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Impact of Mixed-Vehicle Environment on Speed Disparity as a Measure of Safety on Horizontal Curves

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Abstract: Due to the transition of vehicle fleets from conventional driver-operated vehicles (DVs) to connected vehicles (CVs) and/or automated vehicles (AVs), vehicles with different technologies will soon operate on the same roads in a mixed-vehicle environment. Although a major goal of vehicle connectivity and automation is to improve traffic safety, negative safety impacts may persist in the mixed-vehicle environment. Speed disparity measures have been shown in the literature to be related to safety performance. Therefore, speed disparity measures are derived from the expected speed distributions of different vehicle technologies and are used as surrogate measures to assess the safety of mixed-vehicle environments and identify the efficacy of prospective countermeasures. This paper builds on speed models in the literature to predict the speed behavior of CVs, AVs, and DVs on horizontal curves on freeways and major arterials. The paper first proposes a methodology to determine speed disparity measures on horizontal curves without any control in terms of speed limit. The impact of speed limit or advisory speed, as a safety countermeasure, is modeled and assessed using different strategies to set the speed limit. The results indicated that the standard deviation of the speeds of all vehicles (σ_c) in a mixed environment would increase on arterial roads under no control compared to the case of DV-only traffic. This speed disparity can be reduced using an advisory speed as a safety countermeasure to decrease the adverse safety impacts in this environment. Moreover, it was shown that compared to the practice of a constant speed limit based on road classification, the advisory speed is more effective when it is based on the speed behavior of various vehicle types.

Keywords: speed disparity; horizontal curves; connected vehicles; automated vehicles; non-connected vehicles; mixed-vehicle environment

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1. Introduction

Road design and control has evolved as a field of engineering to accommodate the motorized vehicles driven by human operators. Physical and operational characteristics of conventional, driver-operated vehicles (DVs) have, therefore, been used to establish the criteria and guidelines of road design and control. However, vehicles have recently been evolving to allow for more connectivity and automation. New technologies deployed or envisioned in new vehicles are grouped into two major types. The first type focuses on robust connectivity by incorporating network connections to create vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-anything (V2X) communication. However, the driver of a connected vehicle (CV) still performs all driving tasks, but the connectivity technologies allow them to receive real-time information including geometric road features, traffic incidents, congestion, and state of traffic control devices. Access to such additional information can cause CV drivers to adopt speeds that differ from DV drivers.

The second category focuses on automating many or all driving tasks using different sensing and control technologies. A six-level classification system for the automation technologies adopted in any vehicle has been developed by the Society of Automotive Engineers (SAE) varying from L0 (no automation) to L5 (full automation) [1]. Transportation agencies such as the US National Highway Transportation Safety Administration [2] and Transport Canada [3] have adopted this classification system. While the term automated vehicle (AV) is often understood as a synonym of a self-driving (or L5) vehicle, this paper uses the term AV to refer to any vehicle where the driving task at the segment of interest, namely a horizontal curve, is performed without a direct driver input, which corresponds to vehicles at automation level L3 or higher.

Both CV and AV technologies are being promoted for their expected benefits in improving safety, mobility, and environmental quality. As these technologies penetrate the market through adoption in novel vehicles, the existing vehicle fleet will gradually shift from fully DVs to fully connected, automated vehicles (CAVs) equipped with both connectivity and automation technologies. During this transition, vehicles of different technologies will coexist and use the same road facilities in a mixed-vehicle environment. The varying operational characteristics of these different technologies can impact traffic safety in the mixed environment [4]. A potential negative safety impact that has not been covered in the literature can result from the differences in speed behavior that can aggravate problems with speed consistency or speed disparity.

Numerous studies have investigated the relationship between traffic safety and speed measures [5–8]. Speeding, measured in terms of average or 85th percentile speed, has widely been reported to impact collision frequency and severity, although some work has disputed the effect on collision frequency [8]. On the other hand, speed consistency and speed disparity measures have consistently been reported to correlate with various traffic safety issues. Considerable research worldwide has shown that safety on horizontal curves is related to design consistency, where speed measures are the most accepted consistency measures and are thus widely accepted surrogate safety measures. For example, geometric features with higher speed variance, which reflects speed disparity for vehicles traveling on the same road element, were shown to experience greater traffic collision rates [9–11]. Similarly, collision frequencies on a horizontal curve were shown to increase with the increase in ($V_{85} - V_D$), which is a speed consistency measure [12]. As a result, the US Federal Highway Administration (FHWA) has incorporated design consistency based on speed measures in the Interactive Highway Safety Design Model (IHSDM), which has been designed as "a decision-support tool that provides estimates of a highway design's expected safety and operational performance" [13]. Furthermore, the Canadian road design guide has incorporated design consistency as a measure to improve safety on a horizontal curve and setting speed limits on rural roads [14]. However, no research has yet combined driver behavior and surrogate traffic safety measures in setting systems for advisory speed on horizontal curves in a mixed-vehicle environment. Therefore, this paper examines the effects of the mixed-vehicle environment on speed disparity on horizontal curves, as a surrogate measure of traffic safety. Two measures of speed disparity are examined in this paper for a mixed-vehicle system, i.e., the combined standard deviation of the speeds of the overall vehicle population on the curve (σ_c) and difference between the combined 85th percentile speed for all vehicles on the curve (V_{85c}) and the inferred design speed (V_{ID}) of the curve as $(V_{85c} - V_{ID})$.

2. Research Methodology

This section explains the research methodology, which comprises three main parts. The first part involves modeling speed behavior of the different vehicle types that make up the vehicle fleet on a horizontal curve in a mixed environment. The three vehicle types considered in this paper refer to the technologies of CVs, DVs, and AVs. It should be noted that CAVs and AVs are expected to maintain the curve's posted advisory speed as closely as possible under the restrictions of automated vehicle capabilities. Due to this similar speed behavior, both vehicle types are combined as one category referred to as AVs. Second, the approach to assess speed disparity and estimate speed disparity measures σ_c and $(V_{85c} - V_{ID})$ is presented. Finally, the study explains how operational countermeasures can be implemented to reduce speed disparity by setting a curve advisory speed. It also outlines the method for analyzing the change in speed behavior for each vehicle type in relation to the advisory speed.

2.1. Modeling Vehicles' Speed Behaviors

To examine speed disparity in a mixed-vehicle environment, speed prediction models are required for each type of vehicle technology. For CVs, this paper builds on earlier work where data from the Safety Pilot Model Deployment (SPMD) dataset in Michigan, USA, were utilized to predict CV speed behavior on horizontal curves on major arterials and freeways [15,16]. Linear Mixed Effects (LMEs) models were created to predict drivers' speeds at various points on horizontal curves. This paper uses the model set that relates the CV speed at the middle of curve (V_{MC}) to geometric characteristics only. Moreover, speed data acquired on horizontal curves from major arterials and freeways in Ontario, Canada, using an instrumented DV were utilized to build similar LME models for DVs [16]. Equations (1) and (2) show the fixed effects models developed to predict mean V_{MC} for CVs and DVs, respectively, based on curve geometric characteristics.

$$\begin{aligned} \mu_{CV} = 27.48 + 1.61 \times 10^{-3}L - 11.44(1 - RC) \\ + 2.30(1 - Int); \quad \text{Residual variance} = 5.38 \end{aligned} \tag{1}$$

$$\begin{aligned} \mu_{DV} = 25.81 - 3.9 \times 10^{-4}R + 3.92 \times 10^{-3}L - 0.32D - 8.36(1 - RC) \\ + 0.44(1 - Dir) + 3.54(1 - Int); \quad \text{Residual variance} = 4.54 \end{aligned} \tag{2}$$

where μ_{CV} and μ_{DV} = mean V_{MC} for CVs and DVs, respectively (m/s); R = curve radius (m); D = degree of curve (°); L = curve length (m); Dir = curve turning direction (1 = right turn and 0 = left turn); RC = road class (1 = freeway and 0 = arterial); Int = intersection (1 = curves with intersection and 0 = curves with no intersection).

