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Review Article

Simulation-Based Connected and Automated Vehicle Models on Highway Sections: A Literature Review

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This study provides a literature review of the simulation-based connected and automated intelligent-vehicle studies. Media and car-manufacturing companies predict that connected and automated vehicles (CAVs) would be available in the near future. However, society and transportation systems might not be completely ready for their implementation in various aspects, e.g., public acceptance, technology, infrastructure, and/or policy. Since the empirical field data for CAVs are not available at present, many researchers develop micro or macro simulation models to evaluate the CAV impacts. This study classifies the most commonly used intelligent-vehicle types into four categories (i.e., adaptive cruise control, ACC; cooperative adaptive cruise control, CACC; automated vehicle, AV; CAV) and summarizes the intelligent-vehicle car-following models (i.e., Intelligent Driver Model, IDM; MICroscopic Model for Simulation of Intelligent Cruise Control, MIXIC). The review results offer new insights for future intelligent-vehicle analyses: (i) the increase in the market-penetration rate of intelligent vehicles has a significant impact on traffic flow conditions; (ii) without vehicle connections, such as the ACC vehicles, the roadway-capacity increase would be marginal; (iii) none of the parameters in the AV or CAV models is calibrated by the actual field data; (iv) both longitudinal and lateral movements of intelligent vehicles can reduce energy consumption and environmental costs compared to human-driven vehicles; (v) research gap exists in studying the car-following models for newly developed intelligent vehicles; and (vi) the estimated impacts are not converted into a unified metric (i.e., welfare economic impact on users or society) which is essential to evaluate intelligent vehicles from an overall societal perspective.

1. Introduction

With the advancement of the intelligent driving assistance system (IDAS), automobile drivers are becoming less required to perform simple driving tasks. An early stage of the IDAS is a cruise control (CC) system, and this evolves toward adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) systems. These systems mainly assist an acceleration control for longitudinal movements based on the gap distance and speed difference between preceding and current vehicles. In the meantime, connected and automated vehicles (CAVs) have gained increasing attention accompanied by tremendous investments from both public and private sectors [1, 2].

Self-driving (automated) vehicles could play a significant role in the future transportation system. Since this revolutionary concept was first introduced in 1920s, the CAV technology has evolved drastically over the last several decades. Despite the uncertainty as to when the CAV technologies will be publicly available, they will likely have enormous impacts on our transportation systems over the upcoming decades [3–8].

As of April 2009, Google's self-driving cars (Waymo) have been driven over eight million miles using a variety of platforms [9, 10]. Numerous manufacturers—including Audi, BMW, Cadillac, Ford, GM, Mercedes-Benz, Nissan, Toyota, Volkswagen, and Volvo—have begun testing automated vehicles, and they aim to sell such vehicles by 2020 [11, 12]. Meanwhile, partially automated vehicles are now available. The current models are equipped with ACC, collision avoidance, parking assist systems, and lane departure warning features [10, 13].

Researchers acknowledge that the development of CAVs will generate significant changes in our daily life and society as a whole. To estimate the impacts of CAVs, the vast majority

of researchers have been conducting a simulation-based analysis because (i) the real field data on the CAV's performance are limited [14–16] and (ii) many studies deal with high market shares for CAVs [17–19], which is hypothetical, far from the current reality. It is crucial to understand the impacts of CAVs early in their development to avoid costly mistakes before their widespread implementation.

We can broadly categorize simulation-based studies into micro and macro models according to a network scale and fundamental models of the simulation. Most of the micro simulation based studies reviewed in this paper develop their own ACC, CACC, AV, or CAV car-following models to estimate the impacts of these intelligent vehicles. That is primarily because no car-following model had existed to adequately describe the car-following characteristics of intelligent vehicles. Such studies develop the commonly used car-following models, e.g., IDM [20] and MIXIC [21], to mimic intelligent-vehicle characteristics. On the other hand, macro simulation model needs a traffic assignment procedure which can be applied by using activity-based models [22–25] or modified traditional four-step models [5]. Moreover, each simulation study has applied a different approach and examined a distinct performance measure(s) (e.g., micro stability, throughput, acceleration, and headway profiles; macro link traffic volume, link travel time, etc.). In this review paper, we focus mainly on the micro simulation based studies considering longitudinal dynamics.

There have been many newly developed car-following models to analyze the impacts of the intelligent (ACC, CACC, AV, and CAV) vehicles. However, the concepts of the intelligent vehicles, terminologies, vehicle performances, and evaluation criteria vary depending on the research topic. To the best of our knowledge, there have been no review studies summarizing the simulation-based intelligent-vehicle studies and their impact analyses. The primary contributions of this study are (i) to define intelligent-vehicle types with the hierarchical classification; (ii) to offer a summary of the simulation-based intelligent-vehicle studies and its impact; (iii) to discuss the implications from the previous literature and the limitations of previous studies.

The remainder of this paper is structured as follows. In the following section, we define the most commonly used intelligent-vehicle types and propose hierarchical classifications. Section 3 reviews intelligent-vehicle studies and introduce the commonly used car-following models for intelligent vehicles. The intelligent-vehicle's impacts and previous studies' limitations are described in Section 4. The paper concludes with key implications/lessons learned from the review results and our suggestion regarding potential future studies.

