

Trade-Offs Between Efficiency and Safety: AV Behavior Strategies in Uncontrolled Urban Traffic



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ABSTRACT: Autonomous vehicle behavior is not neutral: the same vehicle may be configured to drive cautiously or aggressively, with different consequences for efficiency and safety. In uncontrolled networks, where priority is resolved through gap acceptance rather than signals, these effects remain poorly established. This study examines how cautious, normal and aggressive autonomous vehicle behaviors affect traffic performance and surrogate safety in such a network. A 702,024 m² area of Kirkuk, Iraq, was modeled in PTV VISSIM as a synthetic, uncalibrated experiment. Thirteen scenarios were simulated: an all-human baseline and twelve combinations of three behavioral profiles with penetration rates of 25%, 50%, 75% and 100%. Behaviors were represented using Wiedemann 99 parameters, and unsignalized intersections as conflict areas. A demand of 2,000 vehicles/h was applied at four entry points, with ten runs per scenario. Seven movements were evaluated for travel time, vehicle delay and stop delay, and trajectories processed using the Surrogate Safety Assessment Model. In the modeled network, travel time decreased by up to 22%. Conflicts increased for all behaviors: aggressive produced the most crossing conflicts, cautious the most rear-end, lane-change and total conflicts, while mean time to collision rose. These findings suggest human-oriented surrogate safety measures may misrepresent autonomous car-following.

KEYWORDS: Autonomous Vehicles, Urban Traffic Safety, Vehicle Delay, Travel Time, Conflict Analysis.

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I. INTRODUCTION

Autonomous vehicles (AVs) are expected to change how urban traffic operates, through shorter reaction times, more consistent headways, and the removal of the driver errors implicated in most collisions (Shladover, 2018; Rahman and Thill, 2023). Less widely appreciated is that these effects are not fixed properties of the technology. The same vehicle can be configured to accept small gaps and short headways or to require large ones, and the choice of configuration determines how it interacts with surrounding traffic. Simulation studies represent this choice through behavioral profiles, commonly labeled cautious, normal, and aggressive, which differ substantially in their car-following and lane-change parameters (Desta and Toth, 2022; Azam et al, 2022). Conservative configurations have also been pursued as a design objective in their own right, for instance in selecting speeds that remain safe in the presence of distracted pedestrians (Rosati Papini et al, 2022).

Where that choice matters most is at intersections without signal control. In a signalized network, right of way is imposed externally and a vehicle's willingness to accept a gap affects little beyond its own departure. In an uncontrolled network, priority is negotiated at every conflict point through gap acceptance, so the behavioral parameters act directly on the interaction that determines both delay and conflict frequency. Uncontrolled intersections are common in many urban networks, particularly in cities whose road systems developed without comprehensive signalization, yet they are the setting in which AV behavior has been least examined (Albdairi and Almusawi, 2024; Tian et al, 2025).

The simulation literature has established that increasing AV penetration generally improves network performance (Talebpour et al, 2017; Mahmassani, 2016; Hosseini and Mirzahosseini, 2024; Almusawi et al, 2023, 2024), and several studies report accompanying safety benefits measured through surrogate indicators derived from vehicle trajectories (Morando et al, 2018; Miqdady et al, 2023). That literature is nonetheless narrower than its volume suggests. Most studies represent automation as a single behavioral configuration, so behavioral tuning cannot be separated from penetration rate; most are set in signalized or access-controlled facilities; and those applying surrogate safety measures do so without asking whether measures developed and validated on human driving remain valid when applied to autonomous car-following models, in which the oscillation characteristic of human following has been deliberately suppressed.

This study therefore addresses a specific question: how do cautious, normal, and aggressive AV behavioral profiles affect traffic performance and surrogate safety across a range of penetration rates in a network where every intersection is resolved by gap acceptance, and how far can a human-calibrated surrogate safety measure be relied upon to answer that question? The nature and limits of the evidence offered here should be stated at the outset. This is a synthetic simulation experiment. The network geometry is based on a 702,024 m² area of Kirkuk, Iraq, but no traffic counts, turning movement surveys, travel time runs, or speed measurements were collected there, and no component of the model has been calibrated or validated against field data. The

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demand, speed, and behavioral inputs are assumptions. The results describe how the model responds to controlled variation of its inputs, and they are not predictions of traffic conditions in Kirkuk or in any other real network. All thirteen scenarios share identical inputs except the behavioral profile and the penetration rate, so comparisons between them are internally consistent; the absolute values are not independently verified. The study is accordingly exploratory, and its findings should be read on that basis.

Within that scope, the objectives are:

- i. to compare the effect of cautious, normal, and aggressive AV behavioral profiles on travel time, vehicle delay, and stop delay in an uncontrolled urban network.
- ii. to evaluate how these effects vary across AV penetration rates of 25%, 50%, 75%, and 100% relative to an all-human baseline.
- iii. to examine the conflict frequencies and mean time to collision that a surrogate safety model reports for each configuration, and to assess how far those quantities can be interpreted as measures of risk.

The contribution is twofold. The study provides a controlled comparison of three AV behavioral profiles across four penetration rates in an uncontrolled network, a setting the existing literature has not examined. In the course of doing so it produces a conflict result that is difficult to reconcile with the behavioral parameters that generated it, and which bears directly on the validity of applying human-calibrated surrogate measures to autonomous traffic. The remainder of the paper is organized as follows. Section II reviews the relevant literature and identifies the gap addressed. Section III describes the study network, the demand and behavioral inputs, the intersection coding, and the conflict analysis procedure. Section IV reports the performance and safety results, interprets the conflict findings, and sets out the limitations. Section V concludes.

II. LITERATURE REVIEW

Most recently, the integration of AVs into urban traffic has been the focus of considerable research, as it has immense potential for changing the dynamics of transportation, improving safety, and gaining better operational efficiency. Indeed, several studies have tried to explore the impact of AVs on the improvement in traffic performance under many aspects: market penetration rates, driving behaviors, and mixed traffic conditions. The aim of this literature review is to gather a holistic understanding of how AV penetration has an influence on urban traffic systems by synthesizing findings from key studies to the complex and uncontrolled traffic environment.

A study researched how various SAV market penetration rates influence the performance of road traffic in Budapest. It applied a simulation model with the main objective of studying and analyzing, under metropolitan traffic flow conditions, the impact of its implementation of SAV. These results prove that the improvements in traffic performance are greatly improved by SAV due to a significant boost inside the network performance with increased demand to SAVs. Following the positive impact of any SAV system on flow performance, the study showed the applicability and benefits of SAV integration into urban

environments for improving overall traffic performance (Matalqah *et al*, 2022).

