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Review Article

How PTV Vissim Has Been Calibrated for the Simulation of Automated Vehicles in Literature?

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Recently, in the literature, microscopic simulation is one of the most attractive methods in impact assessment of automated vehicles (AVs) on traffic flow. AVs can be divided into different categories, each having different driving characteristics. Hence, calibrating microscopic simulators for different AV categories could be challenging in AVs' impact assessment. The PTV Vissim microscopic traffic simulation software has been calibrated for simulating diverse types of AVs in a large body of literature. There are two main streams of studies in literature adapting AVs' driving behaviors in Vissim following either internal (i.e., adjusting the parameters of the Vissim's default driving behavior models) or external (i.e., adapting AVs' behavior through external VISSIM interfaces) modeling approaches. The current paper investigates how the PTV Vissim has been internally calibrated for the simulation of different types of AVs and compares the calibrated values in the literature with default values introduced in the recent version of PTV Vissim. In the present paper, the reviewed studies are partitioned into two main categories according to the characteristics of the studied AVs, the studies focused on autonomous automated vehicles (AAVs) and the ones focused on cooperative automated vehicles (CAVs). Our findings indicate that the literature expects a lower value for parameters including standstill distance (CC0), headway time (CC1), following variation (CC2), the threshold for entering "following" (CC3), negative/positive following thresholds (CC4/CC5), speed dependency of oscillation (CC6), oscillation acceleration (CC7), safety distance reduction factor (SDRF), and minimum headway front/rear (MinHW) for AVs than conventional vehicles (CVs). Besides, the literature expects higher values for parameters including standstill acceleration (CC8), acceleration at 80 km/h (CC9), looking distances, and maximum deceleration for cooperative braking (MaxDCB) for AVs. When cautious AVs are introduced, deterring effects are expected in the literature (e.g., higher CC0). Moreover, CAVs can have higher looking distance values compared with AAVs.

1. Introduction

Recently, the impact assessment of automated vehicles (AVs) on traffic flow has become a popular research topic due to their potential mobility benefits to overcome the challenges linked with conventional vehicles (CVs) [1, 2]. Based on how the driving task is executed by the human driver and the vehicle system, the Society of Automotive Engineers has classified AVs into six levels of automation. Conventional vehicles are those without automation and referred to as Level 0, Level 1 is driver assistance, Level 2 is partial automation, Level 3 is conditional automation, Level 4 is high automation, and Level 5 is full automation. The primary driving task is carried out by the human driver in the first three levels of automation. In contrast, the vehicle system handles the majority of the dynamic driving task for the following three levels [3].

Automated driving systems are often referred to as "autonomous" (e.g., [4–6]) and "automated" (e.g., [1, 7, 8]). The term "autonomous" refers to completely automated vehicles that do not need any assistance from a human driver. However, the term "automated vehicle" implies a vehicle system that may be controlled at several levels and does not necessarily need to be fully automated with no human driver interaction under all circumstances [9]. Furthermore, the study by Sala and Soriguera [10] considered "connected autonomous" to describe to vehicles that are fully automated and can communicate with their environment, while studies [11, 12] used "autonomous automated vehicles" and "cooperative automated vehicles." Thus, looking at the large body of works of literature (e.g., [10, 12–13]), the two types of fully automated vehicles are autonomous (without communication capabilities), automated vehicles (AAVs), and cooperative/connected automated vehicles (CAVs). AAVs merely use their own sensors to gather information, but CAVs combine all AAV features with vehicle-to-vehicle and vehicle-to-infrastructure communication to augment the data from their sensors.

AVs are predicted to hit the market soon and will bring both opportunities and challenges to the road transportation system. According to a recent study by Beza et al. [14], the technology has become capable of traversing urban roadways such as roundabouts and pedestrian crossings; however, their operational speed is too low (less than 20 km/h), which is not sufficient for commuters. Furthermore, Zhang and Wang [15] demonstrated that level 4 AV market share in the US cities might reach 34% in 2030 and 75% in 2040. In the form of shared use, AVs are anticipated to significantly penetrate urban roads by the 2030s [16]. Beginning in 2040, AVs will become more affordable; by 2045, it is predicted that AVs will account for 50% of all new vehicle sales [17]. Regarding public acceptance of AVs, studies (e.g., [18–20]) that focused on user attitudes after pilot project experiences revealed that there are positive intentions towards the technology, despite the fact that lower operation speed, inaccessibility to mobility-impaired individuals, and interaction of AVs with pedestrians and cyclists remains the concerns for their large-scale deployment.

There are different methods used in the literature to assess the impacts of AVs including field test experiments [4, 21] and simulation [10]. Microscopic simulation is one of the most popular methods in AVs' impact assessment on traffic flow in the literature. Calibrating the microscopic traffic simulation software for different types of AVs is one of the most challenging steps in AVs' impact assessment using the microscopic simulation method.

The PTV Vissim microscopic traffic simulation software has been calibrated for the simulation of different types of AVs in a large body of literature to assess the impacts of AVs on traffic flow. In the literature, PTV Vissim has been calibrated based on different methods including the use of field data [22–24] and summarization of preceding published studies [5, 25, 26]. According to the characteristics of the investigated AVs, the evaluated studies are grouped into two categories: those that focused on CAVs and those that focused on AAVs. AAVs depend on their onboard sensors, whereas CAVs can intensify onboard sensor information via communicating with other entities such as roadside infrastructures, vehicles, cloud, and/or pedestrians [11, 27, 28]. In literature, PTV Vissim has been mostly calibrated only for a single type of AVs in each study, either AAVs or CAVs; however, in the study [27], both AAVs and CAVs are considered. The investigated scenario in the literature includes the impacts of AVs on urban road intersections and freeway segments. Whereas, some studies assessed the impacts of AVs on a large road network. Even though the majority of works in the literature looks for fully AVs, some studies ([29, 30]) considered level 4 AVs.

The choice of algorithms and parameters for AVs has significant implications for the impact assessments of this disruptive transport technology; the assumed simulation parameters and their calibrations can change the simulation output. Thus, the results might change significantly as well and lead to a different conclusion. More importantly, different Vissim calibration values have been considered in the works of literature as the driving behaviours of AVs are still under investigation. This paper attempts to fill this gap by thoroughly reviewing the works in the literature and summarising the calibrated values for different types of AVs and roadways that could be used for the calibration phase of the AVs simulation studies. To the best of the authors' knowledge, the current review will be unique in its type of microscopic simulations of different types of AVs using PTV Vissim.

The main contribution of the current paper is to carry out the following:

(1) Explore how PTV Vissim car-following, lane-changing, and lateral parameters have been calibrated in the literature for simulating different types of AVs.
(2) Compare the values of AVs' car-following, lane-changing, and lateral parameters that are calibrated in the literature with the ones introduced in PTV Vissim 2020.

The rest of the paper is structured as follows. Section 2 presents the methodological framework. The calibrated car-following, lane-changing, and lateral parameters in the literature are studied in Sections 3 and 4, respectively. Section 5 discusses on the findings of the literature review. Lastly, Section 6 provides conclusions and future research directions.

2. Methodological Framework

A thorough literature review was carried out to map out currently available information and pinpoint knowledge gaps. The literature review methodology in the current paper followed the one proposed by Massar et al. [31], which is the most widely applied methods that includes a number of phases, including designing a review methodology, locating and choosing relevant research, extracting and synthesizing data, and ultimately summarising the findings. The Scopus and Web of Science databases were used to extract the relevant literature. For Scopus search, the combination of the keywords, "TITLE-ABS-KEY (Vissim AND simulation AND (automated OR autonomous) AND vehicles)" was used. On the other hand, the combination of keywords, "ALL = ((automated OR autonomous) AND vehicle AND Vissim AND simulation)" is considered for extracting relevant studies from the Web of Science. To extract the relevant articles, articles published in English, accessible, and published not earlier than 2016 has been considered. Thus, 48 and 53 articles are retrieved from the respective databases and 61 papers are found after removing outputs that were duplicated in the two databases.

Furthermore, in the literature, two primary streams of studies use Vissim to replicate the driving behaviours of AVs using either internal or external modelling techniques. The first stream (e.g., see [7, 12, 25, 32]) uses the internal modelling, and modifies the default Wiedemann driving logic (car-following) and lane-changing parameters to simulate the desired driving behaviours. The second stream, which uses the external Vissim interfaces and the external modelling methodology, sends user-defined algorithms to a dynamic link library to imitate the driving logic of AVs (e.g., see [33, 34]). The present study follows the first stream of the literature. Therefore, further analysis of the search output resulted in 16 relevant studies. Besides, a snowballing technique has been used for additional searches and a total of 32 articles have been reviewed in the current study.

As illustrated in Figure 1, the reviewed studies comprised AAVs and CAVs over different roadway types such as urban road nodes as well as freeway segments. It is also worth mentioning that some studies consider a network-wide simulation.

In its latest version, PTV Vissim 2020 includes three different driving models designed for automated vehicles (AVs) based on field data: AV aggressive, AV normal, and AV cautious. AV cautious implement a safe driving behaviour that absolute braking distance is enforced, and vehicles keep large headways in the course of lane changing. AVnormal performs similar to a human driver with the further capability of determining speeds and distances of nearby vehicles within its sensor range, whereas, in AV aggressive, cooperative characteristics, superficial attentiveness, and predictive abilities are anticipated that could lead to smaller headways [35]. Besides, in PTV Vissim 2020, new driving characteristics including platooning, enforcing absolute braking distance, implicit stochastics, number of interaction objects, and vehicles are incorporated. The software default values are also indicated in Tables 1 and 2, which shows the suggested simulation parameters for AV cautious, AV normal, and AV aggressive in the recent version of the software in addition to the default values for conventional vehicles (CV).