2. Intelligent-Vehicle Classifications and Definitions

Figure 1 illustrates the definitions of four key intelligent-vehicle types with the hierarchical classification reporting the related studies for each category, incorporating the sensing and communications of intelligent vehicles. The ACC is an advanced version of the earlier CC system. The primary function of the CC vehicle is to maintain a desired speed set by a driver. On the other hand, the ACC vehicle controls an acceleration based on a distance gap and a speed difference between preceding and current vehicles. In addition, the ACC systems can appropriately accelerate and decelerate with regard to preceding vehicles' speed changes. The CACC system includes a communication function, compared to ACC, that shares the acceleration, deceleration, a breaking capability, and vehicle positions through vehicle to vehicle (V2V) communications [26]. The communication allows the CACC vehicle to have a significantly shorter time headway (i.e., 0.5 seconds) compared to the ACC (i.e., 1.4 seconds). Moreover, the parameters are shared among the CACC-platooned vehicles, so, theoretically, they do not need to guarantee the minimum safety distance. Many previous studies show that CACC has the potential to improve both the traffic flow [27] and the string stability [28]. The CACC system is not commercially available for now but has been discussed in many studies due to its potential capacity increase under platoon driving. The IDAS's ultimate goal is that humans do not need to control vehicles at all. The USDOT [26] defines the fully automated vehicle as the vehicle capable of full-time automated driving under any road and environmental conditions, while CAVs contain all AV functions with the V2V and V2X functions. For highway sections, one of the key differences between CACC and CAV might be an automated lateral movement. Most of the CACC studies assume the lateral movement is made by human drivers. The above-mentioned vehicle concepts are completely new compared to the conventional car-following movements developed for human-driven vehicles. Therefore, the related terminologies and concepts in the reviewed literature varies and are not firmly classified.

We categorize the literature according to the intelligent-vehicle types. Such studies often use mixed definitions of the intelligent-vehicle types. Therefore, we define the intelligent-vehicle types used in each study and group them in the appropriate category.

3. Connected and Automated Vehicle Simulations

3.1. Simulation-Based Intelligent-Vehicle Studies. Tables 1 and 2 show the studies reviewed in this paper focusing on the simulation-based intelligent-vehicle modeling studies and their impact analyses. The review result shows that most of studies focus on the car-following model development for intelligent vehicles and examine their traffic impacts (e.g., throughput, stability, vehicle speed). Several studies estimate the energy and environmental impacts (e.g., fuel consumption and emission) and safety impacts using travel speed, time-to-collision (TTC), and post-encroachment-time (PET). Our literature review offers a comparative examination of the simulation-based models developed for the intelligent-vehicle analysis. The review is conducted examining the following criteria: (i) the objectives of the study, (ii) base model, (iii) simulation scenarios, (iv) analyzed vehicle types, (v) evaluation criteria, and (vi) main results.

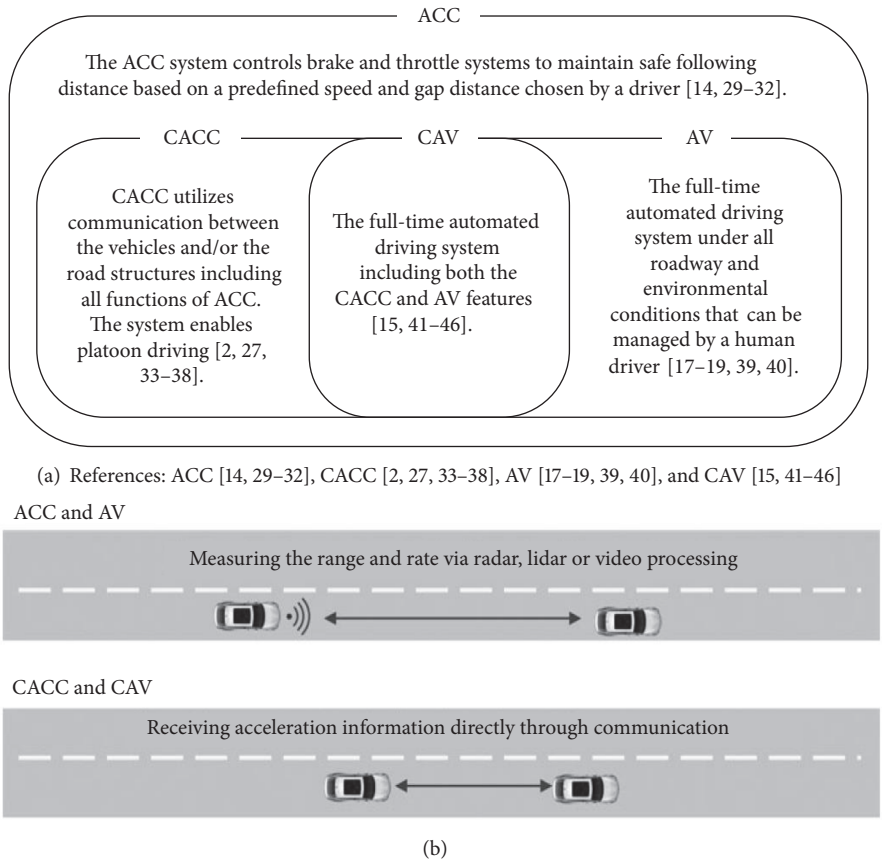

Figure 1: (a) intelligent-vehicle definitions with their classifications, (b) illustrations of sensing and communications by intelligent vehicles. *Source: Figure 1(b) [18].*

Because the use of intelligent vehicles on public roads will gradually increase under mixed-traffic situations with manual vehicles, many studies adopt a variety of scenarios regarding different market-penetration rates of intelligent vehicles. A small number of studies simulate only extreme 100% penetration rate of intelligent vehicles with no consideration of gradual growths [17, 32].

One interesting observation is that most analyzed vehicle types are limited to our four vehicle categories (see Figure 1). However, the studies barely consider manual vehicles equipped with V2V communication transponders, which send the current location and speed of the vehicle to the nearby intelligent vehicles. One study by Shladover, Su [27] defines these vehicle-awareness device (VAD) equipped manual vehicles as the "Here I Am" (HIA) vehicle. The result shows that the increase in the HIA vehicles can also contribute to the improvement of road capacity.

In terms of results, many of simulation-based studies found consistent outcomes in terms of traffic performance: throughput increases with higher intelligent-vehicle penetration rates, while some contradictory results exist for the ACC vehicles' performance. For instance, Kesting, Treiber et al. [14, 31] conclude that the ACC vehicle can improve road capacity under small penetration, but the results by VanderWerf, Shladover [32] and Shladover, Su [27] show the ACC vehicles' impact might be marginal. Meanwhile, a research gap exists regarding inconsistency in the previous studies' assumptions, scenarios, and evaluation criteria.