The Surrogate Safety Assessment Model (SSAM) has been applied widely in the assessment of traffic conflicts. Its development and validation are documented in Gettman *et al* (2008), in which simulated conflicts were compared against observed crash records to establish the relationship between surrogate measures and recorded collisions. Its application to autonomous vehicles is examined in Morando *et al* (2018), which reports conflict outcomes across a range of penetration rates and behavioral configurations.

Several studies assessed the behavior of AVs under various heterogeneous traffic conditions using simulation models. Studies investigated the impact of automation levels and different driving logic on traffic safety and network performance with respect to urban networks; the advanced driving logic resulted in improved network performance, with an increase in the levels of automation, while cautious driving behaviors caused negative impacts related to the performance in roadways in improved conditions. Besides, the study showed a decrease in accidents, energy consumption, pollution, and congestion expenses resulting from AV deployment. The coexistence of AVs with conventional vehicles (CVs) was found to significantly influence traffic performance and urban space utilization (Desta and Toth, 2022).

Simulations of different AV penetration rates on urban transportation in Al-Madinah of Saudi Arabia were performed. In addition, safety and operational performance improvements at 0%, 25%, 50%, 75%, and 100% penetration levels were evaluated. The results indicated that higher AV penetration rates significantly improve the safety and operational performance of the network. Estimated vehicle delays decreased notably with increasing AV penetration, highlighting the potential benefits of AV integration in complex urban freeway networks during the transition period (Abdeen *et al*, 2022).

Another study quantified the impact of AV penetration rates in traffic performance under mixed traffic conditions. The research considered three categories of AVs that are compared with conventional vehicles for different levels of demand. The results indicated that aggressive AVs had a better performance than both the conventional vehicles and other categories of AVs, mainly when higher levels of demand are present. At lower demand levels, AVs and CVs produced similar results. The study concluded that aggressive AV behavior can significantly improve traffic performance in high-demand scenarios, suggesting that AVs are a promising solution for future urban mobility challenges (Azam *et al*, 2022).

One study investigated how different application levels of mixed traffic would affect urban networks. It researched safety and performance impacts from various AV behaviors and a variety of penetration rates. The result is that high levels of autonomous driving substantially improve efficiency in traffic flow. The study concluded that AVs with higher levels of autonomous driving and higher penetration rates positively impact traffic flow, enhancing the overall efficiency of urban traffic networks (Oh *et al*, 2023).

One of the recent research works presents the assessment of traffic safety during the transition period: manual driving to autonomous driving, concerning CAV. It

applies to a simulation-based methodology and presents an analysis of the influence of different CAV penetrations on traffic safety. The finding presented provides evidence that with higher percentages of CAVs, traffic conflicts are reduced. As stated by the authors, human-driven vehicles are more often involved in conflict than CAVs. Gradual penetration of CAVs leads to a significant reduction in traffic conflicts, underscoring the potential safety benefits of autonomous driving technologies during the transition period (Miqdady et al, 2023).

A study conducted by Bilal and Giglio (2023) presents the MFD characteristics for different AVs' penetration rates in urban networks. This research has considered the impact of different behaviors and penetration rates of AVs on traffic safety and traffic performance. In this paper, a theoretical development of the MFD for heterogeneous traffic streams

was developed and analyzed the road network capacity with the incorporation of AVs. Results from the project show that in networks with 25-35% AVs, road capacity could increase as much as 59% over the upcoming 15-year period. This study underscores the significant potential of AV integration to enhance traffic flow characteristics and improve overall network performance (Bilal and Giglio, 2023).

The studies summarized above differ in ways that are not apparent from their individual findings. Table 1 compares them on the four dimensions that bear on the present work: the control environment of the network, the number of autonomous vehicle behavioral profiles represented, the range of penetration rates examined, and the safety measure applied, where one is applied at all. The present study appears as the final row, so that its position relative to this body of work is explicit rather than asserted.

Table 1 Synthesis of reviewed studies on AV penetration and safety.

Study	Network and control	AV behaviors modeled	Penetration rates	Safety measure	Principal finding
Morando et al (2018)	Signalized intersection and roundabout (VISSIM)	Single profile, level 4	0, 25, 50, 75, 100%	SSAM conflict counts	Conflicts reduced 20-65% at the intersection and 29-64% at the roundabout ($p < 0.05$)
Matalqah et al (2022)	City-wide network, Budapest, macroscopic (PTV Visum)	Single (SAV)	Three future SAV demand shares	None	Network KPIs improve as SAV share rises
Abdeen et al (2022)	Urban freeway, Al-Madinah (VISSIM)	Single, assertive (shorter headways, higher acceleration)	0, 25, 50, 75, 100%	None; stops and stop delay used as proxy	Vehicle delay reduced 26% to 74.2%
Azam et al (2022)	Hypothetical four-leg signalized intersection (VISSIM)	Three (cautious, normal, aggressive)	25% steps, at four demand levels (1000-4000 vehicles/t)	SSAM conflict counts	Aggressive AVs best on delay, queue, speed and conflicts at high demand; cautious degrades performance
Desta and Toth (2022)	Motorway, arterial and other roadway types, macroscopic (PCU-based)	Three driving logics (cautious, normal, aggressive)	Various	None	Cautious degrades performance at higher penetration; normal and aggressive improve it
Oh et al (2023)	Network of signalized intersections	Automation levels	Various	None	Higher automation level and penetration improve flow
Miqdady et al (2023)	GR-30 motorway, Granada, 20.27 km three-lane segment (Aimsun)	CAV automation levels	Graduated, to 90%	SSAM conflict counts	Conflicts fall progressively, by 18.9% and upward, as CAV penetration rises
Bilal and Giglio (2023)	Urban network, Genoa, macroscopic (MFD)	Single, demographically quantified	25-35% (derived)	None	Link capacity gains up to 59%
This study	Uncontrolled urban network, priority by gap acceptance (VISSIM)	Three (cautious, normal, aggressive)	25, 50, 75, 100	SSAM conflict counts and mean TTC	Conflicts rise with penetration, ordering not by aggressiveness

Table 1 exposes three limitations in this body of work. First, the evidential base for the claim that automation improves safety is narrower than the volume of the literature suggests: only three of the eight studies apply a surrogate safety measure at all, and among the remainder Abdeen et al (2022) infer safety from stop counts and stop delay rather than from conflicts. Second, only Azam et al (2022) and Desta and Toth (2022) represent more than one AV behavioral profile, and neither does so in the setting examined here; Desta and Toth work macroscopically through passenger car unit factors rather than through vehicle interaction, while Azam et al, although adopting the

same three profiles and the same parameter values used in this study, examine them at a single hypothetical signalized intersection across demand levels rather than across a penetration range in a network. Third, and most directly relevant to the present work, every study listed is set in a signalized, access-controlled, or macroscopically aggregated environment; none examines a network in which right of way is negotiated through gap acceptance at every intersection, which is precisely where car-following and lane-change parameters act on the interaction that determines both delay and conflict. A fourth issue is absent from the table because no study addresses it: of the three that

apply SSAM, none examines whether a measure developed and validated on human driving remains valid when applied to car-following profiles in which following-distance oscillation has been suppressed, as it is by the zero values of CC2 and CC6 in all three profiles used here and in Azam *et al* (2022). This study addresses the second and third points directly, comparing three AV behavioral profiles across four penetration rates in an uncontrolled urban network with demand, geometry, and intersection coding held constant, and its results bear on the fourth, as examined in Section IV.E.