3. Car-Following Parameters

This section investigates the PTV Vissim car-following parameters including standstill distance (CC0), headway time (CC1), following variation (CC2), threshold for entering "following" (CC3), negative/positive following thresholds (CC4/CC5), speed dependency of oscillation (CC6), oscillation acceleration (CC7), standstill acceleration (CC8), acceleration at 80 km/h (CC9), and look settings that have been calibrated for different types of AVs in the literature. The summary of the calibrated values in the literature is also presented in Table 1.

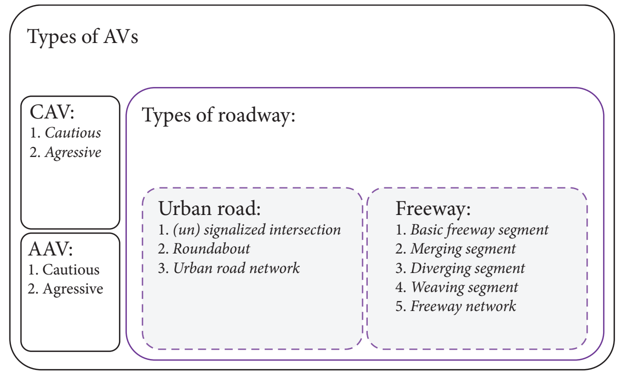

Figure 1: Studied scenarios.

3.1. CC0: Standstill Distance (m). CC0 is the average desired distance between two consecutive stopped vehicles. It determines the jam density of road infrastructure and is inversely proportional to capacity. The default value is 1.50 [36].

In 2016, for CAVs, Aria [37] considered a CC0 value of 1.5 for basic freeway and 2.5 for both merging and diverging freeway segments based on the values proposed by Leyn and Vortisch [22]. Similarly, Motamedidehkordi et al. [38] assumed 1.0 for simulating CAVs in the freeway network proclaiming the absence of data in this research topic at the time. In 2021, Rao et al. [39] considered 5 feet (1.52 m) for AAVs in freeway segments with various geometric and traffic conditions.

In 2015, Bohm and Häger considered a CC0 value of 1.0 based on the values proposed in by Bierstedt et al. [40] for assessing AAVs' impact on the Swedish traffic system that comprises diverse geometric arrangements [41]. Similarly, Deluka Tibljaš et al. [6] simulated AAVs in roundabouts with a CC0 value of 1.0 adopted from preceding published articles. In 2018, Morando et al. [42] adopted two sets of CC0 values that are 0.50 and 0.75 for AAVs in both a signalized intersection and roundabout from related works in the literature to study how this emerging technology impacts the road segments examined. For simulating AAVs on multilane freeways, El-Hansali et al. [43] calibrated the CC0 value to 0.75, and a value of 0.5 was considered for the simulation of AAVs on merging freeway segments by Lee et al. [44].

In the studies that analyse the environmental effects of AAVs on urban roads, a CC0 value of 1.47 was adopted [5, 26]. For measuring AAVs' impact on a congested road network with different segments including freeway interchanges and arterial corridors, Stanek et al. [32] proposed a value of 1.25 based in the study by Bierstedt et al. [40] that is dedicated to adaptive cruise control. Likewise, after investigating related literature, He et al. [25] designated a CC0 value of 1.25 for simulating CAVs in a weaving freeway segment.

TABLE 1: Values of car-following simulation parameters calibrated in the literature.

Ref.	Vehicle type	Road type	CC0 (m)	CC1 (s)	CC2 (m)	CC3 (m)	CC4 (m/s)	CC5 (m/s)	CC6 (1/(m/s))	CC7 (m/s²)	CC8 (m/s²)	CC9 (m/s²)	LAD (m)	LBD (m)	NOV (-)
Default	CV	—	1.50	0.90	4.00	−8.00	−0.35	0.35	11.44	0.25	3.50	1.50	0–250	0–150	2
Default	AV cautious	—	1.50	1.50	0.0	−10.0	−0.10	0.10	0.0	0.10	3.0	1.20	0–250	0–150	2 [x]
Default	AV normal	—	1.50	0.90	0.0	−8.0	−0.10	0.10	0.0	0.10	3.50	1.50	0–250	0–150	2 [x]
Default	AV aggressive	—	1.00	0.60	0.0	−6.0	−0.10	0.10	0.0	0.10	4.00	2.00	0–300	0–150	10 [x]
[41]	AAV	NetW	1.00	0.50	1.00	—	−0.10	0.10	0.0	0.40	4.00	4.00	0–500	0–300	10
[6]	AAV	RAB	1.00	0.50	1.00	−8.0	−0.10	0.10	0.0	0.40	4.00	2.00	0–150	0–280	—
[42]	AAV	RAB/SiI	0.50/0.75	0.50/0.45	0.00/2.00	—	0.00/−0.10	0.00/ 0.10	0.0/0.0	0.45/0.25	3.90/3.50	—	—	—	10/2
[32]	AAV	NetW	1.25	0.25	3	−12	−0.35	0.35	0.0	0.25	3.5	1.5	0–500	0–299	10
[7]	Cau/Agg AAV	NetW	2.50/0.50	2.10/0.50	—	−16.0/ −4.0	−0.60/−0.10	0.60/ 0.10	—	0.05/0.45	3.10/3.90	1.1/1.9	—	—	—
[25]	CAV	WFS	1.25	0.5	3	−12	−0.1	0.1	0.0	0.25	3.5	1.5	0–500	0–500	10
[26]	AAV	NetW	1.47	1.0	0	−13.5	−0.13	0.13	11.40	0.08	3.72	1.6	—	—	—
[5]	AAV	NetW	1.47	0.5	—	−13.54	−0.13	0.13	—	0.08	3.72	1.6	—	—	—
[27]	AAV/CAV	NetW	1.00	0.90/0.50	2.00/1.00	−12.0/ −16.0	−0.35	0.35/ 0.35	0.0	0.10/0.10	3.50/4.00	2.0	150–200/ 5000–5000	150–200/ 5000–5000	8/10
[37]	CAV	BFS/DFS/ MFS	1.50/2.50/ 2.50	0.30	4.00/ 5.00/4.00	—	−0.30/ −0.35/−0.35	0.35	11.44	—	3.50	1.50	150–200	150–200	7/6/6
[50]	CAV	NetW	2.50–0.50	1.80–0.60	—	—	—	—	—	0.10–0.40	3.20–3.80	1.20–1.80	—	—	—
[38]	CAV	NetW	1.00	0.50	4.00	−8.00	−0.10	0.10	0.0	0.25	3.50	1.50	—	—	—
[33]	CAV	BFS	2.64	1.54	—	—	—	—	—	—	—	—	—	—	—
[53]	CAV	BFS	0.65	1.20	3.35	−13	−0.24	0.40	—	0.46	—	—	—	—	—
[46]	Cau/Agg CAV	NetW	2.17/0.50	1.70/0.50	1.00/1.00	−3.33/ −1.00	0.00	0.00	0.0	0.12/0.45	3.50/3.50	1.5/1.5	—	—	—
[45]	AAV	NetW	0.38	0.45	2.00	−8.00	−0.35	0.35	11.44	0.25	3.50	1.50	—	—	—
[39]	AAV	NetW	1.52	1.20	4.00	—	—	—	—	0.91	4.15	—	—	—	—
[52]	CAV	NetW	1.50–1.00	1.50–0.50	0.00	−8.00	0.00	0.00	0.0	0.15–0.45	3.30–3.90	1.30–1.90	800	800	10
[62]	CAV	NetW	—	—	—	—	—	—	—	—	—	—	0–500	0–300	10
[29]	Cau/agg CAV	NetW	0.50/0.50	0.90/0.50	0.00	—	0.00	0.00	—	—	—	—	—	—	—
[51]	CAV	BFS	2.50–0.50	2.10–0.50	0.00	0.00	0.00	0.00	0.0	0.05–0.45	3.10–3.90	1.10–1.90	—	—	10
[30]	AAV	NetW	—	—	—	—	—	—	—	—	—	—	0–500	0–500	—
[47]	AAV	RAB	1.50–1.00	1.50–0.60	0	−10–−6	−0.1	0.1	0	0.1	3–4	1.2–2	—	—	—
[48]	AAV	NetW	1.5–1.0	1.5–0.7	0	−10–−6	−0.1	0.1	0	0.1	3.0–4.0	1.2–2	0–300	0–150	—
[55]	CAV	RAB	1.0	0.5	1.0	−6.0	−0.1	0.1	1.0	0.1	3.0	0.5	20–200	20–100	10
[44]	AAV	MFS	0.5	0.6	0	0	0	0	0	0.4	3.8	1.8	—	—	10
[58]	CAV	NetW	1.0	0.5	0	−6.0	−0.1	0.1	0	0.1	4.0	2.0	—	—	—
[43]	AAV	NetW	0.75	0.45	2.0	−8.0	−0.1	0.1	0	0.25	3.5	—	—	—	—
[56]	CAV	RAB	1.0	0.5	1.0	−6.0	−0.1	0.1	1.0	0.1	3.0	0.5	20–200	20–100	10
[54]	CAV	NetW	1.0–0.5	0.8–0.5	0	−8.0	−0.05	0.05	0	0.3–0.45	3.6–3.9	1.6–1.9	—	—	—
[57]	CAV	NetW	1.0	0.5	0	−6.0	−0.1	0.1	0	0.1	3.5	1.5	—	—	—
[49]	Cau/Agg AAV	NetW	1.0/0.5	0.5	2.0/0.0	—	−0.1/0.0	0.1/0.0	0	0.25/0.4	3.5/4.0	—	—	—	10

LAD: look ahead distance; LBD: look back distance; NOV: number of observed vehicles; NetW: network-wide; RAB: roundabouts; WFS: weaving freeway segment; BFS: basic freeway segment; DFS: diverging freeway segment; MFS: merging freeway segment; SiI: signalized intersections; Cau: cautious; Agg: aggressive; and Nor: normal.[X] the latest version of Vissim use the parameter "Number of interacting objects."