Our review result shows that the IDM and MIXIC models are the most often used models, as benchmark car-following models. Several studies tried to modify these models to explain the longitudinal movements of intelligent vehicles (e.g., IDM [14, 30, 31, 46] and MIXIC [45, 52, 62]). Both models and their applications are discussed in further detail in the following sections.

3.2. Car-Following Models for Intelligent Vehicles. Because of the newly introduced unprecedented systems, we need new car-following models to simulate intelligent vehicles. Conventional car-following models are developed based on human-driving characteristics. However, intelligent vehicles have different car-following characteristics. The accompanied sensor technology allows CAVs to see the down-stream traffic situations beyond human drivers' visibilities. Furthermore, the agile CACCs and CAVs communicate (e.g., V2V or V2X) with each other in order to improve traffic streams. Recently, there have been the research efforts to develop intelligent-vehicle car-following models by enhancing the conventional car-following models (e.g., IDM [14, 30, 31, 46] and MIXIC

Table 1: Simulation-based intelligent-vehicle studies: objectives, models, and scenarios.

Ref #	Objectives	Base model(s)	Scenarios
[32]	Develop the ACC and CACC car-following models and estimate their impact.	An error-based control law for the ACC and CACC. The lane change is under human control.	A 100% market-penetration rate of each vehicle type.
[29]	Examine the ACC vehicles' lane-changing effects compared to manual vehicles.	Manual vehicle: Pipes model [47]. ACC model from [48]. Comprehensive Modal Emissions Model (CMEM).	Position of ACC vehicles (2, 4, 6, 8th in the string of 10 vehicles). Market-penetration rate of ACC (5%, 10%, 15% and 30%).
[31]	Propose the ACC-based traffic-assistance system intended to improve traffic flow and road capacity.	IDM	Market-penetration rate of ACC (0%, 5%, 15% and 25%).
[14]	Propose the ACC-based traffic assistance system aimed at improving the traffic flow and road capacity.	IDM	Market-penetration rate of ACC (0%, 5%, 15% and 25%).
[30]	Propose the new ACC car-following model with its impact analysis	IDM with constant-acceleration heuristic (CAH).	Market-penetration rate of ACC (10%, 20%, 30%, 40%, and 50%).
[18]	Propose an analytical framework to estimate the AVs' impacts on highway sections.	Car-following model for manual vehicles in [49, 50]. First order control law for AVs.	Different combinations of manual vehicles, AVs, and CAVs (0-100 % by 10% gap).
[19]	Develop an improved cellular automaton as an AV modeling platform.	Cellular Automaton	The lane-changing rules in the same and opposite direction. Market-penetration rate of ACC (0%, 50%, and 100%).
[46]	Develop a cooperative IDM (CIDM) to examine the system performance under different proportions of the AVs.	The Full Velocity Difference Model (FVDM) and IDM.	Market-penetration rate of the AVs (0%, 5%, 15%, and 25%).
[45]	Propose an acceleration framework to address the limitations of micro-simulation models in capturing the changes in driver behavior in a mixed environment.	MIXIC model for the AV modeling. IDM for the CAV modeling.	Market-penetration rate of the CAVs and AVs (0%, 20%, 40%, 60%, 80%, and 100%).
[44]	Develop a micro-simulation framework for CAVs to analyze the impact on fuel consumption and travel time.	Optimal control for CAVs. Gipps model for manual vehicles [51].	Two single-lane merging roadways where CAVs communicate to each other.
[15]	Propose a hardware-in-the-loop (HIL) testing system for the CAV applications.	Hardware-in-the loop (HIL) testing.	Type I: String leader's smooth acceleration and deceleration between 20-30mph. Type II: Sharp brakes from 30mph to 10mph and quick recovery to 30mph. Type A: Perfect communication/radar. Type B: Compromised communication/radar (radar delay 100ms; radar noise = 0.05; DSRC Latency = 100ms and DSRC Packet Loss =10%).

Table 1: Continued.

Ref #	Objectives	Base model(s)	Scenarios
	Examine the impact of the CACC vehicles on traffic flow characteristics of a multilane highway.	IDM	Arrival rate scenarios: 7,000v/h (moderate), 8,000v/h (saturated), 9,000v/h (oversaturated), 10,000v/h (oversaturated). Penetration rates of CACC varied in multiples of 20% (truck is fixed in 10%).
[52]	Develop a simulation framework to facilitate the heavy-duty vehicle (HDV) platooning and establish the related concept and operations.	Carbon dioxide emission model [53]. The HDM platoon model with the ACC/CACC car-following model.	Average density, average travel time, and average travel speed.
[17]	Investigate AVs' impact on traffic performance.	Calibration on car following model (Wiedemann 99). Lane changing behavior based on a research project [54].	Each vehicle type of a 100% market-penetration rate.
[37]	Extend the CACC modeling framework to incorporate new algorithms describing the interactions between the CACC and manual vehicles in mixed traffic.	The CACC model reported in [55]. The anticipatory lane change (ALC) for lane changing.	Market-penetration rate of the CACC (0%, 20%, 40%, 60%, 80% and 100%).
[36]	Investigate the impact of the CACC vehicle string operation on the capacity of multilane highway with merging bottlenecks.	The ACC and CACC car-following models developed [33].	Market-penetration rate of the CACC (0%, 20%, 40%, 60%, 80% and 100%).
[56]	Propose a new algorithm for the CACC systems for collaborative driving based on the use of agent technology and information sharing.	Effective CACC (ECACC) algorithm consists of speed and distance control algorithms.	Market-penetration rate of the CACC (0%, 20%, 40%, 60%, 80% and 100%).
[27]	Estimate the effect on highway capacity of varying market-penetrations of vehicles with the ACC and the CACC.	The manual vehicle: NGSIM oversaturated freeway flow model [57]. ACCs: Proprietary to Nissan. CACCs: Car-following behavior was described [33].	The ACC and CACC vehicles 10 % increase proportion.
[21]	Investigate the impact of the CACC on traffic-flow characteristic.	MIXIC model	Market-penetration rate of the CACC (0%, 20%, 40%, 60%, 80% and 100%).
[58]	Develop the models of both ACC and CACC control systems based on real experimental data.	IDM	Ten consecutive CACC and five consecutive ACC vehicles. A mixed case, where the two first followers are ACC-equipped and the next seven are CACC-equipped.