III. METHODOLOGY

This section describes the network modeled, the demand and speed inputs applied to it, the car-following and lane-change parameters representing each behavioral profile, the movements evaluated, the conflict analysis procedure, and the scenario design. Each is set out in turn below.

A. Study Location

The study was conducted in Kirkuk, Iraq, a region characterized by its complex and uncontrolled urban traffic network as shown in Figure 1. This urban area covers approximately 702,024 square meters and includes a mix of residential, commercial, and industrial zones. The road network in Kirkuk has an intricate layout with numerous uncontrolled intersections.

The network was selected for three reasons. First, the study requires a setting in which priority is resolved by gap acceptance rather than by signal control at every intersection, and this district satisfies that condition throughout, which the signalized and access-controlled networks examined in the studies of Table 1 do not. Second, it carries a mix of residential, commercial, and industrial frontage, so the movements evaluated include through traffic and both turning directions rather than a single maneuver type repeated. Third, districts of this kind, in which an urban

street network operates without signal control, are common in cities whose road systems developed without comprehensive signalization, so the configuration examined here is not an unusual one. The modeled extent of 702,024 m² was determined by the four external entry points, which are the locations at which the district's internal street network meets the surrounding arterials; the boundary follows those points rather than a predetermined area, and the figure is the resulting extent rather than a design choice.

The unsignalized intersections within the network were represented in PTV VISSIM using conflict areas. A conflict area was defined at each location at which vehicle movements overlap, with priority assigned so that the major approach retains right of way and the minor approach yields. The gap-time and safety distance parameters governing these conflict areas were retained at the default values documented in PTV Group (2018), were not adjusted during the study, and were held identical across all thirteen scenarios. The network contains no signal control, stop or give-way signage, or other control devices; priority at every intersection is resolved through gap acceptance alone.

The network was coded with motorized vehicles only. Pedestrians, cyclists and other non-motorized road users were not represented, no pedestrian crossings or pedestrian flows were modeled, and on-street parking maneuvers were not included. The results therefore describe vehicle-to-vehicle interaction in isolation from the non-motorized activity present in the study area. The study is a synthetic simulation experiment. The road network geometry is based on that of the study area in Kirkuk, but no traffic counts, turning movement surveys, travel time measurements or speed observations were collected there, and no component of the model has been calibrated or validated against field data. The demand, speed and behavioral inputs described in the following sections are assumptions. The results should accordingly be read as describing the behavior of the model under controlled variation of its inputs, and not as predictions of traffic conditions in Kirkuk.



Figure 1 Overview of the study area in Kirkuk, Iraq, showcasing the urban network and its complex, uncontrolled traffic environment

B. Traffic Volume Data

A demand of 2,000 vehicles/h was applied at the four external entry points of the network, distributed equally at 500 vehicles/h per entry point. This figure represents an estimate of boundary loading during the morning peak

period. It describes flow entering the network at its four external boundaries and is not a measure of total network volume; as described in Section III.E, additional vehicles with randomly generated internal trips were released within the network, so total throughput exceeds this figure. The

demand level was held constant across all thirteen scenarios so that differences between scenarios are attributable to vehicle behavior and penetration rate rather than to changes in loading. Only this single demand level was tested, and the sensitivity of the results to higher or lower loadings was not examined; this is addressed in Section V.

C. Desired Speed Distribution

Desired speeds were drawn from a uniform distribution bounded at 30 km/h and 50 km/h, as shown in Figure 2. These bounds correspond to the posted speed limits applying to the arterials within the modeled area. The distribution is therefore derived from the regulatory speed environment rather than from measured vehicle speeds; no field speed observations were collected, and the distribution has not been validated against observed speeds in the study area. In PTV VISSIM the desired speed defines the speed a vehicle adopts when unconstrained by other traffic. Realized speeds are lower and are determined during the simulation by car-following behavior, gap acceptance at the unsignalized

intersections and turning maneuvers. The distribution in Figure 2 is accordingly an input assumption of the model and not a representation of the speeds the model produces.

D. Car Following Models and Lane Change Models

VISSIM includes two distinct implementations of the Wiedemann car-following model: Wiedemann '99 and Wiedemann '74. While both models share similarities, the primary distinction is that Wiedemann '99 offers more adjustable parameters compared to Wiedemann '74 (PTV Group, 2018), where certain parameters are hard-coded and less modifiable. The driving behavior characteristics (CC parameters) in VISSIM are defined based on regime categorization thresholds and are used to calibrate the Wiedemann '99 model. As noted by PTV Group (2018), these CC parameters, along with their default values for human-driven vehicles (HVs), are outlined in Table 2. These parameters can be modified by the user and include factors such as the number of observed vehicles, look-ahead distance, average standstill distance, and both the additive and multiplicative parts of the desired safety distance.