In 2019, Stogios et al. [7] considered the most cautious and aggressive driving behaviour of AAVs in signalized intersections and freeway networks consisting of different geometric arrangements including on-ramp, lane drop, and off-ramp; by reviewing the works in the literature, they considered a CC0 value of 2.50 for cautious AAVs and 0.50 for aggressive AAVs. Moreover, Rezaei and Caulfield [45] recommended a value of 0.38 in their study that analysed the impacts of AAVs on motorways.

It is worth mentioning that AVs can have cautious or aggressive driving behaviours depending on their level of automation and their driving logic. Thus, Song et al. [46] calibrated the CC0 value to 2.17 and 0.5 for caution CAVs and aggressive CAVs, respectively, for different roadway networks consisting of expressways and secondary motorways. Furthermore, Boualam [47] assumed 1.5 and 1.0 for simulating AAVs with cautious and aggressive driving behaviour on roundabout, respectively. The same values of 1.5 and 1.0 were also considered by Postigo et al. [48] for the simulation of AAVs in freeway networks. On the other hand, Tafidis et al. [49] considered 1.0 and 0.5 CC0 values for AAVs with cautious and aggressive driving behaviours, respectively. Besides, Szimba and Hartmann [29] assumed a value of 0.50 for both level 4 (cautious) and level 5 (aggressive) CAVs in a road network comprised of freeways, arterials, and collectors.

In 2016, Atkins [50] considered a CC0 value in the range of 2.50 to 0.50 for driving behaviour ranging from the most cautious to the most aggressive CAVs in a wide road network that includes urban roads and freeway segments. Correspondingly, Lee et al. categorized CAVs in a four-lane freeway segment into 9 levels of aggressiveness level, adopted from the study by Atkins [50]. Hence, Lee et al. considered it in the range from 2.50 to 0.50, where the first and second values stand for the most cautious and most aggressive driving behaviour of CAVs, respectively [51]. Similarly, Asadi et al. [52] assumed that the value of CC0 in urban roads with (un)signalized intersections and roundabouts can range from 1.50 for the most cautious CAVs to 1.00 for the most aggressive CAVs. Using a genetic algorithm, Liu and Fan [53] calibrated the value of CC0 to 0.65 for CAVs in four-lane basic freeway segments. Another study by Khattak et al. [33] considered a higher value of CC0, 2.64 for CAVs in a multilane freeway compared to other studies. Besides, Budan et al. [54] assumed a value ranging from 1.0 to 0.5 for the simulation of CAVs on urban road intersections.

In 2018, Rossen [27] used a value of 1.00 for both AAVs and CAVs to assess the impacts of these vehicles on the capacity of different freeway segments (basic freeway, merging, diverging, and weaving) using a comprehensive survey of related works in the literature. What is more, 1.0 is used for CAVs in urban road intersections [55–57] and in network-wide simulations [58].

3.2. CC1: Headway Time (s). CC1 is the desired time distance a driver wants to keep; this parameter controls the time distribution of the speed-dependent part of the desired safety distance. In the high volume of traffic, CC1 is the most significant parameter influencing capacity and safety distance. The default value is 0.90 [36].

For AAVs in a signalized intersection and roundabout, Morando et al. adopted a CC1 value of 0.50 and 0.45 for each road type considered from the preceding published literature to assess the impact of two sets of AAVs' driving behaviour [42].

In 2015, Bohm and Häger, adopting from the study [40], considered a value of 0.50 for the simulation of AAVs in a network-wide traffic system [41]. The studies [6] assumed 0.50 for simulating AAVs in urban road intersections, adopted from preceding published articles. Furthermore, Lee et al. [44] calibrated the value to 0.6 for the simulation of AAVs on merging freeway segments.

After looking over the existing literature, He et al. simulated CAVs with a CC1 value of 0.50 in their study to assess CAVs' impact on a freeway weaving segment [25]. In the same way, Tomás et al. considered a value of 0.50 in their study targeted at the investigation of the environmental impacts of AAVs on urban roads [5]. Besides, Motamedidehkordi et al. used a CC1 value of 0.50 for simulating connected highly AVs in a freeway network after comparing several values in the literature [38].

Some studies considered a slightly smaller CC1 compared to the above-cited literature. Thus, the studies [37, 59] considered 0.30 for the simulation of CAVs in an urban traffic system based on the proposed value from an experimental study [60]. Likewise, in 2018, Stanek et al. assumed a CC1 value of 0.25 to estimate AAVs' impact on congested road networks to attain a headway (front bumper to front bumper) of 0.50 seconds between consecutive vehicles at a speed of 80 km/h [32].

In 2018, Rossen [27] designated a CC1 value of 0.90 for AAVs and 0.50 for CAVs for different categories of freeway configuration covering basic freeway, merging, diverging, and weaving segments after investigating diverse works in the literature. In 2020, Rafael et al. [26] simulated AAVs on urban roads with a CC1 value of 1.0, citing previously published research articles. Studies [43, 45] suggested a CC1 value of 0.45 in their study on the impacts of AAVs on motorways while studies [55–58] assumed a value of 0.5 for simulating CAVs' impact on urban roads. Moreover, Tafidis [49] calibrated the value to 0.5 for both cautious and aggressive AAVs on the urban road network.

In some studies, CC1 has been considered differently. Researchers considered it based on the aggressiveness level of AAVs and CAVs. They revealed that aggressive AVs have a lower CC1 value than cautious AVs. Accordingly, a CC1 value in the range of 1.80 for the most aggressive CAVs to a minimum of 0.60 for the most cautious was considered for CAVs for a road network with diverse geometric elements in the study [50]. In 2019, adopting from the study [50] but with a wider range, Lee et al. used corresponding CC1 values that range from 2.10 to 0.50 for assessing CAVs with nine categories of aggressiveness level on a four-lane freeway [51]. Likewise, Asadi et al. adjusted the value of CC1 and can range from 1.50 for the cautious to 0.50 for the most aggressive CAVs in urban roads consisting of (un)signalized intersections

Table 2: Values of lane-changing and lateral behavior parameters calibrated in the literature.

Ref.	AV type	Road type	MinHW (m)	SDRF (−)	MaxDCB (m/s^2)	CLC: maximum speed difference (km/h) and collision time (s)	OSL: minimum lateral distance standing and driving at 50 km/h (m)
Default	CV	—	0.50	0.60	−3.00	Unchecked	Unchecked
Default	AV cautious	—	0.50	1.00	−2.50	Unchecked	Unchecked
Default	AV normal	—	0.50	0.60	−3.00	Checked: 10.8 and 10	Unchecked
Default	AV aggressive	—	0.50	0.75	−6.00	Checked: 10.8 and 10	Unchecked
[32]	AAV	NetW	0.375	0.45	−4.00	Checked: —	Checked: 0.15 and 0.75
[7]	Cau/Agg AAV	NetW	0.80/0.20	0.70/0.10	—	—	—
[25]	CAV	WFS	0.37	0.45	−4.00	Checked: 3 and 10	Checked: 0.75 and 0.75
[5]	AAV	NetW	0.70	0.21	—	—	—
[27]	AAV/CAV	NetW	—	0.60/0.60	—	Unchecked/checked	Unchecked/unchecked
[37]	CAV	BFS/ DFS/ MFS	—	0.60/0.85/ 0.80	−3.0/−9.0/ −6.0	Yes: 3 and 10	Yes —
[50]	CAV	NetW	0.80–0.20	0.90–0.30	—	—	—
[38]	CAV	NetW	—	0.75	3.50	—	—
[33]	CAV	BFS	—	—	−7.06	—	—
[46]	Cau/Agg CAV	NetW	0.50	0.60	−3.00	—	—
[39]	AAV	NetW	—	—	−4.40	—	—
[52]	CAV	NetW	0.70–0.20	0.80–0.30	—	Yes: 10.8 and 10.0	—
[62]	CAV	NetW	0.375	0.45	−4.00	Yes:—	Yes: 0.15 and 0.50
[51]	CAV	BFS	0.80–0.20	0.90–0.30	—	—	—
[30]	AAV	NetW	0.2	0.3	—	Yes: 10.0 and 10.0	—
[48]	AAV	NetW	1.0–0.5	1.0–0.6	−2.5–−6.0	—	—
[44]	AAV	MFS	0.2	0.3	—	—	—
[58]	CAV	NetW	0.50	0.75	−6.0	Yes: 10.8 and 10.0	No
[49]	Cau/Agg AAV	NetW	0.5/0.2	—	—	—	—

NetW: network-wide; RAB: roundabouts; WFS: weaving freeway segment; BFS: basic freeway segment; DFS: diverging freeway segment; MFS: merging freeway segment; SiI: signalized intersections; Cau: cautious; Agg: aggressive; and Nor: normal.

and roundabouts [52]. Recently, in 2022, Boualam et al. [47] used a range of 1.5 to 0.6 for AAVs on roundabouts, while Postigo et al. [48] considered 1.5 to 0.7 for simulating AAVs on a motorway. Besides, Budan et al. [54] assumed a value ranging from 0.8 to 0.5 for the simulation of CAVs on urban road intersections.

