Towards Hybrid Traffic Laws for Mixed Flow of Human-driven Vehicles and Connected and Autonomous Vehicles

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Short summary

Hybrid traffic laws represent an innovative approach to managing mixed environments of connected autonomous vehicles (CAVs) and human-driven (HD) vehicles by introducing separate sets of regulations for each vehicle type. These laws are designed to leverage the unique capabilities of CAVs while ensuring both types of cars coexist effectively, ultimately aiming to enhance overall social welfare. This study uses the SUMO simulation platform to explore hybrid traffic laws in a restricted lane scenario. It evaluates static and dynamic lane access policies under varying traffic demands and CAV penetration rates. The policies aim to minimize average passenger delay and encourage the incorporation of autonomous vehicles with higher occupancy rates. Results demonstrate that dynamic policies significantly improve traffic flow, especially at low CAV penetration rates, compared to traditional dedicated bus lane strategies. These findings highlight the potential of hybrid traffic laws to enhance traffic efficiency and accelerate the transition to autonomous technology.
Keywords: Automated and Connected Driving, Hybrid Traffic Laws, Mixed Traffic Environment, Simulation of Urban MObility (SUMO), Traffic Flow Optimization.

1 Introduction

Existing traffic regulations are fundamentally designed to govern the behavior of human-driven (HD) vehicles. These regulations are built upon the foundation of human perception, decision-making, and reaction times, often incorporating safety margins to account for human error and variability in driving styles [Fuller (2005),Sagberg et al. (2015)]. Furthermore, they are usually created assuming the worst-case scenario driver behavior. For example, speed limits are determined by considering factors such as visibility ranges, road curvature, and the time required for a human driver to perceive and react to unexpected obstacles. These limits are calibrated to human visual acuity and the cognitive processing speed of an average driver [Green (2000)].
Autonomous vehicles (CAVs), or self-driving cars, are transforming transportation [Fagnant & Kockelman (2015)]. CAVs have abilities beyond those of human drivers, such as strictly following traffic laws, processing data rapidly, and communicating with other vehicles quickly [Pendleton et al. (2017)]. Although these capabilities are still developing, they hold much promise. While CAVs may eventually outperform humans, this work focuses on the near future, assuming CAVs can travel as well as, but not better than, competent human drivers. This realistic approach allows for a more solid analysis of policy impacts in the short term. Additionally, we assume that the integration of CAVs into the infrastructure will be a gradual process. Consequently, we analyze the impact of the proposed policies across a range of CAV penetration rates.
This paper argues that the unique capabilities of connected autonomous vehicles (CAVs) allow us to develop a new set of traffic laws tailored to a mixed-traffic environment of both CAVs and human-driven cars. These "hybrid" traffic laws would differentiate between CAVs and human-driven vehicles and are thus relevant only for mixed traffic. By recognizing advanced CAV capabilities, hybrid laws can be designed to optimize traffic flow, enhance safety, and improve overall social welfare. Unlike methods that rely on better driving abilities of CAVs, our hybrid traffic laws rely on the ability of CAVs to obey complex rules that may change dynamically. Differently from other works Mushtaq et al. (2021),Wang et al. (2017), the hybrid traffic laws presented in this paper are more strategic than tactical or operational (as defined in Garrido & Resende (2022)). Strategic

decisions involve long-term planning and overarching goals, tactical decisions focus on medium-term actions and coordination, and operational decisions handle real-time, immediate responses.
This work focuses on a case study of a roadway containing lane reduction and experiencing high traffic demand, resulting in congestion, delays, and reduced overall efficiency. Current traffic management strategies to mitigate such issues often involve the implementation of restricted lanes, such as Dedicated Bus Lanes (DBLs) and High-Occupancy Lanes (HOLs). These approaches aim to minimize average passenger delay by prioritizing the movement of vehicles carrying a greater number of occupants (for a formal definition, see Equation 1). Furthermore, these dedicated lanes incentivize the use of public transportation and encourage carpooling, contributing to a reduction in the overall number of vehicles on the road [Jang et al. (2012)].
However, in many real-world scenarios, the effectiveness of DBLs is hampered by an insufficient number of public transport vehicles, leading to underutilization of the designated lane (see data on Tiltan (2022)). Similarly, while HOLs have demonstrated their potential to improve traffic flow (see results in Section 3), they are unenforceable, as human drivers may violate the occupancy requirements with limited risk of detection [Xu (2014),Nowruzi et al. (2019)].
To address these limitations, this paper proposes a novel hybrid traffic law that leverages the unique capabilities of connected autonomous vehicles (CAVs). Under this proposed regulation, only public transport vehicles and CAVs carrying a minimum number of passengers would be permitted to utilize the restricted lane. This approach capitalizes on the inherent ability of CAVs to adhere strictly to traffic regulations, thus ensuring enforceability. A key assumption underlying this approach, which will be further elaborated upon in the methodology section, is the ability to reliably differentiate between CAVs and human-driven vehicles (HDs) in real-time traffic conditions. The primary goals of implementing this hybrid traffic law are twofold:

