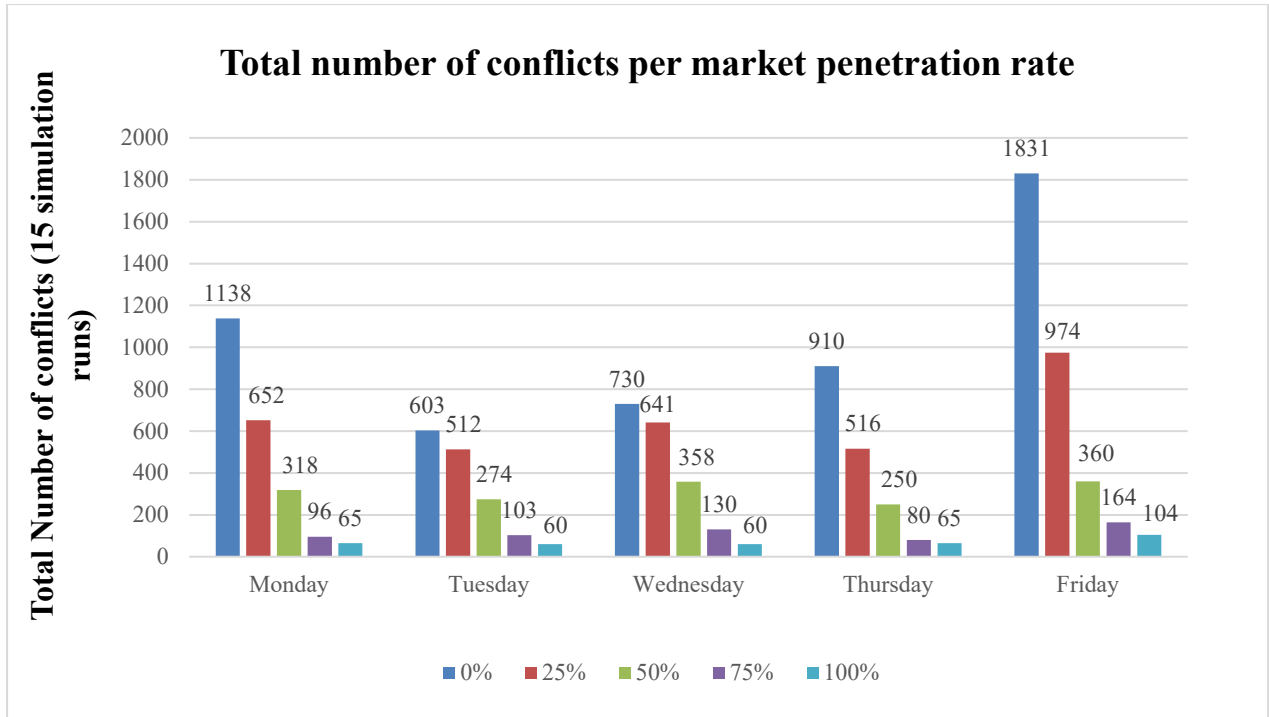
30 SSAM identifies traffic conflicts using specific TTC and PET thresholds. The default threshold
 31 values are 1.5 seconds and 5 seconds respectively. The same values were used in this study
 32 following recommendations found in Lu et al, (2005) for medium and high collision risk
 33 situations. However, it is still unknown which TTC value would be critical for CAV driving.
 34 Only rear end and lane changing conflicts were taken into account according to the manual of
 35 SSAM for motorway scenarios (Pu and Joshi, 2008). It must be noted that even though the
 36 results for TTC threshold value of 1.5 seconds are presented below, a sensitivity analysis for
 37 TTC values of 1.0, 1.5, 2.0, 2.5 and 3 seconds was conducted and the percent reduction of
 38 conflicts per market penetration rate scenario was not affected significantly.

39 Firstly, the percent reduction of conflicts calculated by SSAM and the percent of conflicts
 40 related with CAVs for each of the pre-defined market penetration rates is presented in Table 2.
 41 The reduction of the total number of conflicts per weekday per scenario is graphically shown
 42 in Figure 9. A major reduction of conflicts is clear even at small market penetration rates. A
 43 small number of conflicts is observed at the 100% market penetration rate scenarios. These few
 44 conflicts could happen due to imperfections in the simulation software or be a consequence of
 45 a slow speed lane-changing manoeuvre. It is noticeable that the safety performance of the