In 2019, Stogios et al. [7] simulated AAVs in a road network comprised of a freeway and signalized urban streets with a CC1 value of 2.10 for the most cautious and 0.50 for the most aggressive driving behaviour adopted from preceding published articles. In the same way, Szimba and Hartmann [29] assumed a value of 0.90 and 0.50 for level 4 and level 5 CAVs, respectively, in the study area that includes freeways, arterials, and collectors. The study by Khattak et al. [33] considered a value of 1.54 for CAVs for a multilane freeway. In 2020, Liu and Fan [53], using a method of genetic algorithm, found a calibrated value of 1.2 for CAVs in four-lane basic freeway segments. In 2021, Song et al. calibrated the CC1 value to 1.70 and 0.5 for caution CAVs and aggressive CAVs for roadway networks consisting of arterial highways and secondary motorways in China [46]. Above and beyond, Rao et al. adjusted CC1 to 1.20 for simulating AAVs in freeway networks with different geometric characteristics [39].

3.3. CC2: Following Variation (m). CC2 is the parameter that limits the longitudinal oscillation; it determines how much more distance than the desired safety distance a driver allows before intentionally moving closer to the vehicle ahead. The default value is 4.0, which results in a moderately steady following [36]. Motamedidehkordi et al. considered the default value for connected highly AVs in a freeway, emphasizing the absence of related works in the literature [38]. Besides, in 2021, Rao also used the default value for simulating AVs in different freeway geometry [39].

In 2016, based on the value proposed in the study [22], Aria simulated CAVs with a CC2 value of 4.00 in basic freeway and merging segments of a freeway, while considering 5.00 for CAVs in a diverging freeway segment [37]. In 2018, Stanek et al. assumed 3.00 for AAVs in a congested road network that includes freeway interchanges and arterial corridors after reviewing related works in the literature [32]. Moreover, after broadly investigating related works in the literature, He et al. adjusted CC2 to 3.00 for CAVs simulated in a freeway weaving segment [25]. In 2021, Rezaei and Caulfield [45] suggested a value of 2.00 for AAVs on the motorway networks. Liu and Fan [53] also calibrated the value to 3.35 for CAVs in four-lane basic freeway segments via genetic algorithms.

After reviewing the related literature, Rossen designated CC2 with 2.00 for AAVs and 1.00 for CAVs simulated in different freeway segments comprising basic freeway, merging, diverging, and weaving [13, 27]. Based on the values proposed for adaptive cruise control in the study [40], Bohm and Häger used a value of 1.00 for the simulation of AAVs in the Swedish traffic system [41]. Furthermore, Deluka Tibljaš et al. [6] and Giuffre et al. [55, 56] simulated CAVs in roundabouts with a CC1 value of 1.00.

Different from the above-cited research works, some studies considered CC2 with a value of 0.0, expecting that AVs would have no variation while following. Adopted from the preceding published literature, CC2 value was adjusted to 0.0 for AVs in urban roads [26, 47, 54, 57, 58], AAVs on freeway [44, 48], CAVs in urban roads [52], and CAVs in a four-lane freeway in the study [51]. Similarly, Szimba and Hartmann modified CC2 to 0.0 for both level 4 (cautious) and 5 (aggressive) CAVs in a road network covering freeways, arterials, and collectors [29]. In addition, Morando et al. adopted two sets of CC2 values for simulating AAVs in a roundabout and signalized intersection. Hence, they used both 0.0 and 2.0 for both road types they considered [42]. Tafidis [49] considered 2.0 and 0.0, respectively, for cautious and aggressive AAVs on a network-wide simulation study.

Song et al. considered a CC2 value of 1.00 for both caution CAVs and aggressive CAVs in different road networks comprised of arterial highways and secondary motorways [46]. Besides, the value was set to 2.0 for assessing the safety impacts of AAVs on multilane freeway segments [43].

3.4. CC3: Threshold for Entering "Following" (s). CC3, with a default value of −8.00, is the number of seconds before reaching the safety distance, and it controls the start of the deceleration process. At this stage, the driver perceives a preceding slower vehicle [36]. In 2016, Motamedidehkordi et al. used the default CC3 value for assessing the impacts of connected highly AVs on a freeway congestion pattern, stating the absence of related works in the literature at the time [38]. Besides, Deluka Tibljaš et al. used the same value for simulating the introduction of AAVs in a roundabout [6]. Researchers also recommended using the default value of CC3 regardless of driving behaviour in their simulation study, comprising AAVs on motorways [45] and CAVs on urban roads [52].

In 2020, He et al. designated a CC3 value of −12.0 for simulating CAVs in a freeway weaving segment from a review of related works in the literature [25]. Adopted from formerly published literature, for AAVs in urban roads, −13.50 was considered in the study [26] and −13.54 in the study [5]. Likewise, Stanek et al. assumed a CC3 value of −12.0 for simulating AAVs in a congested road network [32]. Besides, recently in 2022, Boualam et al. [47] assumed a value ranging from −10.0 to −6.0 for AAVs on a roundabout.

In 2018, Rossen reviewed the suggested values in the existing literature and set the CC3 value to −12.0 for AAVs and −16.0 for CAVs in freeway segments that include merging, diverging, and weaving [27]. For basic freeway segments, Liu and Fan [53] calibrated the value to −13.0 for CAVs. Besides, the value was set to −6.0 for microscopic traffic simulation CAVs on roundabout [55, 56] and network-wide simulation [57, 58]. Furthermore, Budan et al. [54] assumed a value of -8.0 for the simulation of CAVs on urban road intersections.

In 2019, Stogios et al. adopted a CC3 value of −16.0 for cautious and −4.0 for aggressive AAVs that were adopted from the review of related works in the literature in their simulation-based study comprised of signalized urban corridors and freeways [7].

El-Hansali et al. [43] considered a value of −8.0 for AAVs on multilane highways. Recently, in 2022, Postigo et al. [48] assumed a narrower range, which is from −10.0 to −6.0 for simulating AAVs impacts on motorway traffic. Similarly, Song et al. considered a CC3 value to −3.33 caution CAVs and −1.00 for aggressive CAVs in different road networks comprised of arterial highways and secondary motorways [46]. Quite different from the abovementioned studies, Lee et al. set the CC3 value to 0.0 for CAVs in a four-lane freeway [44, 51].

3.5. CC4/CC5: Negative/Positive Following Threshold (m/s). Negative and positive following threshold define the negative and positive speed difference, respectively, during the following process. When the value of these thresholds is lower, the drivers' reaction to the acceleration or deceleration of the preceding vehicle will be more sensitive. The default value is −0.35/0.35 for the respective following thresholds [36]. The studies [27, 32, 45] used the software default irrespective of vehicle automation categories.

Lower CC4 and CC5 values were considered in the literature for AVs (AAVs and CAVs) due to the expectation that these vehicles are more sensitive to reacting to the preceding vehicle than human drivers are. In 2015, Bohm and Häger adopted the values proposed for adaptive cruise control in the study [40], used a value of −0.10/0.10 for AAVs in a network-wide study conducted in the Swedish traffic system [41]. Studies also calibrated CC4/CC5 values to −0.10/0.10 for AAVs in roundabouts, adopting from preceding published articles [6, 47]. Likewise, a value of −0.10/0.10 for AAVs and CAVs in the freeway segment in the studies [25, 48].

In 2020, for AAVs in urban roads, the studies [5, 26] calibrated it to −0.13/0.13 by adopting from related works in the literature. For CAVs, a CC4/CC5 value of −0.10/0.10 was considered [38, 43, 55–58]. In 2018, Budan et al. [54] assumed a value −0.05/0.05 m for the simulation of CAVs on urban road intersections. In the studies [51] for CAVs in a four-lane freeway and the studies [29, 44, 46] that simulated CAVs in a roadway with diverse geometric configuration and traffic conditions, CC4/CC5 was adjusted to 0.0/0.0.

In 2019, Stogios et al. considered a value of -0.10/0.10 for aggressive AAVs while considering −0.60/0.60 for cautious driving behaviour of AAVs based on the values proposed in formerly published articles [7]. Moreover, Morando et al. adopted a CC4/CC5 value of 0.00/0.00 and −0.10/0.10 from related works in the literature for simulating two sets of

AAVs' driving behaviour in roadways covering roundabouts and signalized intersections [42].

Differently from the aforementioned works in the literature and Vissim default, Aria used CC4 and CC5 values with different magnitudes, highlighting that the driver response is faster in deceleration than in acceleration. Thus, −0.30 for CC4 for a basic freeway segment with a corresponding CC5 value of 0.35 while considering −0.35/0.35 for CC4/CC5 value for both merging and diverging segments [37]. Similarly, in 2020, Liu and Fan [53] calibrated the value to −0.24/0.4 for CAVs in basic freeway segments. What is more, Tafidis [49] assumed a respective value of −0.1/1.0 for cautious AAVs and 0.0/0.0 for aggressive AAVs in an urban road environment with diverse geometric configuration.