Table 1: Continued.

Ref #	Objectives	Base model(s)	Scenarios
[59]	Estimate the emissions and energy use (i.e., fuel consumption) associated with an Automated Highway System (AHS) using advanced simulation modeling tools.	Smart AHS framework developed at PATH program.	Congestion levels (LOS A - F).
[60]	Analyze roundabout safety level in the circumstances where different numbers of the AVs are mixed with manual vehicles.	Safety impact: Surrogate Safety Assessment Model (SSAM). Manual vehicles: Wiedemann 74. AVs: VISSIM parameter adjustment.	Market-penetration rate of the AVs (0%, 10%, 25%, and 50%).
[61]	Develop the decision-making CAV control algorithm in the VISSIM for safety evaluations.	Safety impact: SSAM. CAV: External driver model API written in C++. Manual vehicles: Wiedemann 99.	Market-penetration rate of the CAVs (0%, 25%, 50%, 75%, and 100%). Daily based estimation, Monday to Friday.

[45, 52, 62]). In this section, we summarize the commonly used car-following models adapted for intelligent vehicles.

3.2.1. Intelligent Driver Model (IDM). In this section, we discuss the IDM, first developed by Treiber, Hennecke [20]. The IDM is the most commonly used model for the intelligent-vehicle simulations because it is one of the simplest and accident-free models producing realistic acceleration profile in a single lane situation [63]. The IDM is closer to the ACC vehicles than to human-driven vehicle characteristics because it does not have an explicit reaction time and is given in a continuously differentiable acceleration function [63]. By changing some parameters, we can use the IDM itself as ACC or a human-driven vehicle model. Additionally, the modified IDM is applied to simulate CAVs [46]. The basic function of IDM is as follows:

$$a_{IDM}(s, v, \Delta v) = \frac{dv}{dt} = a\left[1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s^*(v, \Delta v)}{s}\right)^2\right] \quad (1)$$

$$s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}} \quad (2)$$

where s denotes the current distance to the preceding vehicle, s_0 denotes the minimum gap, $s * (v, \Delta v)$ denotes desired (safety) gap, v denotes the current speed, v_0 is the desired (safety) speed, Δv is speed difference between the current vehicle and the preceding vehicle, δ is the parameter that decides the magnitude of acceleration decrease depending on the velocity v, T denotes the constant desired gap, and a and b denote comfortable acceleration and deceleration rates, respectively.

The IDM results in plausible acceleration and deceleration rates in most situations. However, when the current vehicle gap is significantly lower than the desired gap, the deceleration rate becomes unrealistically high. In fact, when it comes to the human-driven vehicles, drivers assume that the preceding vehicle will not suddenly stop with the hardest deceleration without any reason. Therefore, the current gap smaller than the desired gap distance is considered a relatively mild-critical situation [64]. To address this issue, Kesting, Treiber [30] combined the IDM and the Constant Acceleration Heuristics (CAH) to limit the unrealistic deceleration rates. The fundamental assumption of the CAH model is that the preceding vehicle will not change its acceleration suddenly in following few seconds.

There are three underlying conditions of the CAH: (i) the acceleration of the vehicle under consideration and the preceding vehicle will not change in the applicable future (generally, a few seconds); (ii) no safe time headway or minimum distance is required at any moment; and (iii) drivers react without delay (zero reaction time) [30].

For given actual values of the gap s, current speed v, the preceding vehicle speed v_1, and its acceleration a_1, the maximum acceleration a_{CAH} that prevents crashes is given by

$$a_{CAH}(s, v, v_1, a_1) = \begin{cases} \dfrac{v^2 \widetilde{a_l}}{v_1^2 - 2s\widetilde{a_l}} & \text{if } v_1(v - v_1) \le -2s\widetilde{a_l}, \\ \widetilde{a_l}\dfrac{(v - v_1)^2\,\theta(v - v_1)}{2s} & \text{otherwise}, \end{cases} \quad (3)$$

where the effective acceleration $\widetilde{a_l} = \min(a_1, v)$ is used to avoid artefacts that may be caused by preceding vehicles with higher acceleration capabilities. The condition $v_1(v - v_1) \le -2s\widetilde{a_l}$ is true if the vehicles have stopped at the time that the minimum gap s = 0 is reached. Otherwise, negative approaching rates do not make sense to the CAH and are therefore eliminated by the Heaviside step function Q.

Table 2: Simulation-based intelligent-vehicle studies: analyzed vehicle types, evaluation criteria, and main results.