Unlike CVs and DVs, the automated driving system in AVs is expected to closely follow speed limits. An intelligent speed adaptation (ISA) subsystem can be incorporated in the vehicle to assist speed control tasks [17]. ISA employs a digital mapping system and global positioning system (GPS) to determine the speed limit or advisory speed at different road locations, and then it can inform or warn the driver from surpassing the recommended speed limit or advisory speed [18]. If the system is equipped with a speed limiter, it will enforce the speed limit, which is referred to as mandatory or limiting ISA [18]. Furthermore, García et al. [17] pointed out that present automated driving systems have limited capabilities in properly tracking horizontal curvature at high speeds. Hence, a relationship was established to determine the maximum speed that can be reached by AVs as a function of the curve radius without the vehicle requiring to shift control to the driver [17]. This speed was referred to as automated speed and was modeled using a carefully designed experiment involving an L2 vehicle furnished with lane-keeping assistant (LKA) and adaptive cruise control (ACC). This automated speed was therefore considered the maximum horizontal curve speed that can be adopted by AVs including those of higher automation levels. Moreover, as the driver's role was to ensure vehicle proper operation without impacting the automated speed, no variability was expected in the results if the experiment had employed different drivers. This relationship as shown in Equation (3) was used in this study to calculate the mean AV's maximum speed where the root-mean square error ($RMSE$) was calculated using the primary data shared by the authors.

$$\mu_{AV,max} = \begin{cases} 16.36 + 0.2299R - 0.0001274R^2 & \text{if } R \leq 901.7\text{m}; \ RMSE = 10.08 \text{ km/h} \\ 120 & \text{if } R > 901.7\text{m} \end{cases} \tag{3}$$

where $\mu_{AV,max}$ = mean AV's maximum speed on a horizontal curve (km/h).

2.2. Assessing Speed Disparity

This research focuses on the expected speeds of different vehicle technologies at the midpoint of horizontal curves on freeways and major arterials. The speed disparity analysis encompasses all vehicles traveling in free-flow conditions, where the headway is large enough for their speed to be independent of the front vehicle's speed. The CV, DV, and AV subpopulations are expected to exhibit different speed behaviors in a mixed-vehicle environment, which can be quantified using the models outlined in the previous section. Assuming that the vehicle subpopulation of each technology type contains a large enough number of vehicles, the speeds of vehicles in each category can be simulated using the methods as described in this section.

First, the CV and DV subpopulations are anticipated to follow a normal distribution characterized by mean values, μ_{CV} and μ_{DV}, are calculated using Equations (1) and (2), respectively, and the standard deviation values, σ_{CV} and σ_{DV}, are equivalent to the square root of the residual variance in a specific model. The assumption of normal speed distributions is consistent with the vast majority of relevant research and was verified for the CV and DV speed data utilized in model development [15,16]. Conversely, the speed behavior of the AV subpopulation will depend on whether a speed limit (SL) is specified and the value of SL relation to the automated speed ($\mu_{AV,max}$), with three possible scenarios that are schematically presented in Figure 1 and explained as follows.

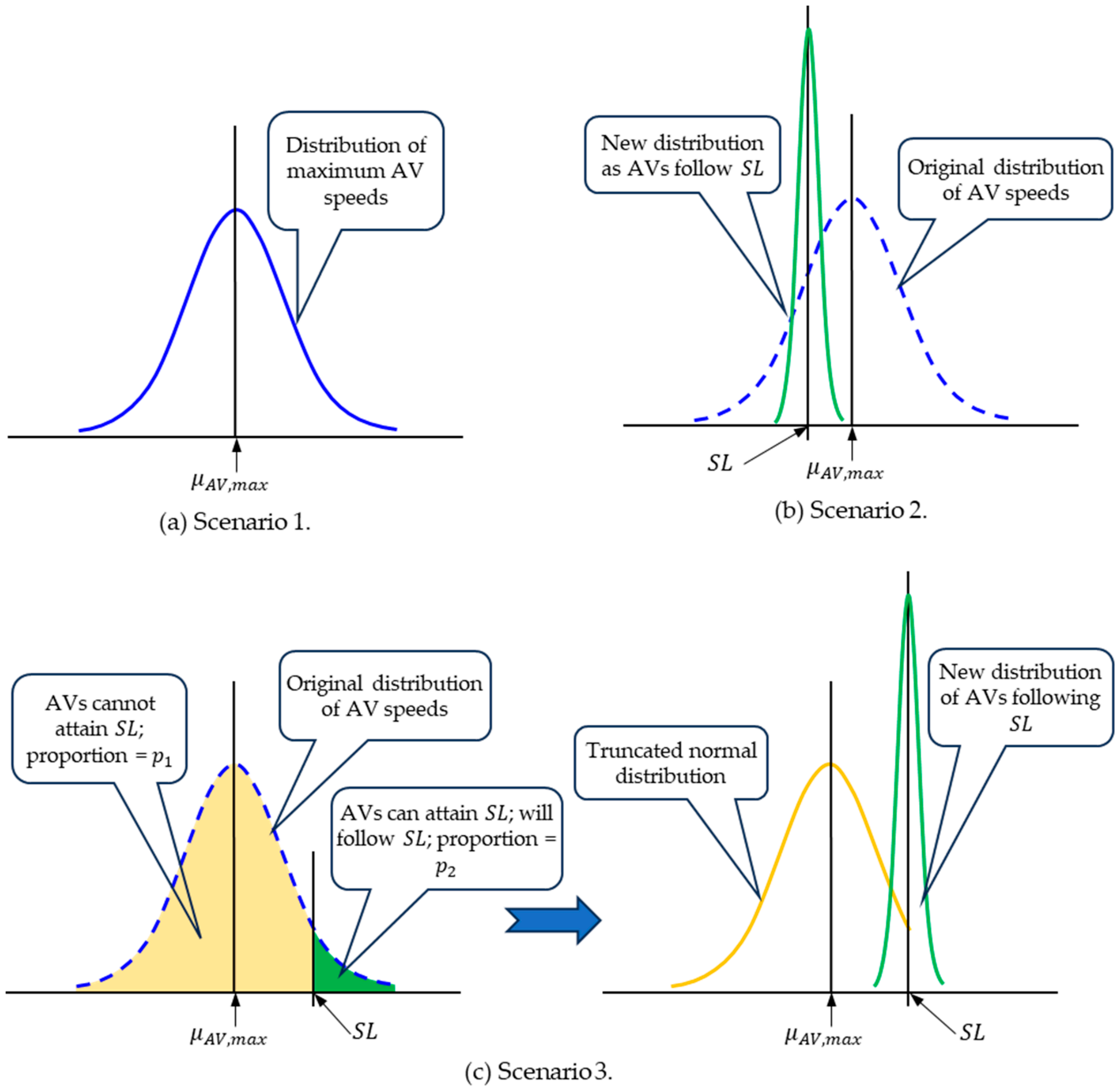


Figure 1. Schematic of AV speed distributions in scenarios 2 and 3 (reprinted from [16]).