3.6. CC6: Speed Dependency of Oscillation (1/(m/s)).

CC6 defines the impact of distance on speed fluctuation during the following process. Larger values lead to greater speed oscillation with increasing distance, while a value of 0.00 points out that speed oscillation is independent of distance. The Vissim default value is 11.44. [36].

Because of the nature of automated driving systems, the literature expects that there will be no significant speed variation in AAVs and CAVs. Given that, several studies considered a CC6 value of 0.00 [6, 25, 27, 32, 38, 41–44, 46–49, 51, 52, 54, 57, 58]. However, some studies considered the default (11.44) (e.g., [37] for CAVs in freeway segments consisting of basic freeway diverging and merging segments). Moreover, other studies adopted a CC6 value of 11.40 for simulating CAVs on urban roads [26] and AAVs on motorways [45]. In contrast to the above-cited works of literature, a value of 1.0 was considered for the simulation of CAVs [55, 56].

3.7. CC7: Oscillation Acceleration (m/s^2).

CC7 is the minimum value for absolute acceleration or deceleration a driver uses when following another vehicle. The default value is 0.25 [36]. Some studies [25, 32, 37, 38, 45] considered the default value.

Based on the values suggested in the study by Bierstedt et al. [40], Bohm and Häger [41] considered a CC7 value of 0.40 for AAVs in the Swedish traffic system. Recently in 2022, Postigo et al. [48] assumed a value of 0.1 for studying AAVs' impact on motorway traffic. A value of 0.4 was used for AAVs in the studies by Deluka Tibljaš et al. [6] and Lee et al. [44] to investigate the impacts of AAVs on a roundabout and a merging freeway segment, respectively. Likewise, Rossen calibrated CC7 to 0.10 for both AAVs and CAVs simulated in freeway segments that comprise merging, weaving, diverging, and basic freeway segments after reviewing related works [27]. In the studies [5, 26], 0.08 was for AAVs simulated in urban roads adopted from related works in the literature. The studies [47, 55–57] set the CC7 value to 0.1 for the impact assessment of AVs on urban road environment. Moreover, Hurtado-Beltran and Rilett [58] calibrated the value to 0.1 for network-wide assessment of CAVs' impact.

Studies also highlighted the importance of considering both cautious and aggressive driving characteristics of AVs in the calibration process of microscopic simulation in PTV Vissim. Accordingly, for the simulation of CAVs in road networks including urban corridors and freeways, Atkins used a value in the range from 0.10 to 0.40 where the first value stands for the most cautious driving behaviour [50]. Adopting from the values proposed in Atkins [50], Lee et al. also considered a CC7 value ranging of 0.05 to 0.45 for CAVs in a four-lane freeway with 9 categories of aggressiveness level ranging from most cautious to most aggressive driving characteristics where the first value stands for most cautious CAVs [51]. Likewise, Asadi et al. assumed a value ranging from 0.15 for caution to 0.45 for aggressive CAVs in urban road networks [52].

In 2019, for simulating AAVs on freeways and signalized urban roads, Stogios et al. adjusted the CC7 value to 0.05 for cautious and 0.45 for aggressive driving behaviour for each road type considered, based on the suggestions in the preceding published literature [7]. In 2021, Song et al. considered a CC7 value of 0.12 for caution CAVs and 0.45 for aggressive CAVs in different road networks comprised of arterial freeways and ancillary motorways [46]. Liu and Fan [53] calibrated the value to 0.46 for CAVs in basic freeway segments. Furthermore, Budan et al. [54] assumed a range of values from 0.3 to 0.45 for the study of CAVs at urban road intersections.

Furthermore, Morando et al. considered two sets of CC7 values for assessing AAVs' impact on a signalized intersection and roundabout. Accordingly, they adopted 0.45 and 0.25 from related works in the literature for each of the considered roadways [42]. Besides, El-Hansali et al. [43] set the value to 0.25 for studying the safety impacts of AAVs in highway network. Different from other literatures, the recent study by Rao et al. considered a higher value of CC7, 0.91, for AAVs in freeway networks [39]. Above and beyond, Tafidis [49] calibrated the CC7 value to 0.25 for cautious AAVs and 0.4 for aggressive AAVs in urban road environments with different geometric alignments.

3.8. CC8: Standstill Acceleration (m/s^2).

CC8 is the desired acceleration of a vehicle when starting from a stopped condition. The default value is 3.50 [36]. Studies also considered the default value in simulating CAVs in a freeway weaving segment [25], AAVs in congested road networks with different geometric arrangements [32], AAVs in motorways [45], and CAVs in diverse roadway configurations including merging, diverging, and straight segments [37]. Similarly, Motamedidehkordi et al. [38] considered the default value for simulating CAVs in a freeway network.

In 2018, Rossen considered a CC8 value of 3.50 for AAVs and 4.00 for CAVs in freeways containing basic freeway, merging, diverging, and symmetrical weaving segments after exploring the formerly published literature [27]. In the studies that assessed the impacts of AAVs on urban road networks, the CC8 value was calibrated to 3.72, adopted from related works in the literature [5, 26]. A CC8 value of 4.00 was considered in the studies that investigated AAVs' influence on the road network with different road segments that comprise both urban roads and freeway segments [41], roundabouts [6], and network-wide simulation [58]. Recently, in 2022, Elawady et al. [57] calibrated the value to 3.5 for studying the impacts of CAVs on urban road traffic. The studies [55, 56] calibrated the value to 3.0 for the simulation of CAVs on urban road setting with roundabout. Lee et al. [44] calibrated the value to 3.8 for the impact assessment of AAVs on a merging segments, while El-Hansali et al. [43] assumed 3.5 for analysing the safety impacts of AAVs on a highway network. Furthermore, Budan et al. [54] assumed a range of values from 3.6 to 3.9 for the simulation of CAVs on urban roads.

In contrast to the above-cited literature, Atkins used a CC8 value in the range of 3.20 to 3.80 for CAVs on roadways that comprises both urban and freeway segments, where the first value stands for the most cautious driving behaviour [50]. Considering the proposed range of values in the study by Atkin [50], Lee et al. used a value of CC8 in the range of 3.10 to 3.90 for simulating the corresponding CAVs' aggressiveness level in a four-lane freeway [51]. Furthermore, Asadi et al. used a value ranging from 3.30 to 3.90, respectively, for caution and aggressive CAVs in urban roads. On the other hand, Song et al. considered a value of 3.5 for both caution CAVs and aggressive CAVs for road segments comprising freeways with various traffic levels [46].

In 2019, Stogios et al. modified CC8 to 3.10 for cautious AAVs and 3.90 for aggressive AAVs in road segments that contain signalized urban corridors and freeway segments based on the related works in the literature [7]. Moreover, Morando et al. simulated AAVs in roundabouts and signalized intersections with two sets of CC8 values that are 3.90 and 3.50 for each roadway type adopted from the literature [42]. Above and beyond, Tafidis [49] calibrated the CC8 value to 3.5 for cautious AAVs and 4.0 for aggressive AAVs on urban road. Different from the abovementioned works of literature, studies [47, 48] assumed a wider range of values, which is from 3.0 to 4.0 for AAVs.

3.9. CC9: Acceleration at 80 km/h (m/s^2). CC9 is the desired acceleration of a vehicle at a speed of 80 km/h. The default value is 1.50 [36]. Researchers considered the default CC9 value for CAVs in freeways ([37, 38]). Stanek et al. also used the default value for AAVs in congested road networks comprising diverse geometric arrangements [32] and motorways [45]. Similarly, the default value was considered in He et al. [25] for CAVs in a freeway weaving segment and in Elawady et al. [57] for CAVs on urban road environment. For freeway merging segments, Lee et al. [44] assumed a CC9 value of 1.8 for AAVs.

In 2018, Rossen used 2.00 for both AAVs and CAVs in a diverse freeway segment covering basic freeway, merging, diverging, and weaving segments [27]. Besides, for AAVs, a value of 2.00 was considered in the studies that focused on network-wide traffic systems [41, 58], and roundabouts [6] adopted from preceding published articles. In 2020, researchers designated a CC9 value of 1.60 for simulating CAVs in an urban roads adopting from the related literature [5, 26]. Recently in 2021, Song et al. considered a value of 1.50 for both caution CAVs and aggressive CAVs for road segments comprising of freeway with various traffic levels [46]. Furthermore, Budan et al. [54] adopted a range of values from 1.6 to 1.9 for the simulation of CAVs on urban roads.

In contrast to the above-cited works of literature, Atkins used in the range of 1.20 to 1.80 for CAVs with a driving behaviour extending from most cautious to most aggressive, respectively [50]. Adopting the values from the study by Atkins, Lee et al. considered a value of CC9 in the range of 1.10 to 1.90 for the corresponding CAVs' driving behaviour in a four-lane freeway [51]. A range from 1.30 to 1.90 is also considered for CAVs in urban roads in the study by Asadi et al. [52]. Similarly, Stogios et al. considered a CC9 value of 1.10 for cautious and 1.90 for aggressive AAVs for assessing its influence on signalized urban roads and freeway traffic based on the values proposed in the preceding published literature [7]. Besides, studies [47, 48] assumed a value ranging from 1.2 to 2.0 for AAVs. Compared to the abovementioned studies, for CAVs on roundabout, Giuffrè et al. [55] and Severino et al. [56] calibrated CC9 to a smaller value, which is 0.5.

3.10. Look Settings. Look settings define the minimum and maximum distances that a vehicle can see to react to other vehicles. It includes look ahead and look back distances. Advanced vehicle communication technologies like vehicle-to-vehicle, vehicle to infrastructure, and vehicle to cloud can extend looking distances to several kilometres.