1. Improve current traffic flow, as measured by a reduction in average passenger delay (APD).
2. Incentivize a shift towards the use of CAVs and promote carpooling.

By granting lane access exclusively to CAVs with higher occupancy, this policy creates a clear benefit for those who choose to travel in such vehicles, potentially accelerating the incorporation of autonomous technology and encouraging more efficient travel patterns.

2 Methodology

This work introduces a hybrid traffic regulation strategy that designates a lane segment exclusively for public transport and connected autonomous vehicles with a minimum passenger count. Positioned before a lane reduction—commonly a congestion bottleneck—this restricted section aims to prioritize high-passenger-count vehicles, thereby reducing the average passenger delay (APD) as defined in Equation 1. This study isolates the policy's direct effects by focusing on a simplified road network while minimizing real-world complexities and noise.
Restricting access to the restricted lane creates a bottleneck at the point where the lane is introduced. However, congestion at the beginning of the restriction point is reduced compared to the original scenario, as only a portion of vehicles need to switch lanes. Merging at the merging point becomes smoother since only a small fraction of vehicles use the restricted lane. Consequently, the restriction allows more efficient road utilization. The results presented in Section 3 will demonstrate the effectiveness of this approach in improving traffic flow and reducing delays, validating the claims made here.

Figure 1: Illustration of the configuration of the road network.

The road network illustrated in Figure 1 depicts a generalized lane reduction scenario. Initially, the road consisted of two general-purpose (GP) lanes extending for 1 kilometer. About 500 meters before the merge point, the left lane transitions into a restricted lane, permitting access to varying vehicle populations, before ultimately merging into a single lane. The speed limit on the whole road is 25 m/s. The experiments in this work were conducted using the Simulation of Urban MObility (SUMO) platform.
Various demand scenarios were tested on the network. The demand parameters are defined as follows:

- **Hourly Vehicle Count (λ_v):** The average number of vehicles entering the network per hour. Two sets of hourly vehicle counts were tested:
  - *Daily_k* : Derived from data on Ayalon Road in Tel-Aviv Tiltan (2022), scaled down by a factor $k \in \{2, 2.5, 3\}$ to fit the two-lane configuration, instead of the original five or four lanes in Ayalon road. These demand profiles enable us to simulate a realistic scenario in which traffic demand varies over time, reflecting the behavior of real road users.
  - *Constant_3000*: A simplified case with constant expected vehicle counts of 3000 per hour over a 1-hour interval. This medium-high demand profile enables us to analyze the behavior of our policy and its impacts, rather than attributing the outcomes to the dynamic nature of the demand profile presented in *Daily_k*.
- **Vehicle Type Distribution:** The probability distribution of vehicle types:
  - $P(\text{HD})$: Percentage of Human-Driven vehicles (appear in Figure 1 highlighted in red).
  - $P(\text{CAV})$: Percentage of Autonomous Vehicles (CAVs) - referred to as the *Penetration Rate* (appear in Figure 1 highlighted in blue).
  - $P(\text{Bus})$: Percentage of buses (appear in Figure 1 highlighted in yellow).
- **Arrival Process:** To obtain statistically significant results, we generated random data by assuming that vehicle arrivals follow a Poisson process, governed by the hourly demand data mentioned above. The number of vehicles arriving during each interval follows a Poisson process with parameter $\lambda_v(t)$. The time between two consecutive arrivals is exponentially distributed in such an arrival process, $\sim Exp(\lambda_v(t))$.
- **Passenger Count Distribution:**
  - **Cars:** The distribution of the number of passengers in cars is depicted in Figure 2, based on real data from (FHWA) (2022).
  - **Buses:** The average number of passengers per bus is 7.05, based on data from Tiltan (2022). Since buses always have access to the restricted lane, only the expected value is considered, without requiring distribution details.