- First, if there is no recommended speed limit (or advisory speed), AVs would travel at the maximum attainable speed, which is already defined as the automated speed. Thus, the AV subpopulation would maintain a normal distribution represented by the mean value $\mu_{AV,max}$ and standard deviation $\sigma_{AV,max} = RMSE$ of Equation (3).
- Second, if there is a recommended speed limit (or advisory speed), AVs will try to adhere to this SL. As discussed earlier, a mandatory ISA system can be utilized in the AV to enforce this behavior. If the SL is low enough relative to $\mu_{AV,max}$, virtually all AVs will attempt to drive at the SL with minor deviations as vehicles accelerate or decelerate to adjust other road users or due to limitations of the vehicle controls. Therefore, it is reasonable to assume that the AV subpopulation has a narrow normal distribution whose mean value μ_{AV} is equivalent to the SL. With the mean value already known, the distribution's standard deviation can be defined presuming a low value of the coefficient of variation (COV) as follows:

$$\sigma_{AV} = COV \times SL \tag{4}$$

- Third, if a SL is set higher that the automated speed for a considerable portion of AVs, these vehicles will not be able to attain the SL. Subsequently, the normal distribution of an AV's maximum speed that was established in the first case can be divided into two parts. The first part to the left of the SL relates to the AVs that cannot reach the SL, and intuitively will drive at the specified automated speed. The mean value $\mu_{AV,1}$ and standard deviation $\sigma_{AV,1}$ of this truncated normal distribution can be calculated using Equations (5)–(8). Alternatively, Matlab's built-in function "*truncate*" can be used to set up the truncated normal distribution from the original distribution. The portion of AVs whose automated speed is higher than the SL will follow the SL with minor fluctuations similar to the AVs in the second scenario. Therefore, the portion can be presumed to have a narrow normal distribution represented by a mean value $\mu_{AV,2}$ equivalent to SL and standard deviation $\sigma_{AV,2}$. These parameters can be calculated using Equation (4). Subsequently, both portions can be combined to estimate μ_{AV} and σ_{AV} of all AVs using Equations (9)–(11).

$$Z_{SL} = \frac{SL - \mu_{AV,max}}{\sigma_{AV,max}} \tag{5}$$

$$p_1 = \Phi(z \leq Z_{SL}) \tag{6}$$

$$\mu_{AV,1} = \mu_{AV,max} - \sigma_{AV,max} \frac{\varphi(Z_{SL})}{\Phi(z \leq Z_{SL})} \tag{7}$$

$$\sigma_{AV,1} = \sigma_{AV,max}^2 \left[1 - Z_{SL} \frac{\varphi(Z_{SL})}{\Phi(z \leq Z_{SL})} - \left(\frac{\varphi(Z_{SL})}{\Phi(z \leq Z_{SL})}\right)^2\right] \tag{8}$$

$$p_2 = 1 - p_1 \tag{9}$$

$$\mu_{AV} = p_1\mu_{AV,1} + p_2\mu_{AV,2} \tag{10}$$

$$\sigma_{AV} = \sqrt{p_1\left(\sigma_{AV,1}^2 + (\mu_{AV} - \mu_{AV,1})^2\right) + p_2\left(\sigma_{AV,2}^2 + (\mu_{AV} - \mu_{AV,2})^2\right)} \tag{11}$$

where Z_{SL} = z-score for the SL in the maximum AV speed distribution; p_1 and p_2 = proportion of AVs relative to the total AV subpopulation that cannot and can attain SL, respectively; φ (Z_{SL}) = normal distribution function for $z = Z_{SL}$; and $\Phi(z \leq Z_{SL})$ = normal cumulative distribution function for $z = -\infty$ to Z_{SL}.

After estimating the μ and σ of the CV, DV, and AV subpopulations, the combined mean speed (μ_c) and standard deviation (σ_c) of the overall vehicle population on a horizontal curve can be calculated as follows.

$$\mu_c = p_{CV}\, \mu_{CV} + p_{DV}\, \mu_{NAV} + p_{AV}\, \mu_{AV} \tag{12}$$

$$\sigma_c = \sqrt{p_{CV}\left(\sigma_{CV}^2 + (\mu_c - \mu_{CV})^2\right) + p_{DV}\left(\sigma_{DV}^2 + (\mu_c - \mu_{DV})^2\right) + p_{AV}\left(\sigma_{AV}^2 + (\mu_c - \mu_{AV})^2\right)} \tag{13}$$

where $p_{CV} + p_{DV} + p_{AV} = 1$.

Finally, assuming a normal distribution for the overall vehicle population, for all vehicles combined, V_{85c} can be calculated using the inverse cumulative distribution function of 0.85 for a standard normal distribution (Φ^{-1} (0.85)) equal to 1.0364, as follows:

$$V_{85c} = \mu_c + \Phi^{-1}\,(0.85)\sigma_c = \mu_c + 1.0364\sigma_c \tag{14}$$

where Φ^{-1} = inverse cumulative distribution function for a standard normal distribution.

2.3. Setting Advisory Speed as a Countermeasure

If potential safety impacts are indicated based on the speed disparity measures, countermeasures can be devised to reduce the values of these measures to improve design consistency and safety performance. This paper proposes setting a specific advisory speed on the horizontal curve (V_{Adv}) as a potential countermeasure to reduce speed disparity. However, different approaches or strategies can be followed to establish the value of V_{Adv} at a specific curve. To increase speed compliance of a specific population of vehicle, V_{Adv} can be set equal to V_{85} of that population. With different vehicle subpopulations corresponding to the different vehicle technologies, five procedures called countermeasures 1–5 (CM1–CM5) were first outlined to establish V_{Adv}. Yet, the predicted AV speeds without a speed limit demonstrated the vehicle ability, not the operator preference, making the mean value the most appropriate for the AV subpopulation. Consequently, new versions of CM1 and CM4 were integrated, known as CM1b and CM4b, derived from the average speed of the AV. Additionally, the CM6 specification sets V_{Adv} as a fixed value solely on the road classification, which is a strategy that numerous jurisdictions employ. Based on the above discussions, eight countermeasures were assessed in this study as indicated below [16]:

- CM1: V_{Adv} is set considering the V_{85} of AVs (V_{85AV}).
- CM1b (variation in CM1): V_{Adv} is set considering the AV's mean speed (μ_{AV}).
- CM2: V_{Adv} is set considering the V_{85} of DVs (V_{85DV}).
- CM3: V_{Adv} is set considering the V_{85} of CVs (V_{85CV}).
- CM4: V_{Adv} is set considering the minimum of V_{85AV}, V_{85DV}, and V_{85CV}.
- CM4b (variation in CM4): V_{Adv} is set considering the minimum of μ_{AV}, V_{85DV}, and V_{85CV}.
- CM5: V_{Adv} is set considering V_{85c} to account for the contribution of each vehicle type.
- CM6: V_{Adv} is set considering a fixed speed limit based only on road classification. The fixed speed limits used in this study are set considering the practice in Ontario, Canada, where the main arterial and freeway speed limits are generally set as 80 and 100 km/h, respectively.

It should be noted that various communication protocols are required to effectively communicate the same V_{Adv} for each vehicle type (see for example [19]). However, these protocols are outside the scope of this research. An additional criterion for all possible values of V_{Adv} is that it should not surpass the inferred design speed of the horizontal curve (V_{ID}), defined as "the maximum speed for which all critical design-speed related criteria are met at a particular location" [20]. For a specific horizontal curve with a known radius and superelevation rate, V_{ID} can be calculated by reordering the point mass formula in the Green Book [21] as indicated below:

$$V_{ID} = \sqrt{127R(0.01e + f_{max})} \tag{15}$$

where R = curve radius (m); e = superelevation rate (%); and f_{max} = maximum lateral friction coefficient.