3.10.1. Look Ahead Distance (m). "Look ahead distance" is a parameter that defines the minimum and maximum distances that a vehicle can see forward within the same link to react to other vehicles in front or aside from it. The default values are a minimum of 0 and a maximum of 250 [36].

In 2016, Aria adopting from the study [61], used 150 and 200, respectively, for minimum and maximum values for CAVs in different freeway segment configurations that include autobahn, merging, diverging, and weaving [37]. Recently, in 2022, Postigo et al. [48] assumed a minimum and maximum value of 0 and 300, respectively, for studying the potential effects of AAVs on motorway traffic.

In 2015, Bohm and Häger doubled the maximum look-ahead distance for AAVs. Hence, they considered minimum and maximum look-ahead distances of 0 and 500, respectively, for simulating AAVs in a Swedish traffic system [41]. Besides, Stanek et al. adopted the values suggested in the study [41] for simulating AAVs on congested road links covering both freeway segments and roundabouts [32]. The study by Tafidis et al. also used a value of 0.00 and 500 for CAVs in intersections for the respective look ahead distances adopted from related studies [62]. In 2020, He et al. reviewed related works in the literature and calibrated the values to 0 and 500, respectively, for minimum and maximum values in simulating CAVs in a freeway weaving segment [25]. In 2021, Park et al. also adjusted the minimum value to 0 and the maximum to 500 in simulating AAVs in an urban road environment with different traffic conditions and geometric configurations, including single lane, multilane, and intersections [30]. Furthermore, Giuffrè et al. [55] and Severino et al. [56] calibrated the minimum and maximum values to 20 and 200, respectively, for the simulation of CAVs in urban road settings with roundabouts.

For simulating AAVs in a roundabout, Deluka Tibljaš et al. [6] adjusted the corresponding values to 0 and 105, specifically based on a calibration conducted for CVs in the study [63]. Furthermore, Rossen adopted respective minimum and maximum values of 150 and 200 for AAVs and 5000 and 5000 for CAVs from the related preceding published literature to assess the impacts of this emerging technology on freeway traffic consisting of merging, diverging, weaving, and straight segments [27]. The study by Asadi et al. recommended a shorter look ahead distance (800) for CAVs on urban roads [52].

3.10.2. Look Back Distance (m). "Look back distance" defines the minimum and maximum distances that a vehicle can see backward within the same link to react to other vehicles behind. The default values are minimum of 0 and a maximum of 150 [36].

In 2015, Bohm and Häger doubled the largest lookback distance for AAVs. Hence, they considered a minimum and maximum look ahead distance of 0 and 300, respectively, for simulating AAVs in a Swedish traffic system [41].

Based on the values suggested in the study by Bohm and Häger [41], Stanek et al. [32] considered it to be 0 and 299 m (980 feet), respectively. For simulating AAVs on a congested road link. Besides, recently in 2020, He et al. reviewed related works in the literature and calibrated the values to 0 and 500, respectively, for minimum and maximum values in simulating CAVs in the freeway-weaving segment [25]. For AAVs in roundabouts, Deluka Tibljaš et al. adjusted the corresponding values to 0 and 280 specifically based on a calibration conducted for CVs in the study [6, 63]. Recently, in 2022, Postigo et al. [48] adopted a minimum and maximum values of 0 and 150, respectively, for simulating the effects of AAVs on motorway traffic. Furthermore, Giuffrè et al. [55] and Severino et al. [56] calibrated the minimum and maximum values to 20 and 200, respectively, for the simulation of CAVs on urban road settings with roundabouts.

In 2016, Aria adopting from the study [61], considered 150 and 200, respectively, as minimum and maximum values for CAVs in different freeway segments that include autobahn, merging, diverging, and weaving [37]. The study by Tafidis et al. adopted a value of 0 and 300 for CAVs in intersections to the respective look back distances adopted from related studies [62]. The study by Asadi et al. also recommended a look back distance of 800 m for CAVs in urban roads [52]. Likewise, Rossen adopted respective minimum and maximum values of 150 and 200 for AAVs and 5000 and 5000 for CAVs from related works in the literature to assess the impacts of these vehicles on freeway traffic consisting of merging, diverging, weaving, and straight segments [27]. Furthermore, Park et al. set the minimum value to 0 and the maximum to 500 for AAVs in urban road networks [30].

3.10.3. NOV: Number of Observed Vehicles (−). This parameter defines how well the vehicles within the link can predict other vehicles' movements and react accordingly. The default value is 2 in the Wiedemann 99 car-following model [36].

Several studies considered a value of 10 for this simulation parameter. It might be from the fact that the maximum number of vehicles possibly added was limited to 10 in the earlier version of the PTV Vissim software. In 2015, Bohm and Häger assumed 10 for simulating AAVs in the Swedish traffic system [41]. The study by Stanek et al. considered the values proposed by Bohm and Häger for investigating AAVs' impact on congested road segments consisting of diverse geometric configurations [32]. Besides, in 2018, Morando et al. used two sets of values that are 10 and 2 for AAVs in both a signalized intersection and a roundabout to study how this disruptive technology affects the road sections examined [42]. Lee et al. [44] also assumed a value of 10 for AAVs on merging freeway segments.

A thought-provoking study conducted by Lee et al. assumed NOV to be 10 for simulating CAVs at a different aggressiveness level in a four-lane freeway [51]. Studies also considered a value of 10 for CAVs in urban roads comprising different geometric configurations [49, 52, 55, 56, 62].

In 2018, Rossen investigated the impacts of AVs on freeway segments containing merging, diverging, weaving, and straight sections. They considered a number of observed vehicles of 8 for AAVs and 10 for CAVs adopted from the review of related works in the literature [27].

4. Lane-Changing and Lateral Parameters

This section investigates the PTV Vissim lane changing and lateral parameters, including minimum headway (MinHW), safety distance reduction factor (SDRF), maximum deceleration for cooperative braking (MaxDCB), cooperative lane change (CLC), and overtaking on the same lane (OSL), that have been calibrated for different types of AVs in the literature. Table 2 presents a summary of the calibrated values from the literature.

4.1. MinHW: Minimum Headway (Front and Rear) (m). It defines the minimum distance between two vehicles that should be available after a lane change so the change can take place. A greater headway might be required in normal traffic flow conditions to keep the speed-dependent safety distance. The default value is 0.50 [36]. In 2021, Hurtado-Beltran and Rilett [58] assumed the default value for simulation of CAVs on roadways with diverse geometric configurations.

In 2018, Stanek et al. assumed a MinHW value of 0.375 for simulating AAVs in congested road links encompassing different geometric configurations [32]. In 2019, Tafidis et al. also used the value assumed by Stanek et al. to assess the impacts of CAVs on urban road intersections [62].

In 2020, Tomás et al. used a value of 0.70 for AAVs in urban freeways based on the proposed values in preceding published articles [5]. Besides, after investigating the existing literature, He et al. adjusted MinHW to 0.37 for CAVs in a freeway weaving segment [25].

In 2016, Atkins used a value in the range of 0.80 to 0.20 for CAVs on a roadway that comprises both urban and freeway segments where the first value stands for the most cautious driving behavior [50]. For simulating CAVs in a four-lane freeway, Lee et al. also considered the same range of MinHW values suggested by Atkins for the corresponding aggressiveness [51]. The study by Asadi et al. considered a smaller range compared to preceding studies. Asadi et al. assumed a value ranging from 0.70 for caution CAVs to 0.20 for aggressive CAVs in urban road environments [52]. In 2021, Park et al. [30] set the value of MinHW to 0.20 for AAVs in urban road environment, while Lee et al. [44] considered the same value for AAVs in merging freeway segments. Recently in 2022, Postigo et al. [48] considered a value in the range of 1.0 to 0.5 for AAVs in motorways.

In addition, Stogios et al. considered a minimum headway of 0.80 for cautious AAVs and 0.20 for aggressive AAVs in a road network comprising urban signalized corridors and freeways [7]. However, Song et al. considered the same value, 0.50, for both caution CAVs and aggressive CAVs in different roadway geometries [46]. In addition, Tafidis [49] calibrated the value to 0.5 for cautious AAVs and 0.2 for aggressive AAVs in an urban road environment.

4.2. SDRF: Safety Distance Reduction Factor (-). “SDRF” reflects a reduction in the safety distances associated with vehicles involved in the lane-changing manoeuvre. When the lane change is accomplished, the original safety distance is considered once more. A smaller value results in more aggressive lane-changing behaviour. The default value is 0.60, which results in a 40% reduction in safety distances [36]. Rossen used the Vissim default SDRF value for both AAVs and CAVs simulated in different freeway segments, including merging, diverging, weaving, and straight segments [27]. Besides, recently in 2021, Song et al. considered the same value, 0.60, for both caution and aggressive CAVs in a road network with different geometric settings [46].

In 2016, Aria considered an SDRF value of 0.60 for a basic freeway, 0.80 for merging, and 0.85 for diverging segments for CAVs based on the proposed value in the study [22, 37]. The study by Tafidis et al. considered 0.45 for CAVs in urban intersections, adopting from preceding published articles [62]. Besides, studies assumed a value of 0.75 to simulate CAVs in diverse roadway configurations [38, 58].

In 2020, Tomás et al. simulated AAVs on urban roads considering an SDRF value of 0.21 based on the values proposed by preceding published research works [5]. Moreover, He et al. designated a value of 0.45 for CAVs in freeway weaving segments after reviewing several works in the literature [25].