1 algorithm at the 25% market penetration rate is better as traffic flow increases. For example,
 2 on Fridays, that the traffic flow is the highest, a greater reduction of conflicts is observed at the
 3 25% market penetration rate than lower traffic weekdays. The reduction of conflicts at the 100%
 4 market penetration rate varies between 90-94%. At first glance, this reduction in simulated
 5 conflicts seems to be very close with the anticipated safety benefit of CAVs according to the
 6 literature (Fagnant and Kockelman, 2015; Kim *et al.*, 2015). However, the results should not
 7 be considered identical. A reduction of 90-94% in traffic conflicts which was calculated in this
 8 study does not necessarily imply a 94% reduction in crashes which was predicted in the
 9 literature. An attempt to model the relationship between conflicts and crashes can be found in
 10 Gettman *et al.*, (2008). Furthermore, a possible explanation for the relatively small
 11 improvement from 75% to 100% market penetration rates could be the fact that even from 75%,
 12 CAVs tended to form long platoons (8+ vehicles), isolating human driven vehicles in their own
 13 lanes and making the interactions between human driven vehicles minimal. Finally, it is
 14 observed that percentage of conflicts involving CAVs is significantly lower than the
 15 corresponding market penetration rate.

16 **Table 2 SSAM conflicts per CAV market penetration scenario**

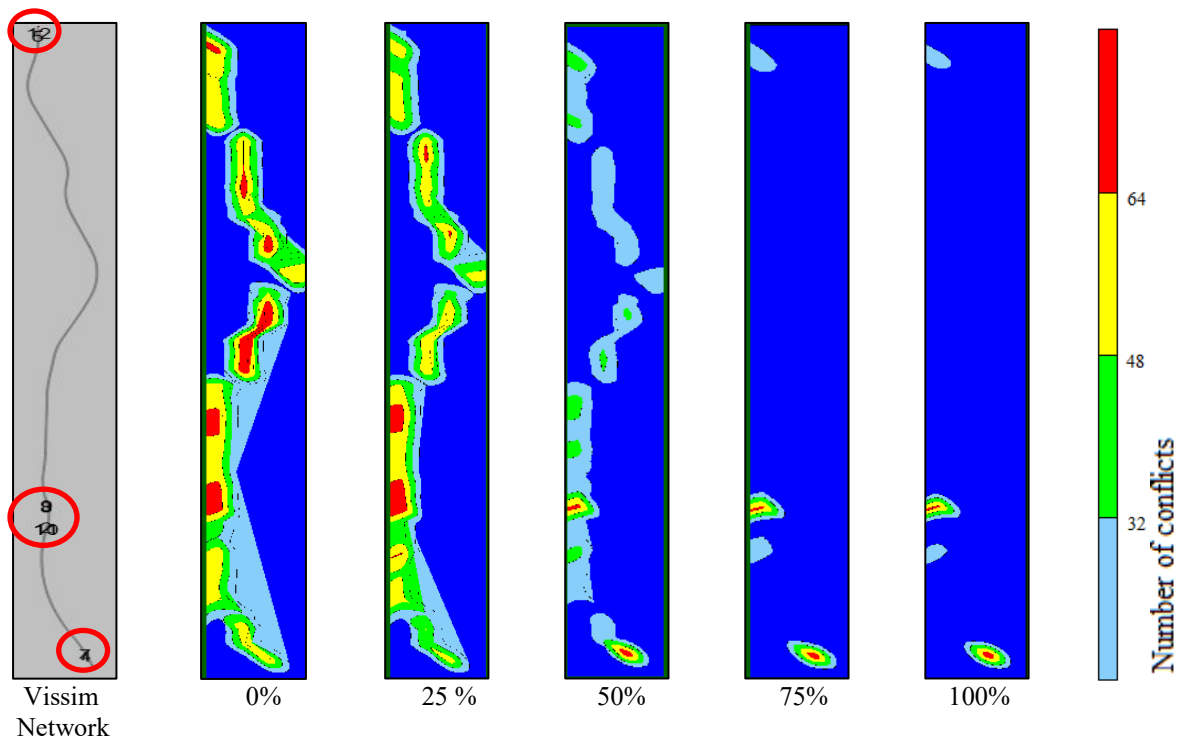
	Total Conflict Reduction %					% conflicts involving CAVs
	Monday	Tuesday	Wednesday	Thursday	Friday	
0%	0.00%	0.00%	0.00%	0.00%	0.00%	-
25%	42.71%	15.09%	12.19%	43.30%	46.81%	4.85%
50%	72.06%	54.56%	50.96%	72.53%	80.34%	14%
75%	91.56%	82.92%	82.19%	91.21%	91.04%	40%
100%	-94.29%	-90.05%	-91.78%	-92.86%	-94.32%	-



1

2 **Figure 9 Reduction in traffic conflicts per market penetration scenario**

3



4

5

6 Network

7 **Figure 10 Heatmap of traffic conflict locations for the different market penetration scenarios**
 8 **aggregated for all weekdays**

9

10 Figure 10 presents the heatmaps showing the concentration of conflicts across the motorway
 11 segment per market penetration scenario. It is obvious that the CAV control algorithm has