To account for the change in f_{max} with V_{ID}, an iterative process was followed to estimate V_{ID} and f_{max} on an existing horizontal curve using the f_{max} values for rural and high-speed urban design in the Canadian design guide [14] as demonstrated in Table 1, which are largely similar to the Green Book [21] at high design speeds.

Table 1. f_{max} for rural and high-speed urban design [14].

V_D(km/h)	f_{max}
40	0.17
50	0.16
60	0.15
70	0.15
80	0.14
90	0.13
100	0.12
110	0.10
120	0.09
130	0.08

It should be noted that concerns have been raised in relation to the inability of the point mass formula of accurately capturing vehicle dynamics on a curve [22]. However, the focus of this research is only on the speed disparity in a mixed-vehicle environment. This paper uses only V_{ID} obtained from the point mass formula because most research on design consistency utilizes ($V_{85} - V_{ID}$) as a consistency measure.

2.3.1. Behavior of AVs

AVs are assumed to try to follow V_{Adv} perfectly in any of these countermeasures. Hence, the behavior of AVs under any countermeasure can be investigated in a similar way to their behavior under an advisory speed limit as discussed in the preceding section.

2.3.2. Behavior of CVs and DVs

For CVs and DVs, an advisory speed is one of the different pieces of information used by the driver to select their driving speed. Due to human factors, CVs and DVs do not strictly follow V_{Adv} in every way. Thus, the effects of V_{Adv} are not universal for drivers. As this research investigates speed disparity concerning all vehicles driving on a horizontal curve, the investigation only encompasses the macro-level effect on V_{Adv} on each type of vehicle. At this level, it is assumed that CVs and DVs will adjust their speeds based on the value V_{Adv}, thereby increasing the proportion of vehicles that adhere this value. Based on the above analysis, the present study hypothesizes a compliance rate (CR) for each vehicle subpopulation in order to investigate the effects of CV and DV speed behavior under an advisory speed as follows:

- The original compliance rate before disseminating V_{Adv} can be assessed from the initial speed distribution as presented schematically in Figure 2a and using the equations indicated below.

$$Z_{Adv} = \frac{V_{Adv} - \mu}{\sigma} \tag{16}$$

$$p_c = \Phi(z \leq Z_{Adv}) \tag{17}$$

where Z_{Adv} = z-score for V_{Adv} in the original speed distribution; μ and σ = mean and standard deviation of the original speed distribution, respectively; p_c = original compliance rate before broadcasting V_{Adv}; and $\Phi(z \leq Z_{Adv})$ = normal cumulative distribution function for $z = -\infty$ to Z_{Adv}.

- If $p_c \geq CR$, more vehicles are already compliant with V_{Adv} than the anticipated CR, and thus no alteration is expected in the speed behavior.
- If $p_c < CR$, the macro speed behavior of the vehicle subpopulation will change so that the proportion of compliant vehicles is equal to CR as presented schematically in Figure 2b. The new speed distribution is defined by keeping COV constant. Hence, the new mean and standard deviation of the countermeasure speed distribution (μ_{cm} and σ_{cm}) can be computed from the following equations:

$$COV = \frac{\sigma}{\mu} \tag{18}$$

$$Z_{Adv,cm} = \Phi^{-1}(CR) \tag{19}$$

$$\mu_{cm} = \frac{V_{Adv}}{1 + COV \times Z_{Adv,cm}} \tag{20}$$

$$\sigma_{cm} = COV \times \mu_{cm} \tag{21}$$

where COV = coefficient of variation for both original and countermeasure speed distributions; $Z_{Adv,cm}$ = z-score for V_{Adv} in the countermeasure speed distribution; Φ^{-1} (CR) = normal inverse cumulative distribution function for CR.

- Following the estimation of μ_{cm} and σ_{cm} of each vehicle subpopulation, the new μ_c, σ_c, and V_{85c} can subsequently be determined using Equations (12)–(14).

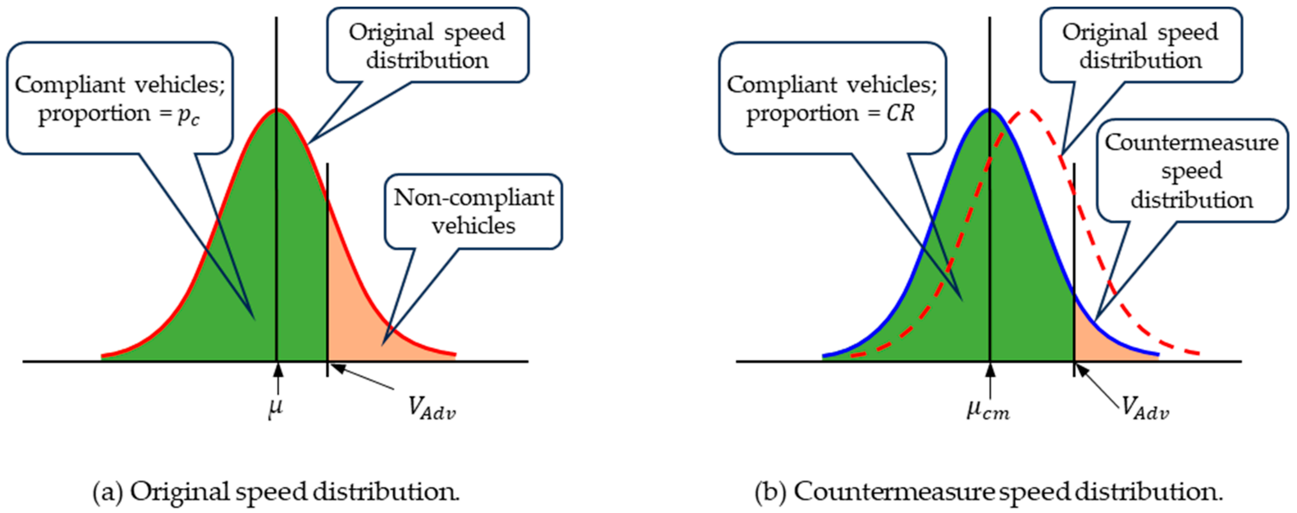


Figure 2. Schematic of compliant and non-compliant vehicles of a specific subpopulation (reprinted from [16]).

As mentioned earlier, different approaches can be followed in setting V_{Adv}, with the most common practice involving a fixed advisory speed or speed limit that depends on road classification and location, referred to earlier as CM6. In a mixed environment, this practice may not yield optimal conditions in relation to the speed behavior of different vehicle types and the resulting speed discrepancy measures. This paper addresses this challenge by examining different approaches for setting V_{Adv} and their impacts on speed disparity as a surrogate measure in assessing road safety on horizontal curves.

3. Results and Discussion

This section provides the results derived from the methods and model described above. A Matlab script was created to perform these calculations, which computed speed measures for various vehicle types, combined speed measures for the entire vehicle fleet under both no control (No CM) scenarios and examined each of the countermeasures. In this section, the results are first plotted on a horizontal curve without CM to assess the speed and speed disparity measures. The subsequent results showcase the efficacy of the various measures implemented. The horizontal curve parameters included in the analysis are as follows:

- Measures are evaluated at the curve midpoint, where speed disparity measures are more constrained by road geometry.
- Road class considers both arterials and freeways.
- The curve is a right turn with no intersection. Hence, speed disparity outcomes depend solely on the horizontal curve.
- A radius (R) = 200–750 m for arterials and 600–1000 m for freeways correspond to the ranges of curve radii used in the speed prediction models.
- Deflection angle (D) = 20°.
- Superelevation rate (e) = 6%.
- Maximum lateral friction (f_{max}) is speed dependent as demonstrated in Table 1.