All experiments use the same random seed across different policies to ensure an identical arrival process for better comparison. Each experiment is repeated ten times to provide statistical reliability.
To determine which vehicles are permitted to use the restricted lane presented in Figure 1, a set of policies was tested as part of developing hybrid traffic laws:

- DBL: A standard Dedicated Bus Lane (DBL), where only buses can use the restricted lane.
- Plus_i: A set of policies where $i \in 1, 2, \ldots, 5$ represents the minimum number of passengers a vehicle must have to access the lane. Under this rule, any vehicle meeting the threshold can use the lane, making enforcement infeasible for the HD vehicle population.
- CAVStaticPlus_i: A set of policies where $i \in 1, 2, \ldots, 5$ represents the minimum number of passengers required. This rule allows **only connected autonomous vehicles (CAVs)** that meet the threshold to enter the lane, ensuring enforceability.
- CAVDynamic: Dynamic policies that adjust the minimum passenger threshold required for a vehicle to access the restricted lane based on real-time speed measurements within the restricted lane. These policies operate with a specific speed parameter: if the lane speed falls below the speed parameter, the threshold increases (allowing fewer vehicles), and if it exceeds the speed parameter, the threshold decreases. A threshold adjustment is made every 60 seconds (empirically chosen). For example, *CAVDynamic_22* uses a speed parameter of 22 m/s, increasing the threshold when speeds drop below 22 m/s and decreasing it when speeds exceed 22 m/s. While other dynamic policies leveraging different features were tested, they demonstrated poor performance compared to this approach.

The primary goal of these policies is to minimize the Average Passenger Delay (APD), which is defined as follows:

D_a := Actual travel time, i.e., the total time a vehicle spends in the system (seconds).

D_t := Free flow travel time (seconds).

timeLoss := $D_a - D_t$

departDelay := Time a vehicle waits before entering the road due to road capacity limitations (seconds).

Vehicle Delay (VD) := timeLoss + departDelay

$\#_{\text{vehicle}}$:= Number of passengers in a vehicle

$$\textbf{Average Passenger Delay (APD)} := \frac{\sum_{\text{all vehicles}} \text{VD} \times \#_{\text{vehicle}}}{\sum_{\text{all vehicles}} \#_{\text{vehicle}}} \tag{1}$$

The APD metric (passenger delay divided by total number of passengers) focuses on reducing the delay experienced by the average traveler, accounting for both time spent in the system and time waiting to enter it. It is important to consider the time waiting to enter the system, as different policies may cause congestion near the entrance to the road, which will affect the departDelay. Our goal is to develop a *robust* policy that enhances the APD across all demand profiles and vehicle type distributions. This approach is necessary because adjusting the policy for every new scenario is challenging in real-world settings.

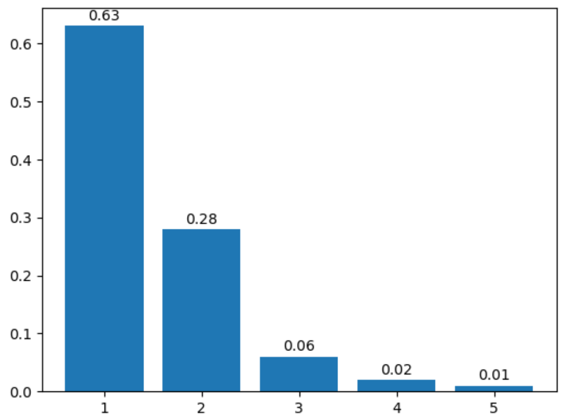

Figure 2: Distribution of the number of passengers in a car, based on real data from (FHWA) (2022).