Differently from the above-cited literature, Atkins considered the SDRF in the range of 0.90 to 0.30, where the first one stands for the most cautious and the second one for the most aggressive CAVs [50]. In 2019, Lee et al. adopted the same ranges of SDRF to the study [50] for the respective driving aggressiveness level of CAVs in a four-lane freeway segment [51]. Correspondingly, Asadi et al. calibrated the value in the range of 0.80 to 0.30 for CAVs in urban road environments [52]. Similarly, Stogios et al. designated a value of 0.70 for cautious AAVs and 0.10 for aggressive AAVs in their study that assessed influence of these vehicles on road links consisting of freeway segments and signalized urban corridors [7]. Recently, in 2022, Postigo et al. [48] considered a narrower range, which is from 1.0 to 0.6 for AAVs in motorways. On the other hand, Park et al. [30] set the value of SDRF to 0.30 for AAVs in urban road settings, while Lee et al. [44] assumed the same value for AAVs on merging freeway segments.

4.3. MaxDCB: Maximum Deceleration for Cooperative Braking (m/s^2). “MaxDCB” is a parameter that defines the maximum deceleration the trailing vehicle driver will accept for cooperation to help the lane-changing vehicle perform its manoeuvre. A higher value means a strong brake and has a high likelihood of lane changing. The default value is −3.00 [36].

In 2016, Motamedidehkordi et al. assumed a value of −3.50 for connected highly AVs in freeways [38]. Similarly, Tafidis et al. adopted −4.00 for simulating CAVs in urban intersections from related works in the literature [62]. Aria assigned MaxDCB varying with types of freeway segment based on the proposed values in the study [22]. Hence, Aria considered −3.00, −6.00, and −9.00 for CAVs in basic freeway, merging, and diverging segments, respectively [37]. Furthermore, in 2021, Hurtado-Beltran and Rilett [58] calibrated the value of MaxDCB to -6.0 for simulating CAVs’ impact on a roadway with a diverse geometric configuration.

In 2020, He et al. used −4.00 for CAVs in a weaving freeway segment after reviewing related works in the literature [25]. Likewise, Stanek et al. considered −4.00 for AAVs in congested road networks covering both urban and freeway road segments [32], while a value of −4.40 is used for AAVs in freeway segments with different geometrical configurations [39]. Recently, in 2022, Postigo et al. [48] set the value from the range of −2.5 to −6.0 for studying AAVs’ impact on motorways.

Recently, Song et al. adjusted the value to −3.00 for both caution and aggressive CAVs in different roadway geometries [46]. The study by Khattak et al. [33] considered −7.06 for CAVs in multilane freeway segments.

4.4. CLC: Cooperative Lane Change (-). This parameter stipulates the circumstances in which the trailing vehicle in the target lane will try to move to another side to create room for the lane-changing vehicle. The vehicle executes the cooperative lane change if the defined maximum speed difference and maximum collision time are not surpassed. The default in PTV Vissim is unchecked [36].

In 2016, Aria et al. activated CLC for CAVs with a maximum speed difference set to 3.0 km/h and a maximum collision time of 10.0 seconds [59]. Other studies also activated this parameter and used the default maximum speed difference (10.0 km/h) and maximum collision time (10 seconds). These include the study by Stanek et al. to evaluate the impacts of AAVs on congested road links [32], the study by Tafidis et al. to assess the impacts of CAVs on urban road intersections [62] and Park et al. in the assessment of AAVs' impact on urban road networks [30]. On the other hand, studies [52, 58] considered a maximum speed difference of 10.80 km/h and a maximum collision time of 10 seconds for CAVs in road environments that comprise (un)signalized intersections and roundabouts.

4.5. OSL: Overtake on the Same Lane (−). When modelling traffic that is not lane bound, it is possible to allow vehicles to overtake within the lane that can be defined via OSL. Vehicles can overtake in the lane to the left or to the right. The default is unchecked [36]. Hurtado-Beltran and Rilett [58] considered the default value for simulation of CAVs in a roadway network with diverse geometric configurations.

In 2013, Chiang and Chan simulated autonomous vehicles on a java virtual machine using an algorithm that was used to overtake in the same lane (left and right) when the safety requirements are fulfilled [64]. Furthermore, Aria et al. activated OSL for CAVs in freeway segments including merging, diverging, and basic freeway, considering 0.15 m and 0.50 m for minimum lateral distance standing and minimum lateral distance driving at 50 km/h, respectively [59].

In 2018, Stanek et al. [32] activated OSL with a minimum lateral distance of 0.15 m and a minimum lateral distance of 0.75 m, respectively. Similarly, Tafidis et al. activated it and used 0.15 m and 0.50 m for the respective distances for CAVs in urban road intersections, adopted from the preceding published literature [62]. Above and beyond, in a recent study in 2020, He et al. used activated OSL for CAVs in freeway weaving segment with the same value (0.75 m) for both minimum lateral distance standing and minimum lateral distance driving at 50 km/h adopted after a review of related works in the literature [25].

5. Discussion

The microscopic traffic simulators play a crucial role in modelling complex traffic behaviours while maintaining computational efficiency. PTV Vissim is one of the most popular traffic simulators, which is a discrete, stochastic, time-step-based, microscopic model with the driver-vehicle unit considered as a single entity. Vissim uses the psychophysical car-following model, which is a model that involves psychological activities (e.g., unconscious car-following and perception-reaction thresholds) and physical activities (e.g., accelerating and decelerating efforts) [65]. Car-following, lane-changing, and lateral behavior are the most important constituents of the simulation models that directly affect vehicle interaction in the network and are vital to mimicking the real-world traffic stream. The PTV Vissim software provides default values for the simulation parameters that can be used as a basis for the simulation of scenarios that reflect the actual vehicular traffic on a roadway with diverse geometric configurations. Nonetheless, the calibrated values for the simulation of automated vehicles (AVs) varied in different literature as AVs are not in traffic yet.

In the literature, different driving behaviours of AVs have been assumed; for example, they can be grouped as cautious and aggressive [7, 50, 51] based on the levels of automation, where level 5 represents the most aggressive AVs. AVs can be further clustered as cooperative/connected AVs (CAVs) and autonomous (without communication capability) AVs (AAVs) [12, 11]. What is more, the types of roadway have a significant impact on the driving characteristics of AVs, as the study [22], for example, showed that vehicles are more conservative on basic freeways than on merging and diverging freeway segments. Several types of roadways have been studied in the literature, including basic freeway segments [27, 51], merging freeway segment [27, 44], diverging freeway segment [25], weaving freeway segment [27, 59], signalized intersections [54, 57], roundabouts [55, 56, 63], and network-wide simulations that include a variety of roadway elements [32, 37, 41].

The comprehensive literature review shows that there is a variation in the assumptions of car-following, lane-changing, and lateral behaviour parameters among the works of the literature as well as the one suggested in the latest version of PTV Vissim. Over all considering the car-following parameters CC0 and CC1, the literature assumed that cautious AVs have a higher values than the conventional vehicles (e.g., [7, 46, 52]) which means that at lower automation and uncertain operation design domain AVs perform less than the conventional vehicle traffic. Furthermore, PTV Vissim 2020 suggests the same value of CC0 for both cautious AVs and normal AAVs while recommending a lower value for aggressive AVs. Regarding CC2, which is a parameter that limits the longitudinal oscillation of a vehicle compared to the one in front, PTV Vissim suggested a value of 0.0 as vehicle automation can remove oscillation. Nonetheless, most of the studies assumed values ranging from 0.0 to 4.0. In comparison to other car-following settings, the values proposed for CC3, CC4, CC5, CC6, CC7, CC8, and CC9 vary relatively slightly across works of the literature and the default value provided by the software (see Table 1). In terms of look ahead distance (LAD) and look back distance (LBD), the literature expected that LAD would be larger for AVs than for normal cars, but the software assumed that LBD is independent of vehicle automation. Furthermore, as shown in Table 2, the literature considered that vehicle automation and connectivity resulted in a lower minimum headway (MinHW) for aggressive AVs and a higher value for cautious AVs despite the fact that the PTV Vissim assumed that they could have the same value as conventional vehicles. Similarly, the calibration value of safety distance reduction factor (SDRF) and maximum deceleration for cooperative breaking (MaxDCB) varies among the works of literature as well as with the software default. Above and beyond, cooperative automated vehicles are assumed to have the capability for cooperative lane-changing overtaking on the same lane (e.g., [12, 27, 37, 59]).

Table 3 shows the types of AVs assessed through the PTV Vissim internal model along with the corresponding study area, Vissim parameters, evaluation criteria, and main findings of the studies included. In this paper, the literature findings on the potential effects of AVs on traffic flow

Table 3: Existing studies on simulations of AVs in different types of roadways through the PTV Vissim internal model.