Ref #	Analyzed vehicle types	Evaluation criteria	Main results
[32]	Manual vehicle, ACC, CACC	Throughput	Throughput of the manual, ACC, and CACC vehicles were, respectively, 2,050, 2,200, and 4,550 vehicles/h.
[29]	Manual vehicle, ACC	Fuel consumptions and environmental effect (CO, HC, CO2, NOx)	The smooth response of the ACC vehicles has a beneficial effect on the environment. These benefits vary with the levels of the disturbance, the position of the ACC vehicle in the string of manually driven vehicles and the ACC vehicle penetration.
[31]	Manual vehicle, ACC	Throughput	A small proportion (5%) of ACC vehicles can improve the traffic flow. An increasing proportion of ACC vehicles reduces traffic congestion.
[14]	Manual vehicle, ACC	Throughput	ACC vehicles improve the traffic stability and the road capacity. 25% of ACC eliminates traffic congestion during simulation (the cumulated travel time without ACC vehicles is 4,000 hours, but with 25% ACC vehicles 2,500 hours).
[30]	Manual vehicle, ACC	Throughput	1% more ACC vehicles will lead to an increase in the road capacities by about 0.3%.
[18]	Manual vehicle, CAV, AV	Throughput	Increasing CAVs will have significant implications on the road capacity of highways. Road capacity efficiency will be dependent on the level of automation. The lane capacity increases from 2,046 to 6,450 vehicles/hour/lane with CAVs increases from 0% to 100%.
[19]	Manual vehicle, AV	Throughput	AVs could considerably improve traffic flow. The lane-changing frequency between neighboring lanes evolves with traffic density. AV lane changing seems to be much less pronounced than that of the AV car-following.
[46]	Manual vehicle, CAV	Average speed dispersion, travel time, space mean speed	Increasing percentage of AVs will reduce the total travel time and smooth traffic oscillations.
[45]	Manual vehicle, connected vehicle, AVs	Stability and throughput	CAVs can improve string stability, and automation is more effective in preventing shockwave formation and propagation. Substantial throughput increases under certain penetration scenarios.
[44]	Manual vehicle, CAV	Fuel consumption, travel time, throughput	CAVs can contribute to significant fuel consumption and travel time reduction. CAVs allow for more stable traffic patterns even for high density traffic.
[15]	Manual vehicle, CAV	Speed, vehicle position profile	Effectiveness of the CACC in absorbing certain disturbance and oscillation of speeds. Speed oscillation decreases as vehicle position in the string increases. Perfect communication/radar contributes string stability.
	Manual vehicle, CACC	Throughput	A low-to-moderate penetration rate of CACC, the CACC impact is not statistically significant (advantages observed with a 40% or more CACC). A very large improvement is noticed at a high penetration rate of CACC, especially in high traffic conditions.

Table 2: Continued.

Ref #	Analyzed vehicle types	Evaluation criteria	Main results
[52]	Manual vehicle, HDV with ACC, CACC functions	Fuel consumption Space mean speed	The increasing HDV platooning in traffic flow results in more dramatic improvements on traffic efficiency. Deceleration of the first HDV to a low speed during platoon formation will increase the formation time to a large extent in medium and heavy traffic.
[17]	Manual vehicle, AV	Average density Average travel time Average travel speed	The average density of autobahn segment remarkably improved (8.09%) during p.m. peak hours in the AV scenario. The average travel speed enhanced relatively by 8.48%. The average travel time improved by 9.00% in the AV scenario.
[37]	Manual vehicle, CACC	Throughput	Freeway capacity is 90% higher in a 100% CACC penetration compared to 0%. The capacity increase is insignificant under low to medium CACC market-penetrations (e.g., 20–60%) in the absence of additional management strategies.
[36]	Manual vehicle, CACC	Bottleneck capacity	The freeway capacity increases quadratically as the CACC increases, with a maximum of 3080 vehicles/hour/lane at 100% CACC penetration. The disturbance from the on-ramp traffic can reduce the freeway capacity by up to 13% but the bottleneck capacity still increases in as CACC increase. There is very little gain in merge bottleneck capacity as CACC penetration increases from 0% to 20% when the on-ramp demand is high. A rapid increase in bottleneck capacity from 80% to 100% CACC penetration, especially with high on-ramp inputs.
[56]	Manual vehicle, CACC	Throughput	The congestion reduction is higher when the market-penetration rate of the CACC-equipped vehicle increases. At a low penetration rate, the effect of the CACC on traffic dynamics is not significant.
[27]	Manual vehicle, ACC, CACC, and Here-I-Am (HIA) vehicle	Highway throughput	The use of ACC was unlikely to change lane capacity significantly. The CACC can increase capacity greatly after its market-penetration reached moderate to high percentages (4000 vehicles/hour if all are the CACC or vehicle awareness device-VAD equipped). The capacity benefits of CACC can be accelerated at somewhat lower market-penetrations, if the rest of the vehicles are equipped with VADs.
[21]	Manual vehicle, CACC	Throughput	The CACC can improve traffic-flow characteristics. A low market-penetration rate of the CACC (< 40%) would not have an impact on the throughput.
[58]	Four ACC and CACC experimental vehicles	Speed, distance gap, time gap	The IDM controller in the experimental test vehicles does not perceptibly follow the speed changes of the preceding vehicle. Strings of consecutive ACC vehicles are unstable, amplifying the speed variations of preceding vehicles. Strings of the consecutive CACC vehicles overcome these limitations, providing smooth and stable car following responses.
[59]	Manual vehicle Non-platooned AVs Platooned AVs	Fuel consumption Emissions (HC, CO, NOx)	The AHS has much lower average fuel consumption operating under congested conditions, because of its smoother traffic flow, but slightly lower average fuel consumption at free-flow. The AHS operating at 60 mph has substantially lower emissions per vehicle-mile traveled than non-automated traffic at the same average speed. Vehicles that platoon in an AHS can expect additional 5 - 15% fuel savings and emission reduction due to the aerodynamic drafting effect.

Table 2: Continued.

Ref #	Analyzed vehicle types	Evaluation criteria	Main results
[60]	Manual vehicle, Heavy commercial vehicle-HGV, AVs	Average travel speed	An increase of travel speed and decrease of average stop delay with the increase of percentage of the AVs. Increases in estimated crash number at roundabouts when the AVs percentage is increased in terms of rear-end conflict.
[61]	Manual vehicle CAV	Conflicts based on the threshold values of TTC (1.5 seconds) and PET (5 seconds).	The CAVs bring about compelling benefit to road safety as traffic conflicts significantly reduce even at relatively low market-penetration rates (12–47%, 50–80%, 82–92% and 90–94% for 25%, 50%, 75% and 100% CAV penetration rates respectively).