Several vehicle shares were considered to account for the continuous change in vehicle composition as the penetration rates of newer technologies increase with time as follows:

- Currently, DVs are the dominant vehicle technology. Six DV proportions (P_{DV}) were included in the analysis as the technology share declines from 1 to 0 at 0.2 increments.
- AVs will gradually obtain market shares at a higher rate compared to CVs. Six AV proportions (P_{AV}) were included in the analysis as the technology share inclines from 0 to 1 at 0.2 increments.
- The CV proportion (P_{CV}) is equal to $(1 - (P_{DV} + P_{AV}))$; P_{CV} does not exceed P_{AV}.

Based on these assumptions, 12 vehicle share combinations were included as demonstrated in Table 2. The vehicle share combination in each cell in the table and in the rest of the manuscript corresponds to $P_{DV} : P_{AV} : P_{CV}$.

Table 2. Vehicle share combinations in speed disparity analysis [16].

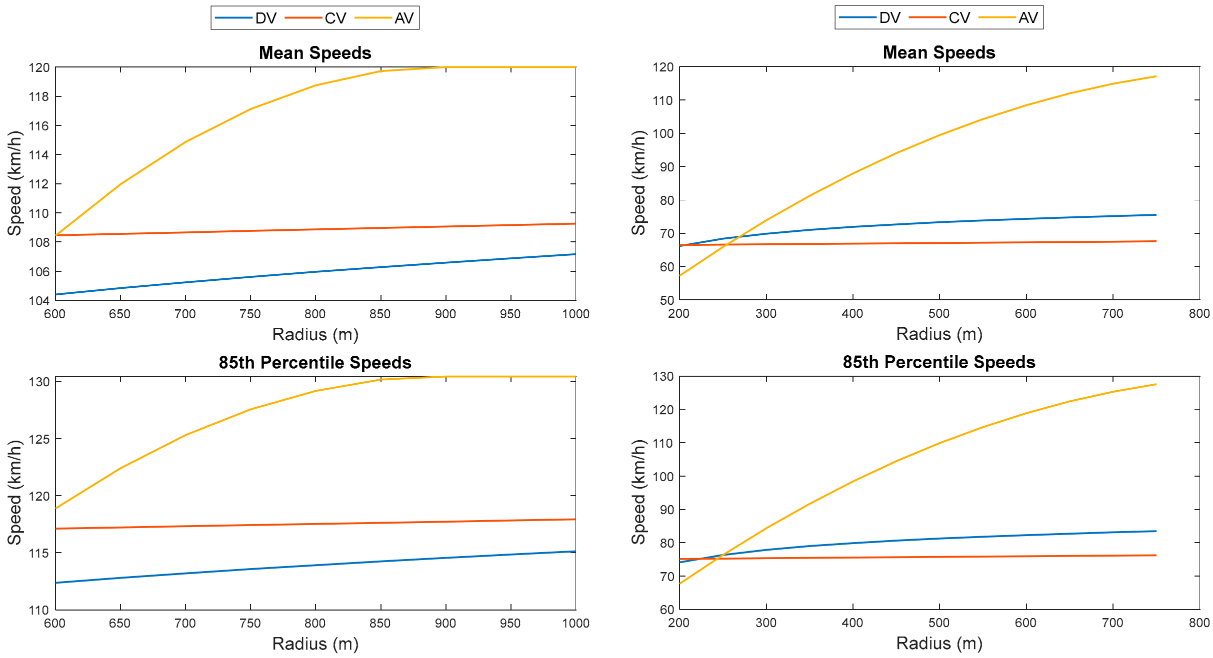
P_{AV}	P_{DV}					
	1	**0.8**	**0.6**	**0.4**	**0.2**	**0**
0	1:0:0	--- [a]	--- [a]	--- [a]	--- [a]	--- [a]
0.2	--- [b]	0.8:0.2:0	0.6:0.2:0.2	--- [a]	--- [a]	--- [a]
0.4	--- [b]	--- [b]	0.6:0.4:0	0.4:0.4:0.2	0.2:0.4:0.4	--- [a]
0.6	--- [b]	--- [b]	--- [b]	0.4:0.6:0	0.2:0.6:0.2	0:0.6:0.4
0.8	--- [b]	--- [b]	--- [b]	--- [b]	0.2:0.8:0	0:0.8:0.2
1	--- [b]	--- [b]	--- [b]	--- [b]	--- [b]	0:1:0

[a] Combination is omitted because $P_{CV} > P_{AV}$. [b] Combination is not possible because $(P_{DV} + P_{AV} + P_{CV}) > 1$.

Finally, as AVs are expected to have minor fluctuations around V_{Adv}, the coefficient of variation (COV) for these AV speeds is presumed to be equal to 0.01. The compliance rate of DVs with advisory speed (CR_{DV}) depends on multiple factors and is presumed to vary in the range of 0.3–0.7. Due to the availability of the more information to CV drivers, the CV compliance rate (CR_{CV}) is assumed to change in the range of 0.5–0.9.

3.1. Speed Disparity Analysis—Case of No Advisory Speed

Figure 3 presents the values of mean speed and V_{85} of individual vehicle subpopulation in the case of no advisory speed (No CM), with parts a and b of the figure corresponding to freeways and arterials, respectively. The figure shows that AV speeds increase more rapidly with the curve radius than DVs and CVs. Consequently, AV speeds are higher compared to CVs and DVs on curves with a radius greater than 250 m, and the difference becomes greater as the radius increases. Therefore, setting V_{Adv} in accordance with AV speed behavior is not expected to reduce speed disparity as the V_{Adv} will be too high for CVs and DVs.