1 eliminated conflicts in the non-merging/diverging areas in high market penetration rate
 2 scenarios. Inevitably, a high number of conflicts is observed at the merging and diverging areas
 3 (Junctions 21, 20 and 19 of the motorway, marked with a red circle in the left-most graph of
 4 Figure 10) due to the high variance of speeds and number of lane changes that take place on
 5 those segments. This finding seems to agree with relevant literature characterising the merging
 6 and diverging areas of the motorway as high risk segments (Ahammedet al 2008). Table 3 can
 7 provide more additional information about this issue; it provides the percentage of each conflict
 8 type per market penetration rate. The percentage of lane changing conflicts is coming close to
 9 the percentage of rear end conflicts as market penetration rate increases (although the absolute
 10 number of conflicts is reduced significantly). All the conflicts in the high market penetration
 11 rate scenarios (i.e. 75% and 100%) are concentrated in or near the merging and diverging areas
 12 where lane changing behaviours are enforced. (see Figure 10) and that the lane changing
 13 conflicts happening in this area are a product of the actual lane changes and the rear-end
 14 conflicts are potentially a consequence of a lane change manoeuvre in this area.

Market Penetration Rate	Rear end	Lane change
0%	9.18%	90.82%
25%	22.55%	77.45%
50%	23.26%	76.74%
75%	32.56%	67.44%
100%	43.68%	56.32%

21 **Table 3 Percentage of type of conflicts per market penetration rate scenario**

22 The SSAM output indicated that in all market penetration rates, the minimum TTC value
 23 observed was 0 seconds, which implied a simulation crash. In some of the previous papers filter
 24 out these values claiming that they are caused by simulation errors (Gettman *et al.*, 2008).
 25 However, others keep these virtual crashes in the analysis (Shahdah, Saccomanno and Persaud,
 26 2015). After close observation of the behaviour of the vehicles in VISSIM some of these
 27 conflicts might have been caused due to simulation error; in the mainline vehicle input points,
 28 vehicles started a lane change at the same moment when another vehicle just entered the
 29 motorway resulting in a virtual crash. This problem was resolved by not allowing a lane change
 30 in the first 50 meters of the simulation network input points.

31 Finally, although the focus of this paper is to evaluate the safety impact of CAVs, in order to
 32 obtain more complete understanding of the impacts of CAVs, the travel time impact of the
 33 proposed algorithm was calculated as well and is presented in Table 4. CAVs seem to increase
 34 the average travel time during all weekdays due to the fact that long vehicle platoons with a
 35 slow leader decreased the average speed of the motorway significantly. This result however is
 36 sensitive to the desired speed distribution of vehicles in VISSIM. Overall, it is observed that,
 37 at the 100% market penetration scenario, CAVs managed to make the travel time almost equal
 38 across all weekdays. This means that CAVs will be able to provide reliable travel times
 39 independent of traffic conditions, a result that seems to agree with previous studies (ATKINS,
 40 2016).

41 **Table 4 Average travel time results for all vehicles for each CAV market penetration scenario**

Monday	Tuesday	Wednesday	Thursday	Friday
--------	---------	-----------	----------	--------

	Travel Time (sec)	Travel Time (sec)	Travel Time (sec)	Travel Time (sec)	Travel Time (sec)
0%	727.28	751.0	748.3	796.9	822.2
25%	820.88	805.1	804.0	830.0	849.76
50%	843.01	835.1	835.3	848.8	858.30
75%	861.89	859.3	859.4	864.2	866.00
100%	874.03	874.2	874.5	875.1	874.00

1

2 With the results being presented, the limitations of this study should be taken into consideration.
3 As real-world CAV data are not widely accessible, the behaviour of CAVs within a network is
4 still unknown and validating simulated CAV behaviour is not possible. This study hypothesizes
5 a CAV behaviour, that the CAV will be able to follow other CAVs more closely, search
6 adjacent vehicles and try to form vehicle platoons. Furthermore, CAV safety in this study is
7 assumed to be identical as human driving safety. Calculating conflicts with the same TTC
8 threshold for CAVs might be not be a suitable safety surrogate as CAVs ideally should be more
9 in control of their movement in relation to the surroundings, than conventional vehicles. The
10 safety of CAVs in the road is strongly connected to software and hardware reliability (Pinto,
11 2012). This study does not consider autonomous driving mode breakdown, neither errors to the
12 autonomous driving due to hardware malfunction or to physics-based causes.