Study	Study area	Type of AVs	Vissim parameter	Market penetration (%)	Criteria	Main findings
[41]	Urban roads, intersections, roundabout, and highway stretches	AAV	CF	100	Traffic performance	Speed is raised by 34%, while delays and number of stops are decreased by 56% and 54%, respectively.
[37, 59]	Autobahn, merging, and diverging	CAV	CF, LC, LB	100	Traffic performance	100% AVs enhanced speed by 8.5% while decreasing density and travel time by 8.1% and 9.0%, respectively, in congested traffic.
[50]	Urban roads and highways	CAV: Cautions, aggressive	CF, LC	100	Traffic flow	Until a high degree of automation and connectivity features is attained, automation may not significantly improve capacity and traffic performance.
[6]	Roundabout	AAV	CF	10, 25, 50	Safety	Conflicts occur more frequently when AVs are present; however, the rate of increase is very mild.
[38]	Freeway network	CAV	CF, LC	5, 10, 20, 50	Capacity	As the market penetration of CAVs rise, a capacity of the entire motorway system will increase by up to 30%.
[42]	Signalized intersection and roundabout	AAV	CF	25,50,75,100	Safety	AVs can reduce the number of conflicts at signalized junctions and roundabouts by up to 65% and 64%, respectively, with a 100% penetration rate.
[27]	Freeway segments	AAV; CAV	CF, LC, LB	8.5, 42.5, 76.5, 85	Capacity	At a low-market share, vehicle automation is expected to reduce capacity, but at a 100% market share, it will enhance capacity by a range of 10 to 20%, with CAVs showing the greatest improvement.
[32]	Freeway, arterial corridors, and intersections	AAV	CF, LC, LB	10, 30,50,70,90,100	Traffic performance	With a higher market penetration, AAVs can reduce delay by 30–33% while increasing speed by 6%–23%.
[62]	Urban road intersections	CAV	CF, LC	20,40,60,80,100	Traffic performance	The performance of uncontrolled junctions was more significantly improved by the deployment of CAVs.
[51]	Four-lane freeway	CAV	CF, LC	10–90 with an increment of ten	Traffic performance, safety	These findings show that cautious CAV manoeuvering might be detrimental to the traffic stream.
[7]	Freeway with diverse geometric segments: Signalized urban corridor	AAV: cautions; aggressive	CF, LC	10, 30, 50, 70, 90, 100	Traffic performance, emissions	Cautious AAVs could worsen traffic efficiency (e.g., at 100% market share, cautious AAVs result in an increase in emissions by 35%, while a 26% reduction is expected for aggressive AAVs at 100% market share).
[25]	Freeway: Weaving segment	CAV	CF, LC, LB	1, 3, 5, 7, 10	Speed	At low-market share, CAVs have no significant impact on the traffic speed.

Table 3: Continued.

Study	Study area	Type of AVs	Vissim parameter	Market penetration (%)	Criteria	Main findings
[26]	Urban road	AAV	CF	30	Air quality	The AAVs encouraged a rise in both NOx and CO2 emissions (+1.8% and +0.7%, respectively), whereas the electric AAVs scenario resulted in emission reductions of roughly 30% for both air pollutants.
[29]	Freeway, arterial, collector	CAV: cautious, aggressive	CF	100	Travel time	Travel time can be reduced by in the range of 20–27%, with the highest benefit from aggressive CAVs.
[5]	Urban freeway	AAV	CF, LC	10, 20, 30	Traffic performance, emissions	According to a route level analysis, AAVs can reduce emissions by 5% while increasing travel time by up to 13%.
[33]	Freeway	CAV	CF, LC	100	Throughput	CAVs led to a throughput improvement of up to 18.4%.
[53]	Four-lane freeway	CAV	CF	10–100 with an increment of ten	Capacity	If AVs' market share is less than 40%, it will have a detrimental effect on the capacity. However, if the AV market share exceeds 40%, capacity will be increased.
[45]	Hypothetical motorway	AAV	CF	10–100 with an increment of ten	Traffic performance.	With a rise in the share of AVs up to a certain level, the quality of traffic improves. For example, shared lane with 60% AVs may be just as effective as one with 100% AV traffic.
[30]	Urban road network	AAV	CF, LC	20, 40, 60, 80, 100	Capacity, travel time, delay, speed.	As AV penetration increased, the average delay time was reduced by up to 31%, and at 100% market share, capacity could be enhanced by 40%.
[39]	Freeway with diverse geometric segments	AAV	CF, LC	10–100 with an increment of ten	Traffic performance	There is a set of ideal behavioural patterns for AV flows to cooperate with CV flows via the V2X features at each level of AV penetration to enhance the capacity and reduce congestion.
[52]	Urban road	CAV	CF, LC	0–25	Traffic performance	Despite the increase in their market share, the increased lane discipline brought on by CAVs may provide significant advantages and reduce the congestion issue.
[46]	Arterial and secondary motorway	CAV	CF, LC	20, 40, 60, 80, 100	Traffic performance and CO_2 emissions.	As the rate of CAV penetration rises, AVs will have a greater impact on reducing CO_2 emissions and traffic efficiency overall.
[47]	Roundabout	AAV	CF	20, 40, 60, 80, 100	Capacity	The 20% and 40% AVs in the flow would raise capacities by around 10% and 20%, respectively.
[48]	Freeway network	AAV	CF, LC	20, 40, 60, 80, 100	Throughput, delays	AVs with more cautious driving logic predominate, there is a considerable influence on delay times and a drop in vehicle throughput.

Table 3: Continued.

Study	Study area	Type of AVs	Vissim parameter	Market penetration (%)	Criteria	Main findings
[55]	Turbo roundabout	CAV	CF, LC	10, 25	Safety	Reduced conflict points by 70% and 83% are expected for CAVs with market penetrations of 25% and 10%, respectively.
[56]	Flower roundabout	CAV	CF, LC	25	Safety	Number of crashes can be eliminated with the introduction of CAVs.
[44]	Merging freeway segment	Level 4 AAV	CF, LC	20, 40, 60, 80, 100	Speed	Up to a market share of 80%, the traffic performance benefit of AAVs is negligible and the average speed was around 33% lower when a lane was dedicated to AAVs.
[58]	Network-wide	CAV	CF, LC	10–100 in 10% increments	PCU estimation	Compared to non-CAV trucks, CAV trucks have PCUs that are, on average, 34.3% lower.
[43]	Multilane freeway	AAV	CF	100	Safety	Approximately, 12% fewer accidents occurred at 100% AAVs compared to conventional vehicle scenario.
[54]	Unsignalized four-way intersection	CAV	CF	10,25,50,75,90,100	Traffic flow, fuel consumption	Average vehicle delays were reduced by over 96%, and fuel usage dropped by up to 37%.
[49]	Urban road network	CAV	CF, LC	25,75	Traffic flow	Conflict points and crash severity were decreased by up to 2.6 times due to AAVs.
[57]	Signalized four leg intersections	CAV	CF	25, 50, 75, 100	Delay, safety	CAVs has the potential of up to 35% decrease in accidents and an 8% improvement in travel time.

CF: car-following; LC: lane changing; LB: lateral behaviour; PCU: passenger car unit.

characteristics, safety, emissions, and energy consumption are reviewed, and it is concluded that AVs, as their market penetration increases, promisingly improve road traffic performance when aggressive driving logic is assumed. However, the long-term effects of AVs, especially on energy consumption and emissions, have uncertainty, and they may have a negative impact in the scenario of heterogeneous and low-market penetration rates. Nevertheless, the findings showed that CAVs have better traffic performance than AAVs.

6. Conclusions and Future Studies

Currently, impact assessment of different types of automated vehicles (AVs), autonomous automated vehicles (AAVs), and cooperative automated vehicles (CAVs) on traffic flow has received immense interest from researchers due to their potential mobility benefit over conventional vehicles (CVs). There are different methods used in the literature to assess the impact of AVs. Microscopic simulation is one of the most popular methods used to investigate the traffic flow impacts of AVs as these vehicles, currently, are not widely available within the traffic system. PTV Vissim is widely used in the literature for AVs impact assessment.

The current paper attempted to investigate how PTV Vissim has been calibrated for the simulation of different types of AVs and compare the calibrated values in the literature with the default values introduced in the most recent version of this software, PTV Vissim 2020. PTV Vissim 2020 comprises new features including platooning, enforcing absolute braking distance, implicit stochastics, a number of interaction objects that helps to model AVs in microscopic traffic simulation. This paper considers the car-following, lane-changing parameters, and lateral parameters.

Our findings write down, in the literature, the calibration of PTV Vissim parameters centres on assumptions from the preceding literature and technological expectations. In general, the literature expects a lower value for the parameters CC0, CC1, CC2, CC3, CC4, CC6, CC7, SDRF, and MinHW while expecting a higher value from the parameters including CC8, CC9, looking distances, and MaxDCB for all types of AVs with a full automation level comparing to values of parameters for CVs. However, when conservative AVs with more safety considerations than CVs are introduced to road transportation, deterring effects are expected in the literature (e.g., a higher CC0 and CC1 while a lesser CC8 and CC9 values). Moreover, the communication feature in CAVs can help them to have higher looking distances compared with AAVs.

In some cases, the literature expects a different setup of simulation parameters from the one suggested by PTV Vissim. For example, considering the SDRF value proposed for aggressive AVs, the literature expects a value smaller than the default while the PTV Vissim suggested a higher value for this parameter. Moreover, the suggested values in PTV Vissim 2020 showed that MinHW is independent of vehicle automation and aggressiveness level. However, the literature expects a lesser value of MinHW for aggressive AVs while expecting a higher value for cautious AVs.

The results from the current study show that the impact assessment of different types of automated vehicles is still in its beginning phase, consisting of various uncertainties. Even though the literature related to internal Vissim models such as car-following, lane-changing, and lateral behavior of AVs, further studies should extend the calibration of different microscopic traffic simulators and compare the sensitivity of each simulation parameter.

Disclosure

The preprint version of this publication has been added to the ResearchGate [66] in order to make the study open and transparent. The authors cited it in this publication and will update the ResearchGate link pointing to the published version.

Conflicts of Interest

The authors declare that there are no conflicts of interest about the publication of this paper.

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