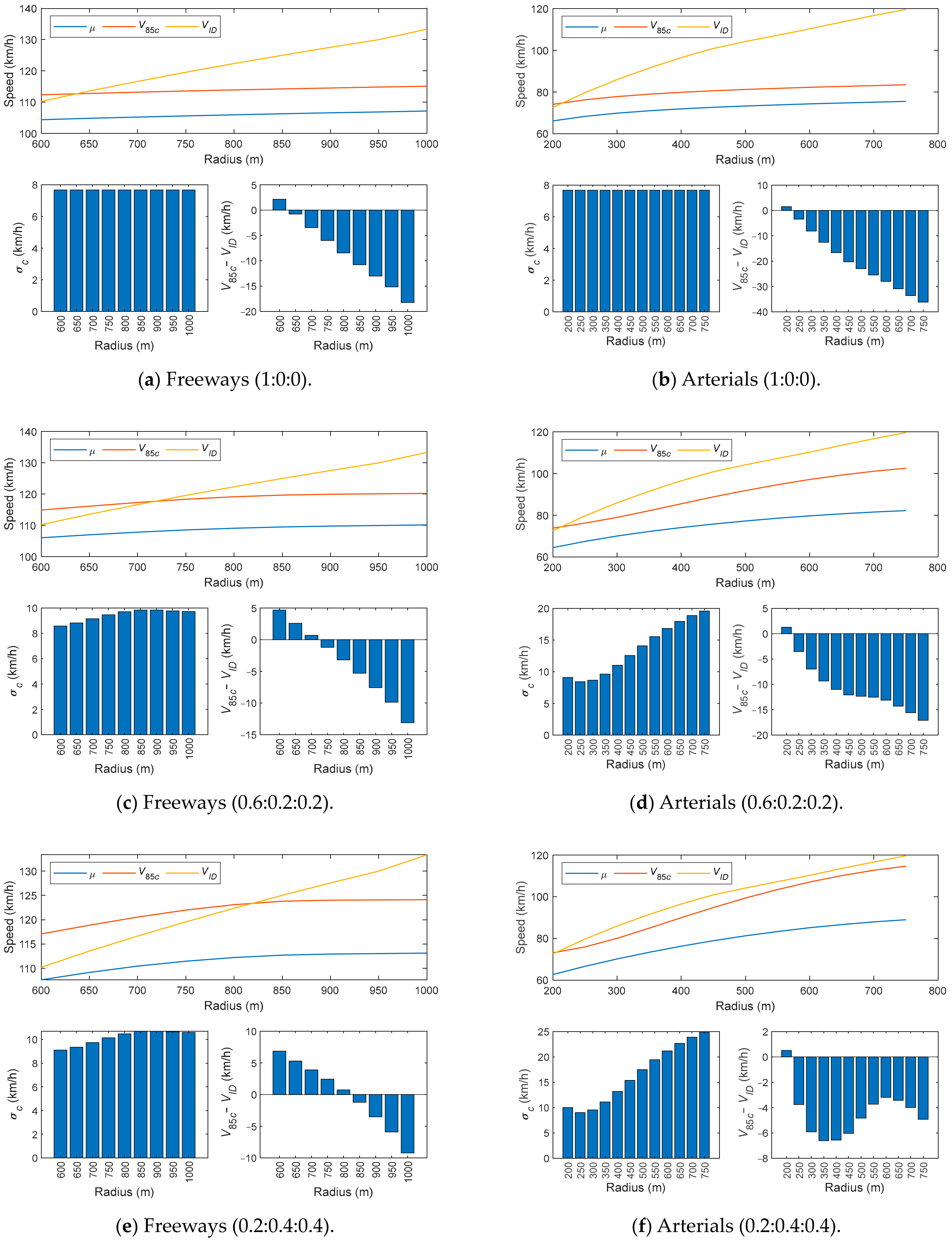


(**a**) Freeways. (**b**) Arterials.

Figure 3. Mean and 85th percentile speeds for each vehicle type (no CM) (reprinted from [16]).

Figure 4 presents V_{ID}, combined speed measures (μ and V_{85c}), and speed disparity measures (σ_c and $V_{85c} - V_{ID}$) at three different vehicle share combinations, where parts a, c, and e correspond to freeways, while b, d, and f correspond to arterials. As illustrated in the figure, the values of ($V_{85c} - V_{ID}$) are generally low and are mainly negative values, due to the comparatively high values of V_{ID}. However, the values of σ_c on arterials can be considerably higher in mixed traffic compared to the case of the all-DV fleet (1:0:0 vehicle share combination). For instance, σ_c on a curve with a 750 m radius can be as high as 19.6 and 24.8 km/h for the vehicle share combinations 0.6:0.2:0.2 and 0.2:0.4:0.4, respectively, compared to 7.7 km/h for the all-DV fleet. The corresponding increase in σ_c on freeways is significantly lower than that on arterials. This trend is easily observable in Figure 5, which shows the maximum values of σ_c and ($V_{85c} - V_{ID}$) on freeway and arterial curves for the twelve vehicle share combinations considered in the analysis. In this figure, the all-DV fleet is shown as the last category on the x-axis as the 1:0:0 vehicle share combination.

It can therefore be stated that σ_c on arterials experienced the highest increase in the mixed-vehicle environment and is the most sensitive measure compared to the shares of various vehicle types. When no control is applied (no CM), the transition of the vehicle fleet to mixed technologies is expected to cause considerably higher values of σ_c on horizontal curves of arterial roads. As indicated in the literature [9–11], the increase in σ_c would accelerate crash rates on horizontal curves in this environment.



(**a**) Freeways (1:0:0). (**b**) Arterials (1:0:0).

(**c**) Freeways (0.6:0.2:0.2). (**d**) Arterials (0.6:0.2:0.2).

(**e**) Freeways (0.2:0.4:0.4). (**f**) Arterials (0.2:0.4:0.4).

Figure 4. Combined speed and speed disparity measures (no CM) for a sample of vehicle share combinations (reprinted from [16]).

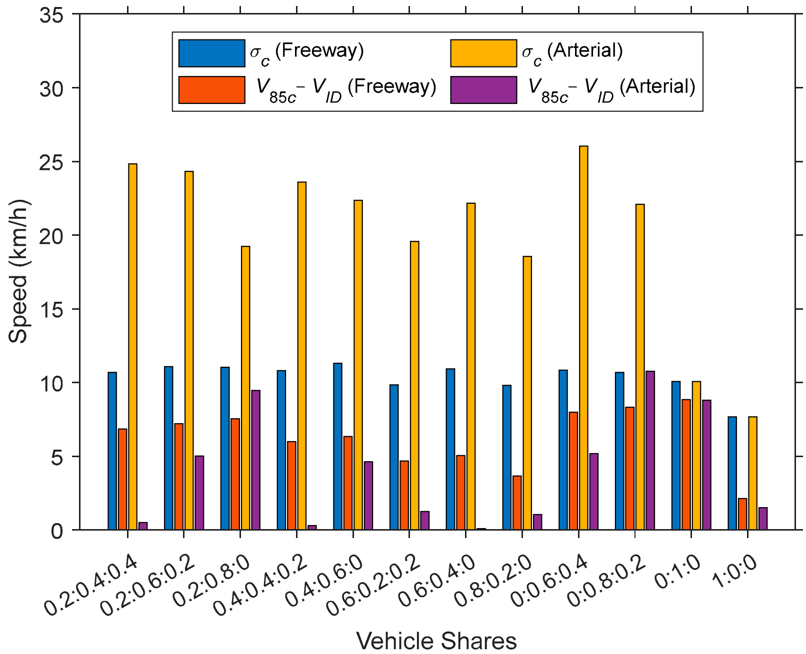


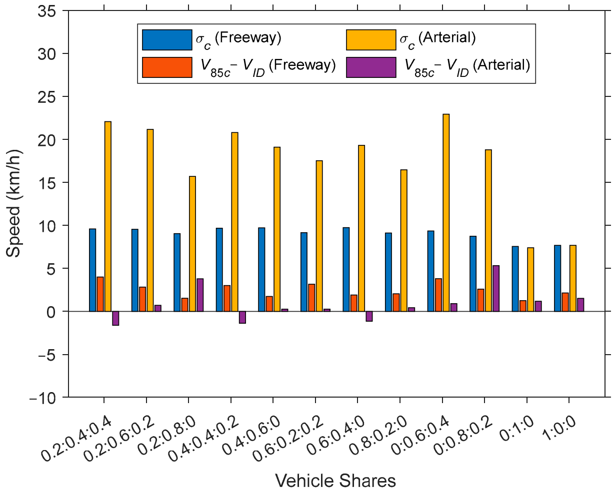
Figure 5. Maximum values of speed disparity measures (no CM) for different vehicle share combinations (adopted from [16]).