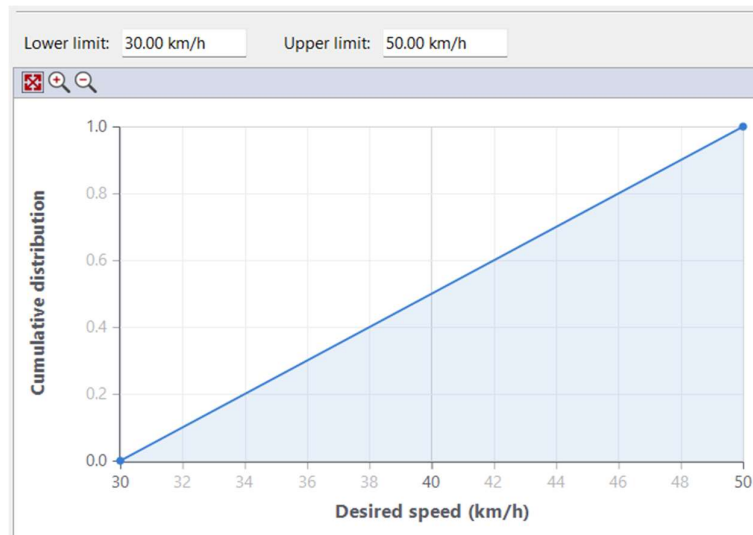


Figure 2 Desired Speed Distribution

Table 2 Wiedemann 99 car-following parameters

Wiedemann 99 following model parameters	AV cautious	AV normal	AV aggressive	Human
CC0 Standstill distance	1.50 m	1.50 m	1.00 m	1.50 m
CC1 Gap time distribution	1.5 s	0.9 s	0.6 s	0.9 s
CC2 'Following' distance	0.00 m	0.00 m	0.00 m	4.00 m
CC3 Threshold for entering 'Following'	-10.00	-8.00	-6.00	-8.00
CC4 Negative speed difference	-0.10	-0.10	-0.10	-0.35
CC5 Positive speed difference	0.10	0.10	0.10	0.35
CC6 Distance dependency of oscillation	0.00	0.00	0.00	11.44
CC7 Oscillation acceleration	0.10 m/s ²	0.10 m/s ²	0.10 m/s ²	0.25 m/s ²

CC8 Acceleration from standstill	3.00 m/s ²	3.50 m/s ²	4.00 m/s ²	3.50 m/s ²
CC9 Acceleration at 80 km/h	1.20 m/s ²	1.50 m/s ²	2.00 m/s ²	1.50 m/s ²

The parameter sets in Tables 2 and 3 follow the cautious, normal and aggressive autonomous-vehicle behavioral profiles developed for PTV VISSIM and applied in comparable simulation studies (Desta and Toth, 2022; Abdeen et al, 2022). They are conventional representations of autonomous driving styles rather than values calibrated against observed autonomous-vehicle operation, and no such calibration was undertaken in this study. Two settings warrant explicit note. CC2 and CC6 are set to zero for all three autonomous profiles, which removes following-distance oscillation entirely and produces closely spaced, steady platoons; the consequences of this for the conflict analysis are addressed in Section IV.E. The maximum deceleration for cooperative braking in the aggressive profile, at -6.00 m/s^2 , lies at the upper limit of passenger-vehicle braking capability and is twice the value applied in the normal profile.

In VISSIM, lane changes are classified into two categories. The first category is mandatory lane changes,

which are triggered by situations such as lane reductions, accidents, or the need for a vehicle to move into a lane that allows a turn at the next intersection according to its route. Key parameters for mandatory lane changes include the maximum allowable deceleration for both the vehicle changing lanes and the following vehicle in the new lane. Table 3 presents the parameters associated with mandatory lane changes in VISSIM, as described by PTV Group (2018). The second category is discretionary lane changes, where a vehicle changes lanes to increase speed or gain more space. This discretionary lane change process involves three steps: the vehicle first decides whether to attempt the lane change, then evaluates the feasibility of the maneuver, and finally performs a gap acceptance check before executing the lane change. The lane change parameter values applied to each behavioral profile in Table 3 follow those used for autonomous vehicles at four-leg intersections by Osman (2023).

Table 3 Lane change parameters

Parameter's	AV cautious	AV normal	AV aggressive	Human
Advanced merging	on	on	on	on
Cooperative Lane change	on	on	on	off
Safety distance reduction Factor	1.00 m	0.60	0.75	0.60 m
Min clearance (front/rear)	1.00 m	0.50 m	0.50 m	0.50 m
Maximum deceleration for Cooperative braking	-2.50 m/s^2	-3.00 m/s^2	-6.00 m/s^2	-3.00 m/s^2

E. Examined Movements

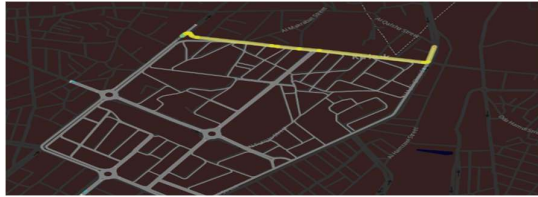
The design approach in the movements that were analyzed in this research involved in-depth mapping of standard patterns of travel in the urban system of Kirkuk, Iraq. The movement route in each one was chosen to capture common types of traffic movement and interactions in the city. The movements were modeled using PTV VISSIM and incorporated a range of thorough movements and turning maneuvers to capture all aspects of traffic dynamics. This provided the capacity to conduct in-depth research on how AV behaviors and AV penetration rates affect the performance and safety of the traffic across different routes. Figure 3 shows the range of different movements that were addressed in the simulation study in the complex urban system of Kirkuk, Iraq. Each subfigure shows a distinct movement route in the system. These movements were chosen to capture a variety of standard patterns of travel in the urban system, and therefore these capture in-depth how different AV behaviors and rates of AV penetration affect the performance and safety of traffic across different routes.

Route choice was determined by VISSIM's dynamic assignment procedure, under which vehicles select the path of least generalized cost on the basis of travel times fed back

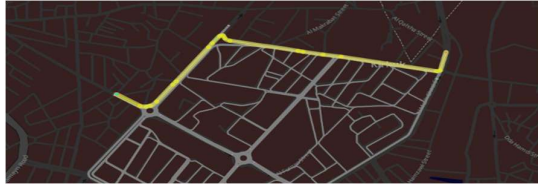
from preceding iterations. The default convergence settings of the software were applied and were not modified, and the assignment configuration was identical in every scenario. The number of iterations executed and the convergence values reached were not recorded. Because the assignment was permitted to resolve independently within each scenario, routes were not held fixed across scenarios; the consequences of this for the interpretation of the travel time results are addressed in Sections IV.A and V. Also, the simulation incorporates vehicles with random trips across the inner part of the network routes, and these are part of what contributes to the overall dynamic of the traffic and interactions.

The seven movements evaluated are origin–destination pairs between the four external entry points of the network. They were selected so that the set spans through movements and both left- and right-turning maneuvers at the internal unsignalized intersections, and so that routes of differing length are included, the longest and shortest differing by approximately a factor of two in traversal time. The set is not exhaustive, and the movements are not weighted by volume. No aggregate network performance measure was derived from them; results are reported separately for each

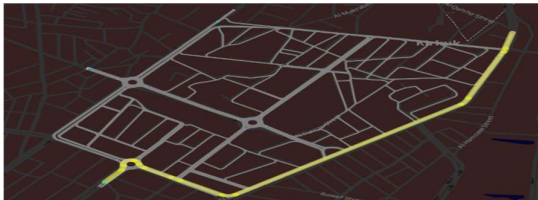
movement in Section IV and should not be read as describing network-wide performance. The conflict measures reported in Section IV.D are distinct in this respect, being obtained at network level from the complete trajectory output rather than from the seven evaluated movements.