To implement this system in a real-world environment, several key assumptions must be considered:

1. Measuring state variables: The ability to measure the defined state variables (e.g., speed) is essential. This can be achieved using sensors or through direct data reporting from CAVs to a central server.
2. Differentiating between CAVs and HDs: It is assumed that advanced smart cameras or other identification technologies are available to distinguish between CAVs and HDs, for example, using vehicle license plate recognition systems. This allows the enforceability of the restricted lane.
3. CAV communication for threshold updates: CAVs are assumed to have the capability to communicate with a central server, enabling them to receive real-time updates on threshold values and adjust their behavior accordingly.

3 Results and discussion

Table 1 shows the APD for the *Daily* demand profiles outlined in Section 2, calculated as the average over 10 simulation runs. The table includes all baseline policies designed exclusively for HD vehicles. Some of these policies are unenforceable, as discussed in Section 1. The DBL is identified as the most effective among the enforceable HD policies, while the optimal unenforceable policy is Plus_3.

Table 1: APD evaluated across various CAV percentages under the *Daily_ k* demand scenario. The results highlight the best policies: underline for the best enforceable policy without CAVs, *italic* for the best unenforceable policy without CAVs, and **bold** for enforceable policies with CAVs that are outperformed by underline.

(a) Baseline Policies (only HDs) - *Daily_ 3*

	DBL	Plus_1	Plus_2*	Plus_3*	Plus_4*	Plus_5*
APD	622.23	1284.12	665.18	*74.61*	301.78	523.53

(b) Dynamic and Static Policies - *Daily_ 3*

Policy / CAVs Penetration Rate	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
CAVStaticPlus_1	64.40	96.93	417.75	**814.21**	**1138.55**	**1214.03**	**1200.22**	**1234.15**	**1308.01**	**1284.12**
CAVStaticPlus_2	272.70	105.55	55.78	51.19	73.94	139.95	254.57	398.74	520.68	**665.18**
CAVStaticPlus_3	522.35	411.34	329.84	277.80	224.15	156.98	130.69	107.47	90.82	74.61
CAVStaticPlus_4	601.41	549.33	520.78	515.31	430.67	410.81	413.61	392.67	329.91	301.78
CAVStaticPlus_5	606.35	596.45	599.69	593.69	556.71	549.08	525.56	525.02	521.62	523.53
CAVDynamic_22	74.37	100.31	329.75	435.17	472.04	372.93	502.79	467.72	515.38	524.88
CAVDynamic_23	80.97	102.35	242.19	317.33	369.81	404.20	423.84	472.52	450.01	447.10
CAVDynamic_24	72.71	102.26	204.44	253.51	266.03	264.72	293.06	326.80	336.15	316.33
CAVDynamic_25	74.07	94.97	159.70	196.04	218.68	208.93	243.70	250.20	272.67	298.02

(c) Baseline Policies (only HDs) - *Daily_ 2.5*

	DBL	Plus_1	Plus_2*	Plus_3*	Plus_4*	Plus_5*
APD	5237.98	6299.91	5622.25	*2882.67*	4348.99	4879.44

(d) Dynamic and Static Policies - *Daily_ 2.5*

Policy / CAVs Penetration Rate	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
CAVStaticPlus_1	2775.80	3305.57	4766.20	**5881.69**	**6316.03**	**6398.49**	**6327.12**	**6358.09**	**6368.99**	**6299.91**
CAVStaticPlus_2	4155.44	3199.45	2651.84	2631.48	3052.58	3636.64	4201.79	4721.06	5214.02	**5622.25**
CAVStaticPlus_3	4984.54	4696.03	4436.90	4194.44	3988.03	3705.87	3490.59	3291.36	3093.36	2882.67
CAVStaticPlus_4	5148.71	5104.23	4987.73	4854.40	4780.42	4694.15	4593.79	4519.39	4435.66	4348.99
CAVStaticPlus_5	5196.95	5120.90	5152.12	5068.39	5058.09	5102.86	5027.29	5006.12	4987.16	4879.44
CAVDynamic_22	2829.07	3307.65	4325.90	4626.76	4714.05	4818.51	4741.75	4697.69	4869.03	4885.22
CAVDynamic_23	2861.25	3227.78	4144.80	4362.01	4609.12	4574.87	4551.78	4465.73	4634.06	4828.97
CAVDynamic_24	2861.81	3291.28	3934.34	4232.49	4302.61	4331.80	4326.16	4418.85	4445.40	4443.11
CAVDynamic_25	2977.70	3288.84	3843.33	4115.29	4124.72	4104.62	4108.70	4168.42	4284.76	4188.85