By combining acceleration from the IDM and the CAH, Kesting, Treiber [30] proposed the ACC model as formulated in (4). The ACC model produces different acceleration rates based on the IDM or the CAH depending on the following conditions. The ACC model produces the same acceleration if both the IDM and the CAH reach the same acceleration output. If the IDM produces the unrealistically high deceleration, while the CAH deceleration is in comfortable deceleration range, the situation is considered to be mildly critical, and the ACC acceleration stays above the CAH acceleration minus the comfortable deceleration. If both the IDM and the CAH result in acceleration significantly below −b, the situation is seriously critical, and the ACC acceleration must not be higher than the maximum of the IDM and CAH acceleration. The ACC acceleration should be a continuous and differentiable function of the IDM and CAH acceleration.

$$a_{ACC} = \begin{cases} a_{IDM} & a_{IDM} \geq a_{CAH}, \\ (1-c)\, a_{IDM} + c\left[a_{CAH} + b \tanh\left(\dfrac{a_{IDM} - a_{CAH}}{b}\right)\right] & otherwise. \end{cases} \tag{4}$$

The ACC model contains one additional parameter c compared to the IDM. c is named as a coolness factor. When $c = 0$, the ACC model reverts to the IDM, while if $c = 1$, the sensitivity of gap changes vanishes under small gaps and no velocity difference exists. Kesting, Treiber [30] have assumed c =0.99 (see Table 1).

Zhou, Qu [46] developed the cooperative intelligent demand model (CIDM) using the IDM as the benchmark model and examined the system performance of CAVs. Communication of the CAV is applied by using the concept of spatial anticipation in the human driver model (HDM) [65, 66]. The HDM anticipation is applied to the CIDM which splits the IDM's a_n into (5) based on (1).

$$a_n\left(\Delta x, v_n, \Delta v\right) = a_n^{free} + \sum_{m}^{n-1} a_{nm}^{int}\left(\Delta x_{nm}, v_n, \Delta v_{nm}\right) \tag{5}$$

The base IDM (1) consists of two parts: one is the acceleration term comparing the current speed v to the desired speed $a_{free} = a(1 - (v/v_0)^{\delta})$, and another one is the breaking term $a_{break} = -a(s^*(v, \Delta v)/s)^2$ that compares the current distance with the desired distance s^*. In (5), a_n^{free} is the same definition of $a_{free}(v)$, and a_{mn}^{int} is the same definition of a_{break} in (1) with the consideration of V2V interaction.

3.2.2. The MICroscopic Model for Simulation of Intelligent Cruise Control (MIXIC). To estimate the impact of intelligent vehicles, the modeling framework should be able to analyze different assumptions of intelligent-vehicle characteristics according to different functionalities. Furthermore, the modeling frameworks should be capable of estimating their impacts on traffic performance, safety, fuel consumption, emission, and noise emission. With consideration of these requirements, a stochastic simulation model MIXIC is developed by Van Arem, De Vos [62]. As an early developed intelligent-vehicle model, the MIXIC is one of the most applied models for the cooperative intelligent-vehicle simulations. The reasons behind its widespread application are the following: (i) The MIXIC model incorporates the V2V communication by sharing speed, acceleration, and/or braking capabilities between the preceding and current vehicles. Such model capability allows better simulations of the characteristics of CACC. (ii) The model is calibrated for different two-, three-, and four-lane situations, which results in a well-adjusted traffic flow model, corresponding to real-life situations. Additionally, the MIXIC results were found reliable where the detailed calibration of vehicles' performances is not available [62]. In this section, we discuss the basic MIXIC model and its applications.

For the basic MIXIC model [21], the acceleration system can be divided into two distinct components: (i) the acceleration controller delivering reference values and (ii) a vehicle model transforming the reference values into actually realized values. Therefore, the reference acceleration is determined by a controller and then fed into the vehicle model.

The reference acceleration (6) can be computed based on the difference between current and intended speed (a_{ref_v}) or the distance and the speed (a_{ref_d}) differences between the current vehicle and the preceding vehicle. The acceleration demand is given by the most restrictive one of the two. The acceleration (2m/s^2) and deceleration (-3m/s^2) are limited for driver comfort.

$$a_{ref} = \min\left(a_{ref_v}, a_{ref_d}\right) \tag{6}$$

where v_{int} and v denote the intended and the current speed of the CACC vehicle in meters per second. The reference acceleration demand based on speed difference is given by

$$a_{ref_v} = k \bullet \left(v_{int} - v\right) \tag{7}$$

where k as a constant speed-error factor.

The distance-based reference acceleration computation is slightly more complex. Let v_p denote the speed of the preceding vehicle and let r and r_{ref} denote the current and reference clearances relative to the preceding vehicle in meters, respectively. Let a_p denote the acceleration of the preceding vehicle. The reference acceleration based on the distance and speed difference between current and preceding vehicles is given by

$$a_{ref_d} = k_a \bullet a_p + k_v \bullet \left(v_p - v\right) + k_d \bullet \left(r - r_{ref}\right) \tag{8}$$

with k_a, k_v, and k_d being constant factors frequently used in previous studies [45, 67] as 1, 0.58s^{-1}, and 0.1s^{-2}, respectively.

The reference clearance r_{ref} is defined as the maximum value among the safety following distance (r_{safe}), the following distance according to the system time setting (r_{system}), and a minimum allowed distance (r_{min}), set at 2 meters.

$$r_{ref} = \max\left(r_{safe}, r_{system}, r_{min}\right) \tag{9}$$

The safe following distance (r_{safe}) is computed using the current vehicle speed (v), deceleration capability of the preceding vehicle (d_p), and the current vehicle (d).

$$r_{safe} = \frac{v^2}{2} \bullet \left(\frac{1}{d_p} - \frac{1}{d}\right) \tag{10}$$

For simplicity, the MIXIC model assumes a communication delay to be zero. In addition, the current and preceding vehicles can share braking capabilities using a V2V communication. The communication information includes the precise speed, acceleration, maximum braking capability, warnings regarding hazards in front, and fault warnings. The following distance according to the system time-gap setting is given by

$$r_{system} = t_{system} \bullet \mathrm{v} \tag{11}$$

where t_{system} is assumed as 0.5 seconds if the preceding vehicle has the CACC function and 1.4 seconds otherwise.

