Analyzing the operational performance of mixed traffic comprising autonomous and human-driven vehicles at varying penetration rates on Indian urban arterials

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Abstract. The autonomous vehicle (AV) market is in a nascent stage; as time progresses, more users will shift to AVs. This shift from conventional/human-driven vehicles (HDV) to AVs will have an impact on traffic systems in the future. Initially, the percentage of AVs will be less on the roads, but as the time and market penetration rate (MPR) progress, there could be a higher percentage of AVs on roads. Urban arterials in the Indian context are characterized by several traffic issues such as congestion, non-lane-based traffic, unsafe driving practices, etc. The traffic congestion in such urban areas will only increase going forward as the country develops, which reduces the operational performance of such traffic facilities. The shift from HDV-only traffic to mixed traffic consisting of AVs and HDVs will influence the operational performance of the arterials. The effect on operational performance due to increasing AV percentage on roads needs to be explored further to understand the implications of AVs on HDVs. Further, AVs have interesting properties such as better assertive movements than HDVs, and a higher ability to understand and comprehend complex traffic situations. This study attempts to understand the effect of increasing the MPR of AVs on the operational performance of traffic systems. A micro-simulation tool (VISSIM) is used to quantify the effects of MPR on the operational performance of urban arterials. Results show that as the market penetration of AVs increases the performance of the urban arterials improved in terms of enhanced capacity, space utilization and other microscopic characteristics

Keywords: Operational performance, Mixed traffic, Urban arterials, Autonomous vehicle, VISSIM simulation.

1 Introduction

Urban arterials connect the main activity areas and carry a significant volume of traffic; as a result, they regularly face congestion issues. These arterials are the foundation of urban transportation networks. They typically have closely spaced signalized and unsignalized junctions. These intersections make it easier to access nearby land, but they can increase traffic conflicts, bottlenecks, and performance and safety risks. Thus, when developing urban arterials and their access points require special attention[1]. It is anticipated that the introduction of automated vehicle technology would convert the roads, which are currently used as areas for mobility, into resourceful spaces, bringing

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about hitherto unheard-of shifts in how people live. Vehicle platooning, which involves numerous vehicles traveling together at an adequate safety spacing using V2X (vehicle-to-everything) connectivity, is one of the services offered by automation. Trucks will be the main target of platooning operations due to their properties. Truck mishaps resulting from human variables, such as carelessness, are common and tend to be severe. Along with an economic impact, platooning is typically anticipated to have positive implications on safety, fuel efficiency, and the environment [2]. In the transportation network, automated vehicles (AV) have reached the operational level. It is expected that the share of AV will steadily rise in the coming years. But widespread driverless mobility is still a way off. Given the vast number of traditional vehicular traffic, mixed traffic flow is the primary option for implementing automated driving. Studies suggest that the AV market will grow at a Compound annual growth rate (CAGR) of 13.3% [3]. This growth in AV market will also be reflected in India. The freeway environment offers the potential, which is easier than urban streets, will be where this potential first appears. The performance of highway traffic will undoubtedly be significantly impacted by the coexistence of AV and traditional cars. This study tries to quantify the effects of such a situation on the urban arterials of India.

2 Literature Review

The impact assessment of CAVs is widely done with the help of microscopic simulators. VISSIM has been used by some authors to investigate how CAVs would affect the capacity of the traffic [4]. The findings demonstrated that as CAVs accelerate more quickly and maintain smaller gaps, traffic capacity would grow. However, if these new vehicles drive more cautiously than the current fleet of vehicles, the capacity might drop by up to 40%. Shelton [5] tested CAVs in a complicated urban traffic system using a multi-resolution model that incorporates macroscopic, mesoscopic, and microscopic modeling tools. With complete market penetration of CAVs, it was discovered that the capacity may increase to 4000 veh/hr/lane. Hartmann et al. [6] also used VISSIM to evaluate the effect of driverless cars on motorway throughput. According to the modeling results, an increase in the percentage of vehicles with a lower and higher level of autonomy would result in a capacity reduction of up to 7%. Capacity will significantly rise by up to 30% only with a high penetration rate of CAVs that maximize cooperative driving and reduce gaps.

The network's traffic operation, capacity, speed, and journey time are all improved by AVs, particularly whenever it's congested[7]. Hoogendoorn et al. [8] also demonstrated that AVs might increase the effectiveness of vehicular traffic, but it's important to consider the impact of conventional vehicles as well as other human variables, such as user acceptability and behavioral adaptation. VanderWerf et al. [9] suggested that the use of partially autonomous cars equipped with cooperative adaptive cruise control results in a significant increase in capacity (CACC). Other research assessed how AVs affected the capacity, operation, and merging points of highways [10].

3 Methodology

In order to quantify the consequences of varying levels of autonomous vehicle (AV) market penetration rate (MPR), a typical Indian urban arterial with three lanes was generated in VISSIM using multiple links to estimate the capacity with various combinations of regular vehicles (RV) and AVs. The overall simulation time for each MPR is 90 minutes, with one-third time set aside for the system's warm-up period. There is a 0.1-second simulation step. Every five minutes, the traffic flow and density at each and every 10m strips considered throughout the stretch are recorded. Five simulations are performed with various random seeds to accommodate the stochastic nature of simulations. The average aggregated traffic flow for the 1 hour of simulation time is the capacity.