(e) Baseline Policies (only HDs) - *Daily_ 2*

	DBL	Plus_1	Plus_2*	Plus_3*	Plus_4*	Plus_5*
APD	12509.23	13907.27	13400.91	*9728.62*	11440.02	12171.34

(f) Dynamic and Static Policies - *Daily_ 2*

Policy / CAVs Penetration Rate	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
CAVStaticPlus_1	9570.94	10434.51	12535.66	**13742.24**	**14180.84**	**14158.71**	**14010.83**	**13921.37**	**13965.78**	**13907.27**
CAVStaticPlus_2	11223.45	10092.46	9472.68	9450.08	10115.75	10903.54	11664.73	12301.68	**12914.75**	**13400.91**
CAVStaticPlus_3	12156.70	11873.63	11579.42	11285.50	10979.13	10681.01	10416.42	10175.09	9944.67	9728.62
CAVStaticPlus_4	12399.15	12300.18	12163.56	12052.19	12044.36	11874.59	11784.37	11691.48	11574.32	11440.02
CAVStaticPlus_5	12479.14	12450.63	12406.30	12389.03	12427.17	12301.07	12248.17	12223.47	12158.86	12171.34
CAVDynamic_22	9708.91	10280.21	11812.24	12447.89	12326.51	12462.63	12377.29	12361.78	12476.93	12405.53
CAVDynamic_23	9717.59	10321.33	11479.91	12136.50	12098.51	11986.29	12286.10	12045.64	12232.87	12256.05
CAVDynamic_24	9705.37	10226.77	11296.26	11732.61	11721.49	11727.96	11781.21	11868.54	11910.43	11901.82
CAVDynamic_25	9775.91	10257.83	11022.40	11520.51	11474.68	11582.24	11510.73	11571.32	11586.74	11653.17

* represents unenforceable policies.

As shown in 1b, 1d and 1f, simple policies like *CAVStaticPlus_ 3* consistently outperform the DBL baseline across all tested scenarios. Given their simplicity and ease of implementation under the assumptions of this study, static policies present a promising solution for immediate incorporation in the near future.

The entries highlighted in bold in Table 1b represent instances where static enforceable CAV policies are outperformed at certain penetration rates by the best enforceable HD policy, DBL. Examining these entries demonstrates the limitations of static CAV policies under specific conditions. However, our dynamic CAV policy consistently outperforms DBL and, in some cases, even surpasses the performance of the optimal unenforceable policy, Plus_3. Across all scenarios in Table 1, the dynamic policies demonstrate consistent improvements over the DBL baseline for every demand profile and penetration rate, highlighting their robustness (as defined in Section 2). Moreover, our dynamic policy is robust to the exact choice of control parameters and consistently outperforms the baseline policies across various parameter configurations.

It is worth noting that the performance of the proposed dynamic policies diminishes as CAV penetration rates increase. In Tables 1d and 1f, representing scenarios with higher demand, certain static policies not only outperform DBL but also exceed the performance of dynamic policies at high CAV penetration rates. However, our primary efforts are concentrated on lower penetration rates (below 30%), as this work is exploratory, and higher penetration scenarios may benefit from more advanced strategies such as platooning [Malikopoulos (2023)].

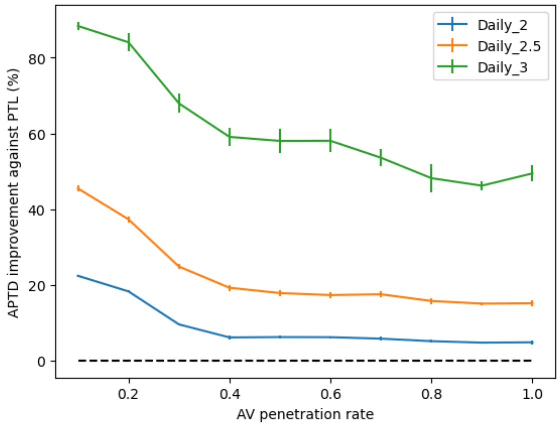

Figure 3: APD change (in %) of CAVDynamic_24 compared to DBL across different demands and vehicle type distributions.