(a)



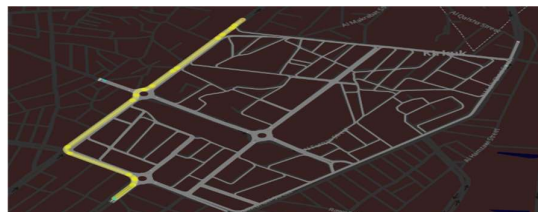
(b)



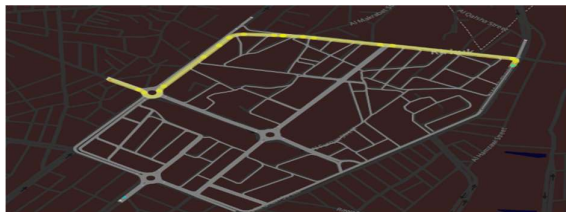
(c)



(d)



(e)



(f)



(g)

Figure 3 Examined traffic movements within the urban network of Kirkuk, Iraq: (a) Movement 1: 1-2, (b) Movement 2: 1-3, (c) Movement 3: 1-4, (d) Movement 4: 2-3, (e) Movement 5: 2-4, (f) Movement 6: 3-1, (g) Movement 7: 3-4.

F. Evaluation of Conflict Points

The model was analyzed across the conflict types considered in this study: crossing conflicts, rear-end conflicts, lane-change conflicts, total conflicts and mean time to collision. Analysis involved trajectory files generated from PTV VISSIM simulations, and these were later assessed using the SSAM, version 3.0 (Federal Highway Administration, 2008). The SSAM tool provided in-depth insights into the safety performance of the network by assessing several types of conflicts. The analysis classified conflicts based on their angle to determine potential safety problems and measure the risk levels involved in each conflict type as presented in Figure 4. Conflicts were classified by the conflict angle θ , defined as the angle between the trajectories of the two vehicles at the point of conflict, according to Eq. (1) (Federal Highway Administration, 2008):

$$\begin{aligned} \theta < 30^\circ &\rightarrow \text{rear-end}; & 30^\circ \leq \theta \leq 85^\circ &\rightarrow \text{lane-change}; & \theta > 85^\circ &\rightarrow \text{crossing} \end{aligned} \quad (1)$$

Events were retained as conflicts where the minimum time to collision was at or below 1.5 s and the post-encroachment time at or below 5.0 s, these being the default filtering thresholds of the SSAM. Conflict frequencies reported in this study are conditional on these thresholds and are not directly comparable with results obtained using different threshold values. The safety measure reported in Section IV as mean time to collision is the arithmetic mean, taken across all events retained by this filter, of the minimum time to collision recorded by SSAM for each event. It is therefore conditioned on the thresholds above: it describes the average severity of the events counted, and not the number of events, which is reported separately.

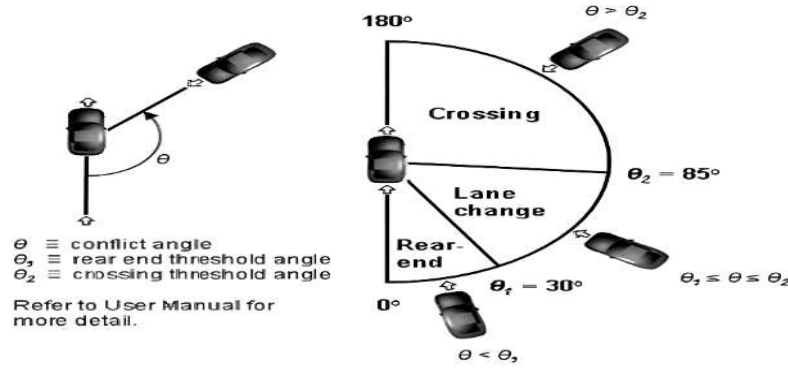


Figure 4 Conflict Angles Used in SSAM Analysis.

G. Simulation Scenarios

The simulation study assessed the effect of autonomous vehicle behavior and penetration rate on traffic performance and surrogate safety within the uncontrolled urban network of Kirkuk, Iraq. Thirteen scenarios were defined: a base scenario in which all vehicles were human-driven, and twelve scenarios combining the three autonomous behavioral profiles; cautious, normal and aggressive; with four penetration rates. Each scenario contained a single autonomous profile, so that the effect of behavior and the effect of penetration could be examined independently; mixed combinations of autonomous behaviors were not tested. The full scenario matrix is given in Table 4.

Penetration rates of 25%, 50%, 75% and 100% were selected to provide even coverage of the full penetration range and to permit direct comparison with prior studies adopting the same intervals in comparable urban networks (Abdeen et al, 2022). The range below 25% penetration, which corresponds to early adoption conditions, was not sampled. A demand of 2,000 vehicles/h of boundary loading was applied in every scenario, as described in Section III.B, and was held constant across all thirteen scenarios so that differences between scenarios are attributable to vehicle behavior and penetration rate rather than to changes in demand. Each scenario was preceded by a 15-minute warm-

up period, during which the network was loaded and no measurements were taken. This period corresponds to approximately five times the longest mean route traversal time in the network, ensuring that all evaluated movements carried traffic before data collection began. No formal steady-state or stationarity criterion was applied to confirm that network conditions had stabilized by the end of the warm-up period.

Each of the thirteen scenarios was simulated across ten runs using differing random seeds, and all results reported in Section IV are means across those ten runs. Only the aggregated means were retained; per-run outputs were not preserved, and measures of dispersion across runs are therefore not available. The specific seed values used and the length of the evaluation period following the warm-up were not recorded. The performance measures recorded were travel time, vehicle delay and stop delay, each evaluated separately for the seven movements described in Section III.E. The safety measures recorded were crossing conflicts, lane-change conflicts, rear-end conflicts and mean time to collision, obtained at network level as described in Section III.F. Comparisons were then made across scenarios to assess the influence of autonomous driving behavior and penetration rate on network performance and conflict frequency.

Table 4 Overview of scenarios with different AV penetration rates and approaches

Scenario No.	AV cautious (%)	AV normal (%)	AV aggressive (%)	Human (%)
1	0	0	0	100
2	25	0	0	75
3	0	25	0	75
4	0	0	25	75
5	50	0	0	50
6	0	50	0	50
7	0	0	50	50
8	75	0	0	25
9	0	75	0	25
10	0	0	75	25
11	100	0	0	0
12	0	100	0	0
13	0	0	100	0

IV. RESULTS AND DISCUSSION

All values reported in this section are means across the ten simulation runs performed for each scenario, as described in Section III.G. Measures of dispersion across runs were not retained, and no difference between scenarios has been tested for statistical significance; the comparisons below are accordingly descriptive. Full numerical values underlying each figure are given in Tables 5 to 9.