Talebpour and Mahmassani [45] developed the CAV model based on the MIXIC model considering sensor detection ranges of CAVs. The study uses individual sensors to create the input data for the MIXIC model. The assumed sensors are Smart-Micro Automotive Radar (UMRR-00 Type 30) with 90 m ± 2.5% detection range and ±35 horizontal Field of View (FOV). Each sensor updates the sensing information every 50 milliseconds and can track up to 64 objects.

The fundamental assumption of the study is that the speed of AVs is low enough to allow it to stop at the sensor detection range since an autonomous vehicle can observe vehicles only in its sensor detection range. This is equivalent to the assumption that there is a vehicle at a complete stop right outside of the sensor detection range. Moreover, if a preceding vehicle is spotted, it is reasonable to assume that the speed of the autonomous vehicle should be low enough to allow stopping if its preceding vehicle decides to decelerate with its maximum deceleration rate and reach a full stop. Considering the maximum of the possible deceleration for the autonomous vehicle and its leader, we can calculate the maximum of the safe speed using the following equations:

$$\Delta X_n = \left(X_{n-1} - X_n - l_{n-1}\right) + v_n\tau + \frac{v_{n-1}^2}{2a_{n-1}^{decc}} \tag{12}$$

$$\Delta X_n = \min\left(SensorDetectionRange, \Delta X_n\right) \tag{13}$$

$$v_{max} = \sqrt{-2a_i^{decc}\Delta \mathrm{X}} \tag{14}$$

where n and $n-1$ denote the autonomous vehicle and its leader, respectively. X_n is the location of vehicle n, l_n is the length of vehicle n, v_n is the speed of vehicle n, τ is the reaction time of vehicle n, and a_n^{decc} is the maximum deceleration of vehicle n. Then, the acceleration of a vehicle can be calculated by

$$\begin{aligned} a_n^d(t) = {} & k_a a_{n-1}(t-\tau) + k_v\left(v_{n-1}(t-\tau) - v_n(t-\tau)\right) \\ & + k_d\left(s_n(t-\tau) - S_{ref}\right) \end{aligned} \tag{15}$$

where S_n is the spacing and s_{ref} is the maximum of the following three values: the minimum distance (s_{min}), the following distance based on the reaction time (s_{system}), and the safe following distance (s_{safe}). In the study by Talebpour and Mahmassani [45], the minimum distance is set at 2.0 meters and s_{system} and s_{safe} are calculated as follows.

$$s_{safe} = \frac{v_{n-1}^2}{2}\left(\frac{1}{a_n^{decc}} - \frac{1}{a_{n-1}^{decc}}\right) \tag{16}$$

$$s_{system} = v_n\tau \tag{17}$$

Finally, the acceleration of the autonomous vehicle can be calculated using the following equation:

$$a_n(t) = \min\left[a_n^d(t), k\left(v_{max} - v_n(t)\right)\right] \tag{18}$$

where k is a model parameter which is the same as the basic MIXIC model [45].

4. Discussions

In this section, we summarize the literature review results regarding intelligent vehicle's impacts according to different vehicle types and performance measures. Additionally, the limitations and implications from previous studies are discussed. An increasing number of researchers have been studying intelligent vehicles with a recognition of its potential impacts on the future transportation system. However, important future impacts/developments remain uncertain, i.e., the capacity increase, the market-penetration growth, safety issues, public acceptance, regional economic impact, and/or future policies. Under such uncertainties, many researchers conduct simulation-based intelligent-vehicle analysis based on their own assumptions. However, the concept, assumptions, and even terminologies across various studies are inconsistent and even conflicting because the real-life data acquisition is not accessible at present. Our review results offer the following insights into simulation-based intelligent-vehicle studies.

First, we notice that most studies predict that the throughput could be increased with growing market-penetration rates of intelligent vehicles under the mixed-traffic condition with manual vehicles [14, 18, 19, 27, 30–32, 36, 37, 45]. However, the results are contradictory regarding vehicle types. The ACC studies conducted by Kesting, Treiber et al. [14, 31] show that the small portion (5%) of ACCs can still improve lane capacity. Furthermore, approximately 25% of the ACC eliminates traffic congestion during their simulation. In addition, Kesting, Treiber [30] estimate the road capacity elasticity of the ACC penetration: 1% more ACCs can increase road capacity by about 0.3%. Conversely, a few other studies have been skeptical regarding the ACC vehicles' impacts on road capacity. VanderWerf, Shladover [32] show that the ACC road capacity impact (i.e., 2,200 vehicles/hour/lane) could be minor compared to manual vehicles (i.e., capacity 2,050 vehicles/hour/lane) while the CACC could offer a significant impact (i.e., capacity up to 4,550 vehicles/hour/lane). Moreover, Shladover, Su [27] conclude that ACCs are not likely to change lane capacity significantly while the CACC can substantially contribute with moderate to high penetration rates (e.g., approximately 4,000 vehicles/hour/lane when all vehicle are the CACC or VAD-equipped vehicles).

Meanwhile, most CACC and CAV simulation studies estimate a positive road capacity increase with increasing market-penetration rates. Olia, Razavi [18] simulate the CAVs under mixed-traffic conditions with the assumption of increasing 10% gap of CAVs. The result shows a 100% penetration rate of CAVs could increase road capacity from 2,046 to 6,450 vehicles/hour/lane. Liu, Kan [37] conduct multilane and mixed-traffic highway simulations by increasing CACCs' gap by 20%. The results show that the freeway capacity could be approximately 90% higher with a 100% CACC penetration rate, compared to 0%. Although researchers conduct micro simulations based on different assumptions, they concede that vehicle connectivity (V2V) is one of the key factors in improving road capacity which could allow short headways while maintaining high-speed levels.