Figure 3 highlights the above observations by focusing on a specific dynamic policy compared to the DBL baseline. The relative improvement is measured compared to the baseline DBL, and the error bars are calculated using the empirical standard deviation. It is evident that for lower penetration rates, there is a substantial improvement, whereas for higher penetration rates and certain demand levels, the improvement is small. This outcome is intuitive, as higher demand scenarios experience most of the delay outside the road network, specifically while waiting to enter the simulation. As a result, the scope for policy intervention is limited, leading to similar performance between the baseline and the proposed policy.

Table 2: timeLoss (defined in Section 1) of CAVs and HDs across different scenarios and penetration rates using CAVDynamic_24.

Demand	**vType**	**numPass**	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Daily_2	HD		192.8075	174.4502	178.586	186.6696	190.8419	193.6343	196.8692	197.7708	204.2912	201.317
	CAV	1		131.0794	135.8888	148.8604	161.7307	170.5922	177.5414	183.7817	188.0875	192.2795
		2		123.2912	119.0482	125.8434	137.7245	145.6153	153.4509	158.6836	163.5224	165.8215
		3		121.9301	108.3618	109.0211	117.0173	123.8617	131.4685	136.6799	140.2904	142.6441
		4		119.5082	105.7319	101.3724	104.969	110.9661	112.0425	117.3363	118.5929	119.6316
		5		118.8228	105.9128	100.6134	99.32158	102.9467	106.3301	108.1566	109.3695	109.5974
Daily_2.5	HD		193.2504	181.7295	192.1111	204.0548	209.8675	212.1832	216.5011	218.646	223.8874	220.4699
	CAV	1		131.6632	143.3066	160.0464	174.2366	185.389	193.9482	200.653	207.0123	210.806
		2		123.1039	121.3499	129.8217	142.777	154.4216	164.8314	169.3807	174.6785	180.3309
		3		120.8517	110.141	109.8906	118.9824	126.7184	135.6798	141.7187	145.0163	148.8438
		4		122.0472	108.9387	102.2998	107.4497	109.7095	116.0933	119.4	122.3172	124.7952
		5		121.4315	110.2402	101.7723	102.688	105.1889	107.6653	109.3261	110.4058	112.5789
Daily_3	HD		142.8618	57.50357	69.85652	107.2592	117.6958	121.1946	123.5185	131.5189	137.3365	137.0107
	CAV	1		38.99002	51.26042	82.72547	96.843	105.1141	110.5352	119.4374	124.5683	131.8042
		2		37.81332	43.11235	65.98568	77.90601	86.70729	91.14111	98.91568	104.9222	111.2531
		3		35.8457	42.34916	57.16978	64.7012	68.94654	73.11388	79.75148	82.56191	89.15968
		4		33.70021	38.87541	51.62696	60.25454	64.80327	65.55316	69.22968	71.92686	74.78586
		5		35.92674	37.21651	49.47757	57.46019	58.10816	59.49245	63.52464	64.90312	70.35529

We now evaluate whether the proposed hybrid traffic law achieves the second objective: encouraging passengers to switch to CAVs and carpool. Table 2 compares timeLoss (1) between CAVs with varying passenger counts and HD vehicles under a dynamic policy. TimeLoss is used instead of

APD to focus on vehicle experiences within the network, as departDelay treats all vehicles equally without prioritization.
The dynamic policy occasionally improves HD timeLoss but often results in only minor improvements or slight detriments. In contrast, CAVs consistently experience significantly lower timeLoss. At low penetration rates (e.g., 10%), CAVs see approximately 30% less timeLoss than HDs, as the threshold is typically set to 1, allowing all CAVs access to the restricted lane. This provides a strong incentive for HD passengers to switch to CAVs, as discussed in Section 1.
As penetration rates rise, incentives to switch to CAVs grow stronger, and timeLoss differences based on passenger count become evident. At 30% penetration rate, CAVs with one passenger experience more delays than those with three or more passengers. Higher penetration rates further widen this gap, reinforcing the incentive to carpool. These trends, driven by self-interest, encourage a shift toward carpooling in CAVs.
Such results cannot be achieved with a static policy, as it requires scenario-specific adjustments. The dynamic policy, however, adapts automatically to achieve these outcomes.