3.2. Reducing Speed Disparity through Advisory Speeds

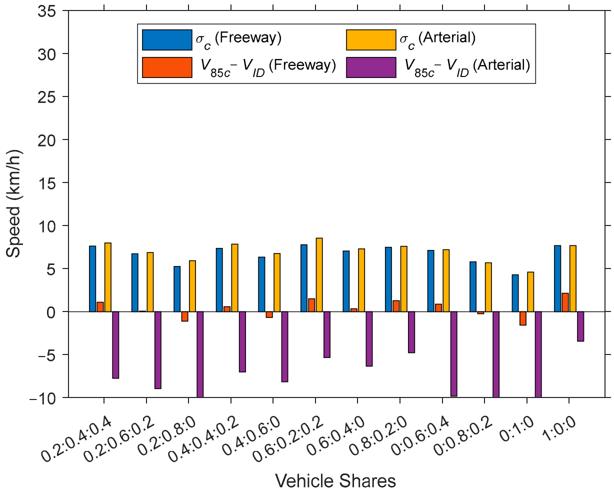
As mentioned earlier, an advisory speed, set using eight different approaches, was considered to reduce speed disparity. The approaches for advisory speed were referred to as countermeasures, which were listed as CM1–CM6 in addition to CM1b and CM4b. All eight countermeasures reduced speed disparity by decreasing the values of σ_c and $(V_{85c} - V_{ID})$. However, the countermeasure determines the extent to which such a reduction is achievable. Figure 6a,b show examples of the two countermeasures CM1 and CM4b, respectively, that produce the lowest and highest reduction in σ_c and $(V_{85c} - V_{ID})$. Figure 6a shows that σ_c on arterial roads in CM1 is much higher in a mixed-vehicle environment than in the case of the all-DV fleet. On the other hand, the same measure in CM4b may be slightly higher or lower in the mixed-vehicle environment than the value in the all-DV fleet.

Figure 7 illustrates the maximum value of σ_c based on the case of no control (no CM) and all eight countermeasures on arterials. As shown in the figure, speed disparity assessed in terms of σ_c can be lowered using an advisory speed set using all proposed strategies, except for the strategies in CM1, CM1b, and CM5. As discussed before, the relatively high AV speeds would mean that setting V_{Adv} equal to the AV's mean or 85th percentile speed would cause the value of V_{Adv} to be too high for CVs and DVs to maintain, and in turn would not produce enough change in speed behavior to reduce speed disparity. The figure also shows that CM6, which is equivalent to the traditional practice of using a fixed V_{Adv}, would reduce σ_c. However, this approach is outperformed by CM2, CM3, CM4, and CM4b in most or all vehicle combinations.

In summary, all considered approaches to set an advisory speed would reduce speed disparity in a mixed environment. This includes the common practice of a fixed advisory speed considering road types. However, further reductions in speed disparity can be achieved by setting the advisory speed considering the speed behavior of the various vehicle classes.



(**a**) CM1.



(**b**) CM4b.

Figure 6. Maximum values of speed disparity measures for two countermeasures (reprinted from [16]).

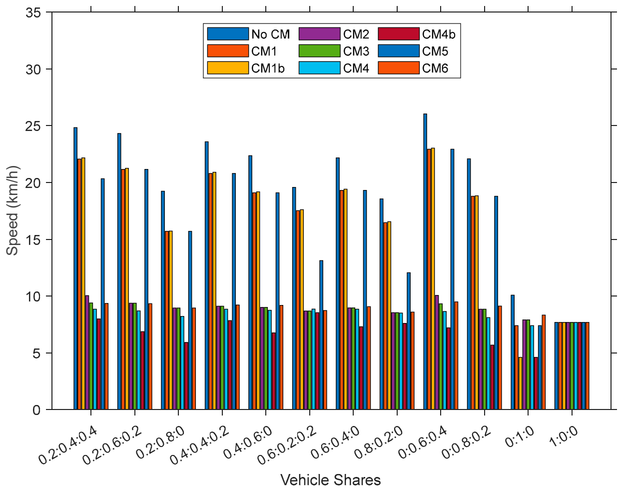


Figure 7. Maximum σ_c on arterial roads for the case of no CM and all countermeasures (reprinted from [16]).

3.3. Sensitivity of Speed Disparity to Advisory Speed Compliance Rates

Despite the uncertainty in modeling speed behaviors of emerging CV and AV technologies, the methodology developed in this paper relied largely on intuitive assumptions. Although an increase in CV and DV speed compliance in relation to an advisory speed is also an intuitive behavior, the extent of this compliance is uncertain. Therefore, the sensitivity of σ_c on arterial roads was analyzed in relation to CV and DV compliance rates, referred to as CR_{CV} and CR_{DV}, respectively. As mentioned earlier, CR_{CV} and CR_{DV} were assumed to vary within wide ranges of 0.5–0.9 and 0.3–0.7, respectively. The maximum value of σ_c on arterial road curves was then calculated for each combination of CR_{CV} and CR_{DV} values within this range to create a 5×5 matrix of σ_c values for each countermeasure. Subsequently, these matrices were utilized to generate heatmaps of σ_c for the combined vehicle shares. Figure 8 shows the resulting heatmaps in CM4b as an example for the case where σ_c was found to visibly change with the compliance rates. In contrast, Figure 9 presents the case of CM6 as an example of σ_c that virtually does not change with the change in compliance rates.

For most countermeasures, the heatmap plots showed that the maximum σ_c exhibited little sensitivity as CR_{CV} and CR_{DV} changed within the assumed ranges, and relatively more sensitivity was evident in CM4 and CM4b. Hence, the compliance rates of both CVs and DVs are not expected to have a substantial impact on speed disparity or the general findings noted in the previous section.

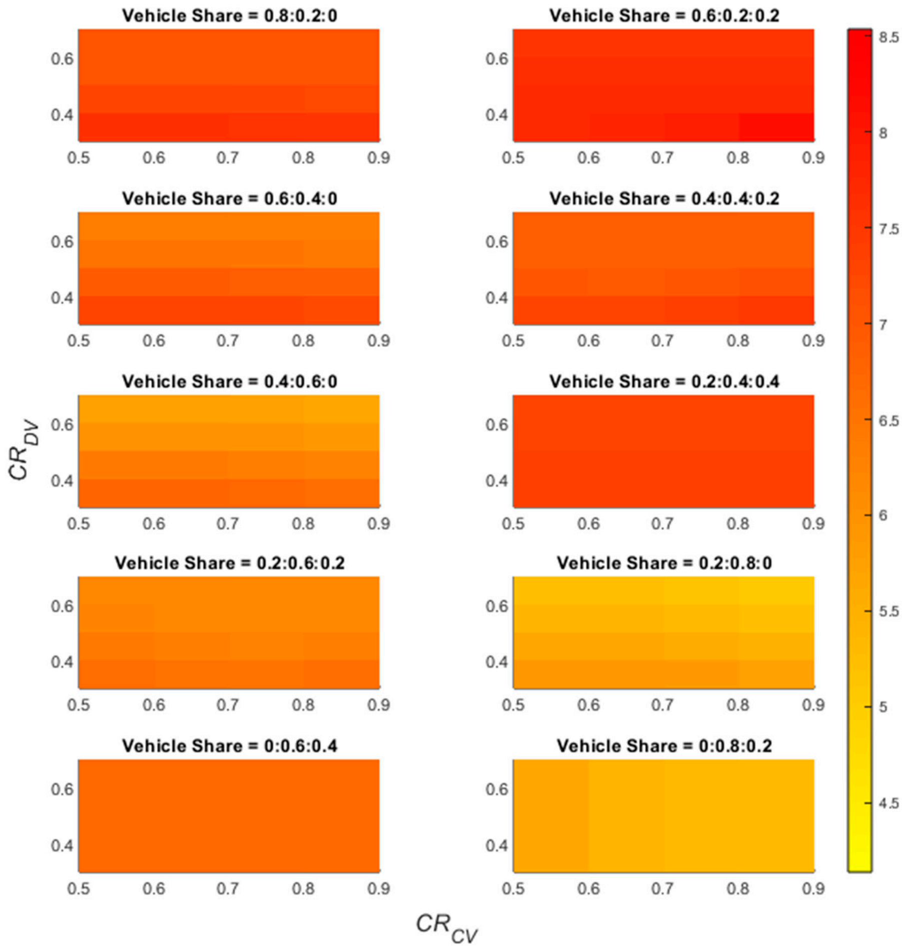


Figure 8. Heatmap of σ_c with CR_{CV} and CR_{DV} in CM4b (reprinted from [16]).