Second, both longitudinal and lateral movements of intelligent vehicles could offer benefits in terms of reducing energy and environmental costs. Ioannou and Stefanovic [29] estimate the environmental effects (i.e., CO, HC, CO_2, NOx, and fuel consumption) caused by lateral movements of the ACC vehicles based on different market-penetration rates and the position of the ACC vehicle in a string of 10 vehicles. Their results show that the smooth lane change feature has a positive effect on environment. Barth [59] estimates emissions and energy consumption under the automated highway system (AHS) operation at various congestion levels (LOS A-F). The study result shows that an AHS has a slightly lower average fuel consumption (5-15%) than a nonautomated highway operating at free flow conditions, but much lower average fuel consumption, under congested conditions because of smoother traffic flows of AVs. Additionally, platooned vehicles in an AHS can expect additional 5-15% fuel savings and emission reductions due to aerodynamic-drafting effects. Analyzing the AV impacts on GHG emissions and energy use, Wadud, MacKenzie [4] developed several illustrative scenarios and showed that AVs can reduce GHG emissions and the energy use by nearly half. However, the study did not employ empirical data or micro simulation for the estimation and simply used the results from previous simulation studies. Rios-Torres and Malikopoulos [44] develop a micro simulation framework for CAVs to estimate fuel consumption and travel time. The result shows that CAVs can significantly reduce fuel consumption and travel time.

Third, none of the parameters in the AV or CAV simulation models is calibrated by the real field data. However, there have been ongoing efforts trying to connect intelligent-vehicle simulations (e.g., CACC or low-automation level AVs) to actual field experiments. Bu, Tan [33] develop a V2V-based CACC experimental system retrofitted on two Infinity FX45s models that are originally equipped with the ACC systems. The experimental result indicates that the CACC-equipped vehicles can perform better than the ACC vehicles by operating with a 0.6 to 1.1 second-gap, compared to a range of 1.1 to 2.2 seconds with the ACC. The shorter gap by the CACC implies a potential highway capacity increase. Milanés, Shladover [2] used the dedicated short-range communication (DSRC) equipped with four Infinity M56s models (ACC equipped) to test the CACC systems under various road situations (different vehicle gaps, cut-in and -out of manual vehicles) on public roads. The CACC vehicles clearly show their potential in increased highway capacity and traffic flow stability.

Fourth, since the first car-following concept was introduced by Pipes [47] and Reuschel [68], traffic engineers and traffic psychologists have developed various car-following models to explain human-driven vehicle characteristics [69]. However, a research gap exists for modeling machine-driven car-following characteristics. This gap leads to a high dependency on a few previously developed car-following models (e.g., IDM or MIXIC) in the literature. Furthermore, we found that the vast majority of simulation-based studies aim to measure only the longitudinal performance of intelligent vehicles. Note that the introduced IDM and MIXIC models

are also limited to the analysis of a longitudinal movement's impacts. In fact, very few studies focus on the impacts of the lateral movement of intelligent vehicles [29, 37]. This can be because lateral movements are expected to have relatively lower benefits than those of longitudinal movements. As a result, existing models are limited to the explanation of intelligent vehicles' lateral movements.

Finally, as our review shows, many studies are dependent on simulation-based intelligent-vehicle analysis. Additionally, the intelligent-vehicle impacts have been calculated according to various performance measures (e.g., throughput, environmental effect, energy consumption, and safety). However, there is much less attention to their broader impacts, combining these impacts into a unified metric (e.g., the overall economic impact or social welfare impacts). Without such overarching criteria, we are unable to provide a clear optimal pathway about how to implement and regulate AVs when comparing intelligent-vehicle alternatives to each other.

5. Conclusion

With the fast growth in intelligent-vehicle technologies, the conventional transportation system will experience drastic changes. This evolutionary transportation system is challenging researchers and practitioners to estimate intelligent-vehicle impacts on road transportation and society. In this paper, we review and summarize the simulation-based impact analysis studies for intelligent vehicles. The present study is, therefore, timely and significant in terms of both understanding the current stage of intelligent-vehicle analysis and predicting the future impacts.

In our literature review, we found that the concept of intelligent vehicle is simulated based on a variety of assumptions. Furthermore, there are no firmly defined terminologies for each vehicle type. To offer insights, we define and classify the commonly used intelligent vehicles into four categories (ACC, CACC, AV, and CAV). One important note is that different studies use their own assumptions for the intelligent vehicles' capabilities. This can lead to inconsistent conclusions.

More than a half of intelligent-vehicle studies adopt the road capacity as the primary performance measure. Intuitively, one of the most effective functions of intelligent vehicles is the vehicle connections that enable high-speed operations under small headway gaps. This is suggested as a solution that could considerably increase road capacity. Despite inconsistent results, most studies agreed that vehicle connectivity can significantly contribute to the road capacity increase. In addition to the connectivity, the general agreement of most studies is that the increase in the market-penetration rate of intelligent vehicles highly improves roadway capacity.

Regarding simulation models, the most frequently adapted car-following models are the IDM [20] and MIXIC model [62]. However, the IDM assumes unrealistically high deceleration rates when the current vehicle's gap to the preceding vehicle is much smaller than the desired gap. To overcome this issue, Kesting, Treiber [30] adapt the CAH model and develop the ACC acceleration control model. On the other hand, the MIXIC model is simulated for the CACC by Van Arem, Van Driel [21] and Talebpour, Mahmassani [45]. However, we should note that none of parameters for the AV or CAV is calibrated based on real field data since level 3 or higher levels of AVs are still immature [16]. Therefore, no adequate empirical data for the calibration of intelligent vehicles is available at present.

Our findings indicate that the impact analysis of intelligent vehicles is still in a preliminary stage involving many uncertainties. Although new models have been developed to capture the car-following and lane-changing characteristics of intelligent vehicles, empirical data are needed for the model calibration. Furthermore, a set of standardized driving characteristics of intelligent vehicles is necessary for future research studies as most studies use different assumptions on the key features of intelligent vehicles.

Conflicts of Interest

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

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