13 As far as CAV traffic characteristics are concerned, this paper assumed that CAVs would want
14 to mimic human throttle control and breaking behaviour, in order for the passengers to feel safe
15 and comfortable. Hence, no special CAV desired acceleration-deceleration limits were used.
16 However, the acceleration-deceleration values of CAVs were within the human driving values.
17 Moreover, there was no limit to the length of the platoon that CAVs could form in the motorway
18 in this study. This resulted in the formulation of long platoons (15+ vehicles), especially in
19 high market penetration rates. A vehicle platoon this long could potentially cause several
20 disturbances in the traffic flow of a motorway environment; e.g. blocking a vehicle from exiting
21 the motorway at the merging/diverging areas or making it hard for human driven vehicles to
22 navigate around them. Due to the non-congested traffic conditions tested in this paper, such
23 problems were not observed in the simulation. Vehicles were able to change lane in advance
24 in order to merge in and exit the motorway without causing traffic instability problems and
25 platoons were able to dissolve at the off ramps without a problem. Additionally, the human
26 driven vehicles seemed to adapt their driving behaviour due to vehicle platoons resulting in
27 smaller speed variance in the motorway segment. Nonetheless, the authors are considering
28 implementing a limit to the platoon length and possibly limiting the platoon formulation in
29 certain lanes. However, it is still uncertain whether the platoon size will be limited in the real
30 world when the CAV market penetration reaches high percentages and whether platoons will
31 be allowed to form in specific lanes only. Finally, the authors are also looking for further
32 improvements to the CAV control algorithm to optimize its performance and to resemble CAV
33 behaviour more accurately.

34 The use of a validated CAV control algorithm could provide more trustworthy results, while
35 more and better real world TTC data may improve the calibration of the model. A sensitivity
36 analysis on the parameters of the CAV control algorithm such as time gap for both car-
37 following, lane-changing situations and platoon size could be useful. Furthermore, adding a
38 probabilistic term to data available to CAVs in VISSIM could represent a more dynamic CAV
39 traffic environment. Finally, it would also be interesting to investigate the safety impact of
40 CAVs in different scenarios namely a dedicated CAV lane in the simulation network or the re-

1 routing of the CAV fleet in real time due to a disruption in the motorway. The limitations and
2 concerns raised above, cover a narrow range of the spectrum of the challenges arising from the
3 interaction between human driven vehicles and CAVs and mainly refer to a motorway
4 environment. Further research is needed in order to fully investigate this interaction especially
5 in more complicated (i.e. urban) road networks. Evaluating the safety impact of these competing
6 traffic scenarios and traffic management would be the key in answering this important issue:
7 where and when the safety benefit of CAVs is going to be maximised.

8

9 5. CONCLUSION

10 Simulating CAVs in order to evaluate their safety impact is a big challenge and this has not
11 been widely addressed in existing literature. This paper developed a decision-making CAV
12 control algorithm implemented in a simulated, real world motorway environment in the
13 standard traffic simulation software VISSIM, using its External Driver Model Application
14 Programming Interface. The algorithm included both longitudinal control and lateral decision
15 making in which CAVs were able to search nearby vehicles in the motorway, identify nearby
16 CAVs and by using the data available to them, change lanes in order to follow other CAVs
17 with a shorter headway (0.6 seconds). Vehicles controlled by the API were able to calculate
18 their acceleration at each simulation time step in order to keep a steady headway to other
19 vehicles, ultimately forming vehicle platoons. A part of M1 motorway in the UK was simulated
20 and five different simulation models were created, one for each day of the week (Monday to
21 Friday) in order to test the CAV control algorithm in varying traffic conditions. The simulation
22 model was calibrated and validated using real-world inductive loop detector data and time-to-
23 collision (TTC) data calculated from radar measurements collected by the Loughborough
24 University's instrumented vehicle. In order to investigate the effect of human driven vehicles
25 – CAV interaction on safety as the technology is gradually adopted by road users, five different
26 CAV market penetration rates were tested namely 0% (baseline), 25%, 50%, 75% and 100%
27 and 15 simulation runs were conducted per scenario.

28 The vehicle trajectory files were consequently input to SSAM. SSAM calculated the total
29 number of conflicts for each market penetration scenario and for each weekday using pre-
30 defined TTC and PET thresholds. The results indicated that the CAV control algorithm
31 improves road safety significantly, as the reduction of conflicts was 12-47%, 50-80%, 82-92%
32 and 90-94% for the 25%, 50%, 75% and 100% penetration rates respectively. It was found that
33 the algorithm was more effective at low market penetration rates on weekdays with higher
34 traffic volume. Additionally, the reduction of conflicts achieved at 100% penetration rate
35 seemed to agree with existing predictions in the literature. It was also apparent that CAVs
36 provided reliable travel times regardless of traffic conditions. The results of this paper could
37 provide useful initial insights to network operators about traffic conditions and road safety after
38 the implementation of CAVs. The CAV control algorithm developed here could formally be
39 integrated into a traffic microsimulation platform to simulate CAVs at a corridor-level in a
40 mixed traffic stream and under different infrastructure and vehicle based scenarios.

41

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