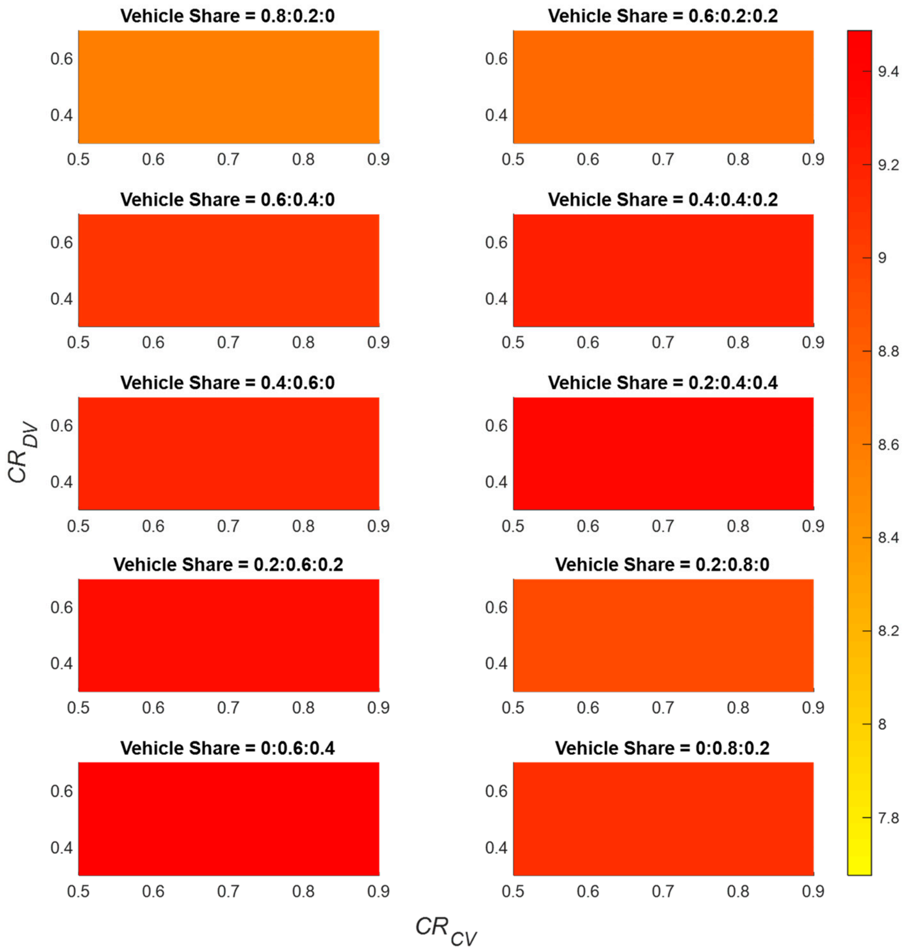


Figure 9. Heatmap of σ_c with CR_{CV} and CR_{DV} in CM6 (reprinted from [16]).

4. Conclusions

This study focused on developing a new and comprehensive methodology for assessing speed disparity in a mixed-vehicle environment based on two measures: the combined standard deviation of the speeds of the overall vehicle population on the horizontal curve (σ_c) and difference between the combined 85th percentile speed for all vehicles on the curve and the inferred design speed of the curve as $(V_{85c} - V_{ID})$. The methodology builds on speed models in the literature that can be used to predict the distribution of CV, DV, and AV speeds on horizontal curves based on the curve geometric parameters such as radius, deflection angle, and superelevation rate. A fundamental difference between these models is noted in the relevance of CV and DV models on one hand and the AV model on the other hand. While the CV and DV models predict the speed of choice of these vehicles' drivers, the AV model predicts the maximum speed attainable in automated driving. Based on these models, the developed methodology predicts the overall or combined speed behavior of the vehicle fleet comprising CVs, DVs, and AVs on horizontal curves considering different countermeasures in terms of the recommended speed limit.

The analysis showed that, relative to the case of the all-DV fleet, σ_c on arterial roads experienced the largest increase in the mixed-vehicle environment and is sensitive to the shares of various vehicle types. When there is no recommended speed on the curve (case of no control), horizontal curves on arterial roads can experience considerably higher values of σ_c in mixed-vehicle environments than the corresponding values for the all-DV fleet. As the literature has consistently indicated a higher collision experience with higher speed variance, the substantial increase in σ_c in a mixed environment is expected to have negative safety impacts. To mitigate these negative safety impacts, eight different approaches to set the advisory speed were considered as safety countermeasures. It was also shown that the high σ_c values can be considerably reduced using the proposed countermeasures involving setting an advisory speed on the curve. Compared to the traditional practice of setting a fixed value based on the advisory speed or speed limit, a more effective countermeasure would require establishing the advisory speed as the minimum of V_{ID}, V_{85} of DVs, V_{85} of CVs, and mean speed of AVs. The findings did not indicate a significant reliance on CV and DV compliance rates to the advisory speed. This study and findings are useful to road transportation agencies that are responsible for setting speed limits. These agencies can adopt the most effective approach for setting advisory speeds and communicate these speeds using variable message signs (VMSs) to all vehicles, intelligent speed adaptation (ISA) to AVs, and V2I communication for CVs.

It is important to note that the speed prediction models included in this study rely on data gathered from various jurisdictions. There is an assumption that the quality of driving for Michigan (USA) and Ontario (Canada) is similar as driver behavior does not vary much. Furthermore, it is reasonable to assume that the AV limitations observed in L2 would also apply to higher levels of automation. Though, the study should benefit from additional data to model the speed behavior of various vehicle technologies within a single jurisdiction. Models on other road classifications would also allow us to replicate the study on these roads. This study can also benefit from more data on CV and AV speed behavior considering other types of road geometrics, such as vertical curves or intersections and different weather conditions as the technology becomes more developed and more widely adopted. This study could be enhanced by incorporating behavioral factors such as driver adaptability to advisory speeds, driver reaction times, and vehicle-to-vehicle communication effectiveness in mixed-vehicle environments. Moreover, this study concentrated on the speed behavior of passenger cars only, which has been the subject of most speed consistency and disparity studies. Further analysis involving heavy vehicles may be warranted depending on the percentage of this vehicle type in the vehicle fleet.

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Abbreviations

AV	Automated vehicle
CM	Countermeasure
COV	Coefficient of variation
CR	Compliance rate
CR_{CV}	CV's compliance rate
CR_{DV}	DV's compliance rate
CV	Connected vehicle
DV	Conventional non-connected vehicle
SL	Speed limit
V_{Adv}	Advisory speed on horizontal curve
V_{ID}	Inferred design speed of a curve
V_{85c}	Combined 85th percentile speed of all vehicles on the curve
μ	Mean speed
σ_c	Combined standard deviation of the overall vehicle population on the curve

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