A. Travel Time

Table 5 reports average travel time for the seven movements. Travel time falls as penetration increases in twenty of the twenty-one movement-behavior series. Reductions at full penetration range from 2.1% on Movement 3 under cautious behavior to 22.2% on Movement 6 under aggressive behavior. The single exception is cautious behavior on Movement 7, where travel time reaches a minimum of 91.20 s at 50% penetration and then rises to 91.45 s at 100%. Aggressive behavior produces the shortest travel time in twenty-four of the twenty-eight movement-penetration combinations. In the remaining four

it is marginally slower than normal behavior: on Movement 2 at 25% penetration, at 163.50 s against 160.25 s, and at 50%; and on Movements 5 and 6 at 75%, where the differences are 0.10 s and 0.30 s respectively.

The latter two differences are smaller than can be resolved without a dispersion estimate and are reported for completeness rather than as findings. The largest reductions occur on Movement 6, the longest route, where all three behaviors reduce travel time by more than 20% at full penetration. The smallest occur on Movement 3, where cautious behavior yields a 2.1% reduction against 7.5% for aggressive behavior. These reductions should be understood as the combined effect of two mechanisms. The behavioral change alters car-following and lane-changing directly, and the resulting change in travel times alters route choice through the dynamic assignment procedure described in Section III.E. As routes were not held fixed across scenarios, the two cannot be separated in this analysis, and the values reported above should not be read as the effect of driving behavior alone.

Table 5 Average travel time (s) by movement, autonomous vehicle behavior and penetration rate. All values are means across ten simulation runs.

Movement	AV behavior	0% (HV)	25%	50%	75%	100%
Movement 1: 1-2	Cautious	104.00	101.95	99.70	97.20	93.70
	Normal		101.90	99.50	96.90	92.65
	Aggressive		101.75	99.40	96.40	92.30
Movement 2: 1-3	Cautious	165.30	162.00	157.30	154.20	147.90
	Normal		160.25	157.20	153.20	145.90
	Aggressive		163.50	158.10	151.85	145.80
Movement 3: 1-4	Cautious	173.20	172.40	171.90	170.60	169.55
	Normal		171.65	171.05	170.40	167.20
	Aggressive		164.85	162.80	161.50	160.25
Movement 4: 2-3	Cautious	63.80	63.35	62.95	61.25	59.45
	Normal		62.95	62.05	60.75	58.80
	Aggressive		62.80	61.50	59.95	58.45
Movement 5: 2-4	Cautious	130.90	130.00	127.60	125.20	123.80
	Normal		128.55	126.25	123.40	121.15
	Aggressive		128.10	125.65	123.50	120.60
Movement 6: 3-1	Cautious	183.20	169.90	163.90	153.20	145.60
	Normal		165.90	159.70	151.30	143.20
	Aggressive		164.80	159.60	151.60	142.60
Movement 7: 3-4	Cautious	93.60	92.25	91.20	91.35	91.45
	Normal		91.10	90.10	89.50	86.25
	Aggressive		90.85	88.80	85.50	84.40

B. Vehicle Delay

Table 6 reports average vehicle delay. The overall direction is downward, but the trend is not monotonic in five of the twenty-one series, all of them involving cautious or normal behavior. Cautious behavior on Movement 3 falls to 3.78 s at 50% penetration and then rises to 4.67 s at 100%, and on Movement 4 peaks at 4.54 s at 50% before falling. Cautious autonomous vehicles do not uniformly outperform the all-human baseline. In eleven movement-penetration combinations the delay under cautious behavior exceeds that

baseline: on Movement 3 at every penetration level, reaching 4.67 s against a baseline of 3.50 s, an increase of 33.4%; on Movement 4 at 25%, 50% and 75%; on Movement 7 at 25%, 50% and 75%; and on Movement 2 at 25%. Normal behavior exceeds the baseline in three further cases. Aggressive behavior is below the baseline in every case.

This qualifies the general proposition that increasing automation reduces delay. Where the autonomous profile is conservative, delay on some movements exceeds that of fully human traffic and remains higher at full penetration.

Table 6. Average vehicle delay (s) by movement, autonomous vehicle behavior and penetration rate. All values are means across ten simulation runs

Movement	AV behavior	0% (HV)	25%	50%	75%	100%
Movement 1: 1-2	Cautious	9.18	9.12	8.85	8.37	7.51
	Normal		9.05	8.68	7.98	6.53
	Aggressive		8.93	8.51	7.71	6.27
Movement 2: 1-3	Cautious	16.20	16.30	14.80	14.00	12.25
	Normal		14.58	13.78	12.20	9.87
	Aggressive		14.33	13.20	12.05	9.50
Movement 3: 1-4	Cautious	3.50	4.12	3.78	4.46	4.67
	Normal		3.47	3.53	3.34	3.28
	Aggressive		3.35	3.31	3.13	3.11
Movement 4: 2-3	Cautious	3.72	4.09	4.54	4.10	3.24
	Normal		3.73	3.77	3.66	2.62
	Aggressive		3.61	3.21	2.86	2.30
Movement 5: 2-4	Cautious	7.42	8.42	7.62	7.05	7.00
	Normal		7.00	6.24	5.22	4.42
	Aggressive		6.47	5.68	4.18	3.87
Movement 6: 3-1	Cautious	41.00	30.60	24.90	19.10	13.90
	Normal		27.00	22.80	17.00	11.85
	Aggressive		25.70	22.70	17.30	10.30
Movement 7: 3-4	Cautious	6.82	7.03	8.55	8.10	6.60
	Normal		6.00	5.87	5.68	5.00
	Aggressive		5.77	5.50	4.55	4.35

C. Stop Delay

Table 7 reports average stop delay. The pattern follows that of vehicle delay: predominantly decreasing, with five non-monotonic series again concentrated in the cautious profile. Cautious behavior on Movement 3 rises from 0.327 s at 50% penetration to 0.617 s at 100%, exceeding the human baseline of 0.430 s.

Stop delay on Movement 1 is reported for completeness but should not be interpreted. All values lie between 0.000 s and 0.015 s, a range in which the apparent differences between behaviors are smaller than the resolution at which the measure carries meaning.