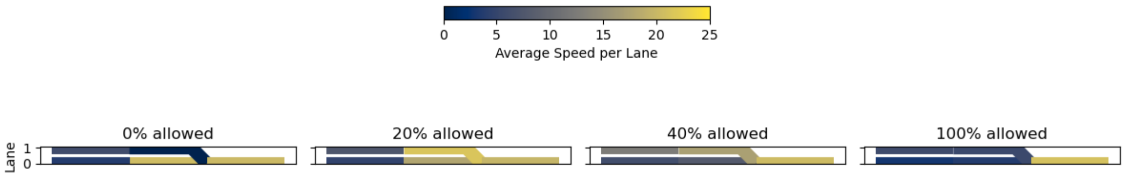

Figure 4: The average speed across each segment of the road under demand scenario *Constant_ 3000*, analyzed for varying proportions of vehicles permitted to access the restricted lane.

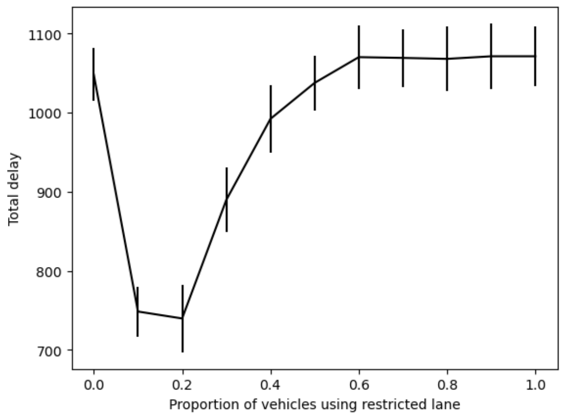

Figure 5: The VD under demand scenario *Constant_ 3000* analyzed for varying proportions of vehicles permitted to access the restricted lane. The error bars are based on the standard deviation of the measured data..

Figures 4 and 5 demonstrate that optimal traffic efficiency is achieved when approximately 20% of vehicles are granted access to the restricted lane. Figure 4 shows that at this proportion, merging occurs smoothly, with minimal congestion. Conversely, allowing 40% or more vehicles leads to inefficient merging and reduced speeds across the road. Figure 5 further confirms that the lowest vehicle delay (VD) occurs at the 20% access point, with delays increasing significantly when access is unrestricted. These results align with the above outcomes, which indicate a low APD for policies that allow about 10-20% of the vehicles to use the restricted lane.

4 Conclusions

This research presents a novel approach to traffic management by introducing hybrid traffic laws tailored to mixed environments of autonomous and human-driven vehicles. The proposed policies leverage the unique capabilities of connected autonomous vehicles to enforce lane restrictions and optimize traffic flow. Simulation experiments found that dynamic policies, which adjust access

thresholds in real-time, consistently outperform baseline policies in reducing average passenger delay (APD). These improvements are most notable at low penetration rates of connected autonomous vehicles, where dynamic policies incentivize the incorporation of CAVs and promote shared mobility practices, such as carpooling.
By granting restricted lane access exclusively to CAVs with higher occupancy rates, the policies create clear advantages for travelers who opt for shared mobility solutions. This not only accelerates the transition to autonomous technology but also encourages more efficient travel patterns, reducing overall vehicle congestion and environmental impacts. However, as penetration rates of CAVs increase, static policies can achieve comparable performance, particularly under high-demand conditions. This highlights the importance of adaptable policies to accommodate diverse traffic scenarios. Our findings contribute valuable insights into the design of enforceable and effective traffic laws, promoting a smoother transition towards a more sustainable and efficient transportation system.
Future research can focus on developing dynamic policies that consistently outperform static policies across a wide range of scenarios. Additionally, other hybrid traffic laws could be explored, such as utilizing CAVs for variable speed limits, facilitating smoother merging on highway ramps, enabling road clearance for emergency vehicles, and more.

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