Table 7 Average stop delay (s) by movement, autonomous vehicle behavior and penetration rate. All values are means across ten simulation runs

Movement	AV Behaviour	0% (HV)	25%	50%	75%	100%
Movement 1: 1-2	Cautious	0.002	0.004	0.004	0.011	0.015
	Normal		0.002	0.001	0.001	0.000
	Aggressive		0.001	0.001	0.000	0.000
Movement 2: 1-3	Cautious	3.180	2.740	1.550	1.240	0.360
	Normal		2.000	1.150	0.720	0.170
	Aggressive		1.730	1.080	0.690	0.150
Movement 3: 1-4	Cautious	0.430	0.445	0.327	0.413	0.617
	Normal		0.298	0.199	0.128	0.099
	Aggressive		0.205	0.144	0.070	0.053
Movement 4: 2-3	Cautious	0.940	0.838	0.855	0.505	0.195
	Normal		0.748	0.708	0.452	0.178
	Aggressive		0.660	0.492	0.300	0.138
Movement 5: 2-4	Cautious	1.960	1.655	1.290	0.850	0.345
	Normal		1.105	0.885	0.450	0.257
	Aggressive		1.155	0.745	0.515	0.195
Movement 6: 3-1	Cautious	13.850	7.450	5.400	2.900	1.650
	Normal		5.850	4.850	2.150	1.150
	Aggressive		5.350	4.200	1.650	1.050
Movement 7: 3-4	Cautious	1.590	1.670	1.430	1.610	1.025
	Normal		1.340	0.925	0.645	0.535
	Aggressive		1.320	0.910	0.635	0.510

D. Conflicts

Table 8, Table 9 and Figure 5 report the surrogate safety measures. Total conflicts increase with penetration for all three behaviors, from 3,570 in the all-human baseline to between 5,861 and 7,223 at full penetration. The increase is not, however, ordered by aggressiveness. Crossing conflicts do follow that ordering. They are most frequent under aggressive behavior at every penetration level, rising from 13 events at 25% to 49 at 100%, against 35 for cautious behavior at full penetration. This is the least numerous conflict class by two orders of magnitude. Lane-change conflicts are most frequent under cautious behavior at every penetration level, reaching 818 events at full penetration against 812 for aggressive and 778 for normal behavior.

Rear-end conflicts, which account for approximately 85% of all conflicts, invert the expected ordering at full

penetration. Cautious behavior produces 6,370 events against 5,100 for normal and 5,000 for aggressive behavior: the most conservative profile produces 27% more rear-end conflicts than the most aggressive. Because rear-end conflicts dominate the totals, cautious behavior also records the highest total conflict count at full penetration, at 7,223 events against 5,861 for aggressive behavior.

Mean time to collision increases with penetration for all three behaviors, from between 0.720 s and 0.750 s at 25% penetration to between 0.870 s and 0.975 s at 100%. The all-human baseline records the lowest mean time to collision of any scenario, at 0.720 s. As a longer time to collision indicates a less imminent conflict, the events detected in the autonomous scenarios are individually less severe than those in the human baseline even as they become more numerous.

Table 8 Network-level surrogate safety measures by autonomous vehicle behavior and penetration rate. All values are means across ten simulation runs.

Measure	AV behavior	0% (HV)	25%	50%	75%	100%
Crossing conflicts	Cautious	0	1	10	15	35
	Normal		4	13	18	40
	Aggressive		13	14	19	49
Lane-change conflicts	Cautious	665.5	713.0	760.0	814.0	818.0
	Normal		693.0	739.5	746.5	777.5
	Aggressive		701.0	745.0	796.0	812.0
Rear-end conflicts	Cautious	2905	3285	3350	3945	6370
	Normal		3275	3455	4250	5100
	Aggressive		3400	4460	4830	5000
Mean TTC (s)	Cautious	0.720	0.750	0.760	0.790	0.975
	Normal		0.720	0.750	0.820	0.900
	Aggressive		0.750	0.820	0.820	0.870

Table 9 Total conflicts, being the sum of the three conflict classes, by autonomous vehicle behavior and penetration rate

AV behavior	0% (HV)	25%	50%	75%	100%	Change at 100% vs HV
Cautious	3570	3999	4120	4774	7223	+102.3%
Normal	3570	3972	4208	5014	5918	+65.7%
Aggressive	3570	4114	5219	5645	5861	+64.2%

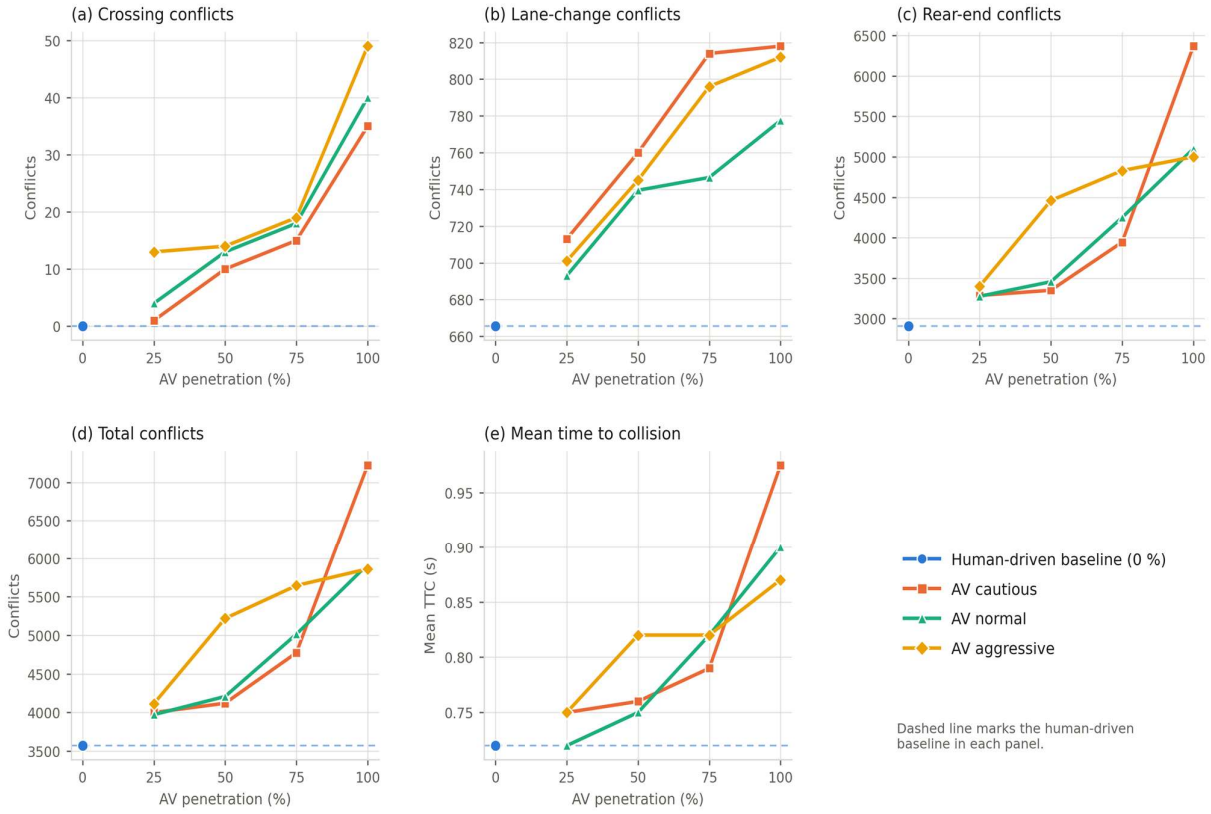


Figure 5 Network-level conflict measures and mean time to collision against autonomous vehicle penetration rate, for the cautious, normal and aggressive behavioral profiles: (a) crossing conflicts, (b) lane-change conflicts, (c) rear-end conflicts, (d) total conflicts, (e) mean time to collision. The dashed line in each panel marks the all-human baseline. All values are means across ten simulation runs.

E. Interpretation of the Conflict Results

The conflict results in Section IV.D are not consistent with a straightforward safety interpretation. The cautious profile has the longest gap time of the three, at $CC1 = 1.5$ s against 0.6 s for the aggressive profile, together with the largest standstill distance and the lowest accelerations. It nonetheless records the greatest number of rear-end conflicts at full penetration. A configuration maintaining larger gaps generating more short-headway events than one maintaining smaller gaps requires explanation, and two are available.

The first is behavioral and has precedent. Azam *et al* (2022), applying the same three profiles and the same parameter values used here at a signalized intersection, report the same ordering and attribute it to merging: cautious vehicles accept only large gaps, so they merge slowly, and the queue that forms behind a vehicle waiting for an acceptable gap generates rear-end conflicts of its own. That mechanism is available in the present network, where every intersection is resolved by gap acceptance and a cautious vehicle waiting for a gap obstructs the approach behind it. It predicts that conflicts under the cautious profile are real.

The second is a property of the measurement. All three autonomous profiles set $CC2$ and $CC6$ to zero, as shown in Table 2, removing following-distance oscillation entirely. Vehicles track their leaders at a constant target headway rather than fluctuating about it, forming steady platoons. The SSAM identifies conflicts from the kinematics of vehicle pairs and was developed and validated on human driving (Gettman *et al*, 2008), in which sustained low-variance

following of this kind does not occur. A stable platoon holding a fixed short headway can satisfy the time-to-collision criterion continuously without the following vehicle being at risk, because the leader's speed is smooth and the follower's response immediate. This mechanism predicts that conflicts under the cautious profile are partly an artifact of applying a human-calibrated measure to autonomous car-following.

The two explanations are not exclusive, and this study cannot separate them. One observation bears on their relative weight. Mean time to collision rises with penetration for all three profiles, and the all-human baseline records the lowest value of any scenario. Because the reported quantity is a mean over events retained by the threshold filter, a rise indicates that the events counted became less imminent on average as they became more numerous. An increase in genuine rear-end risk would be expected to produce more severe events rather than milder ones, so the direction of the mean time to collision is more readily reconciled with a filter admitting a growing population of mild, sustained threshold crossings than with a growing number of near misses. This is suggestive rather than decisive and distinguishing the two would require surrogate measures validated for autonomous driving.

The results also stand against Morando *et al* (2018) and Miqdady *et al* (2023), the two studies in Table 1 that apply the same class of measure and report conflicts decreasing as automation increases. Two differences appear material. Both examined signalized or access-controlled facilities, in which

gap acceptance at uncontrolled conflict points is not the governing interaction, whereas it governs throughout the network examined here. Conflict counts are also sensitive to the time-to-collision and post-encroachment-time thresholds applied, which differ between studies.

We therefore do not conclude that autonomous vehicles reduce safety in this network, and neither do we conclude that the conflict counts are without meaning. They should be read as the joint product of a merging mechanism that is plausibly real and a measurement whose validity for autonomous car-following is unestablished. Determining the balance between the two would require surrogate measures validated for autonomous driving, which was beyond the scope of this study.

F. Limitations

The results should be interpreted considering several limitations. The model was not calibrated or validated against field data, so the absolute results remain unverified, although scenario comparisons are internally consistent. Ten runs were used per scenario, but dispersion measures, random seeds and evaluation-period details were not retained, and no significance testing was performed. Dynamic assignment was independently resolved, meaning travel-time and delay changes may reflect both behavioral changes and route redistribution. Surrogate safety measures rely on thresholds and a model developed for human driving, limiting their applicability to autonomous vehicles. Only one assumed demand level of 2,000 vehicles/h was tested, representing mainly undersaturated conditions, while penetration rates below 25% were not examined. Behavioral and speed parameters were adopted rather than field-calibrated; notably, the aggressive profile used -6.00 m/s^2 braking, whose sensitivity was not tested. A 15-minute warm-up was applied without a steady-state or longer warm-up sensitivity test. Pedestrians and cyclists were excluded, potentially affecting delay and conflict measures, particularly at uncontrolled intersections. Finally, the seven evaluated movements were not volume-weighted and no aggregate network measure was derived; therefore, the findings should not be interpreted as network-wide performance.

V. CONCLUSION

This study examined cautious, normal, and aggressive autonomous-vehicle behaviors in an uncontrolled urban network in Kirkuk using PTV VISSIM and the SSAM across thirteen scenarios and ten runs per scenario. Traffic performance generally improved with penetration, with travel time decreasing in 20 of 21 movement-behavior series by up to 22.2%, although cautious behavior increased vehicle delay in some cases, reaching 33.4% on Movement 3. These changes reflect both behavioral effects and route redistribution. Safety results did not follow a consistent aggressiveness pattern: aggressive behavior produced the most crossing conflicts, whereas cautious behavior generated the highest lane-change and total conflicts, including 6,370 rear-end conflicts at full penetration. Because surrogate safety measures were developed for human driving and may classify stable autonomous platoons as conflicts, these results should not be interpreted directly as collision risk. Given the lack of field calibration, statistical dispersion, and broader demand and penetration-

rate testing, the findings are exploratory. Future work should examine penetration below 25%, multiple demand levels, fixed-route comparisons, and, most importantly, validate whether surrogate-model conflicts in autonomous traffic correspond to actual collision risk.

AUTHOR CONTRIBUTIONS

H. S. Abdulrahman: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **M. Albdairi:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **J. Oner:** Validation, Writing – review & editing. **A. Almusawi:** Supervision, Writing – review & editing.

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