A 3-lane urban arterial with various classes of vehicles was simulated, which represents a mid-block section as in the dataset considered. Vehicles were simulated using the Wiedemann-99 car following logic; even though the Wiedemann-74 model represents urban traffic, was adopted, to have a better hold of the microscopic traffic behavior of the traffic. HDV traffic simulation was done after calibration and validation using the trajectory dataset of an urban mid-block road section in Surat (India) available in open source [11], into which AVs were infused using the internal logic of VISSIM and parameters were set according to VISSIM protocols and manual. Data was collected after an initial warm-up period, given to populate the road. The output data were collected for each lane separately for each 10m long strip. MPR percentage was varied from 0% to maximum penetration level (0% represents HDV-only traffic and 100% represents AV-only traffic), and the performance of the traffic was analyzed at different levels of service (LOS). The initial study was on a macroscopic level, which comprises of understanding how the percentage of AV in traffic affects the capacity of the mid-block. Secondly, the effects on microscopic parameters such as speed and density variation were analyzed. Heat maps were drawn to capture the variation of the density throughout the stretch of road and the simulation period. Statistical tests were conducted to understand whether the speed data collected at different LOS and MPR trends or variations.

Table 1 LOS and the corresponding range of v/c values

Level of Service	Range of v/c ratio
A	< 0.125
B	0.125-0.276
C	0.276-0.479
D	0.479-0.715
E	0.715-1.00
F	>1.00

The borders of various levels of traffic congestion are established using the level of service as specified by the Highway Capacity Manual (HCM) [12]. In this study, the effects of four traffic LOS were assessed to take into consideration varied volume levels. In this study as the location is specific, which is Dumas Road (Surat), which is a city located in the western Indian state of Gujrat. Patel et al. [13] have done studies on similar sections to quantify the v/c (volume to capacity ratio) corresponding to different LOS. The values from the above-mentioned study is adopted here to generate traffic regimes with various LOS. The v/c values corresponding to different LOS levels are shown below in Table 1

3.1 Calibration and simulation of mixed traffic

Regular vehicles were simulated using the Wiedemann-99 car-following model. The base data used for calibration is "extended trajectory data of Dumas Road (Surat)". The section of the road is 10.5 m wide (3 lanes of each 3.5 m) and 600 m long (trap length). This section of the road has three lanes without any acceleration/auxiliary lane.

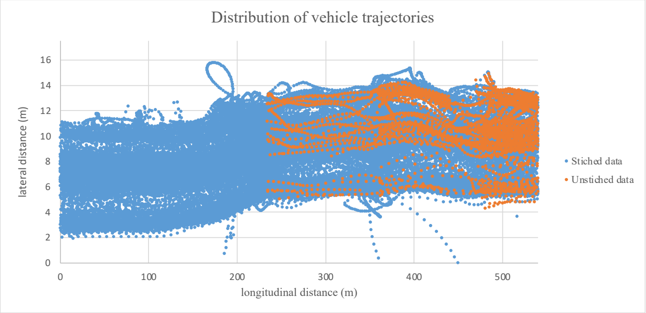

Fig. 1 Vehicle positions along the section of Dumas Road (Surat)

The trajectory data contains 591 vehicle data for 20 minutes. Fig. 1 shows the section of the Dumas Road, which is derived from the trajectories of the vehicles moving in it, the orange-colored scatter points represent unstitched data while the blue-colored points represent stitched data. The graph is in distorted scale to make it easy to understand and deduce inferences. Positions of all the vehicles along the section of the study stretch over a period of 20 minutes are plotted to get a rough idea about the road position. The calibrated parameters of the car following model for vehicle classes that contribute the major percentage of traffic is shown in Table 2. AVs were simulated using the parameters suggested in PTV VISSIM protocols and manual [14]. Connectivity and hence platooning is assumed to be absent in this study.

Table 2 Calibrated parameters for regular vehicles

Parameter	Auto	Bike	Car
CC0	0.65	0.2	0.55
CC1	0.9	0.9	0.9
CC2	4.39	3.13	4.62
CC3	-0.55	-0.48	-0.96
CC4	-3.43	-7.02	-5.24
CC5	-7.98	6.52	4.79
CC6	11.44	11.44	11.44
CC7	0.25	0.25	0.25
CC8	3.5	3.5	3.5
CC9	1.5	1.5	1.5

4 Results and discussion

In this study, the effect of AVs on urban arterial capacity and performance was evaluated. AVs are able to operate without assistance from human drivers. As per literature even though safety and comfort are the main factors driving the adoption of AVs, these vehicles can also increase highway capacity, especially at high MPR values. Few researchers, nonetheless, have examined the capacity effects of AVs in situations that are actually encountered, such as driving in mixed traffic or merging lanes with AVs when the MPR is below 100%.

The following sections elaborate the effects on traffic capacity and operation, using the framework outlined above. Effect on arterial capacity is studied by changing MPR values ranging from 0% to 100% and measuring the volume of traffic. The assessments of network traffic operation using traffic density and speed are fully described below.

4.1 Capacity

The section of the arterial we have considered in this study comprises of 3 lanes each having width of 3.5m. Fig. 2 shows how the capacity is changing with respect to the MPR %. The capacity of the section without AVs was 2280 veh/hr/lane while the penetration when increased to 25% increase the capacity by a small proportion, which may not be considered as an improvement. Further increment in MPR to 50% and 75 % increase the capacity to 2480 veh/hr/lane & 2550 veh/hr/lane respectively. 100% penetration increased the capacity to 2680 veh/hr/lane. This suggests that,

- When MPR is in the lower ranges i.e., the AV adoption is in its early stages the capacity of urban arterials will only be affected marginally
- As the penetration increases to reasonable levels when AVs constitute half of the traffic the effect on capacity starts to be evident.
- While the MPR value reaches about 75 % the capacity increases around 10%. When the penetration levels increase and reach a state where the traffic constitutes only of AVs the capacity increases by around 20% (absolute percentage calculation is not done since the results are stochastic in nature)

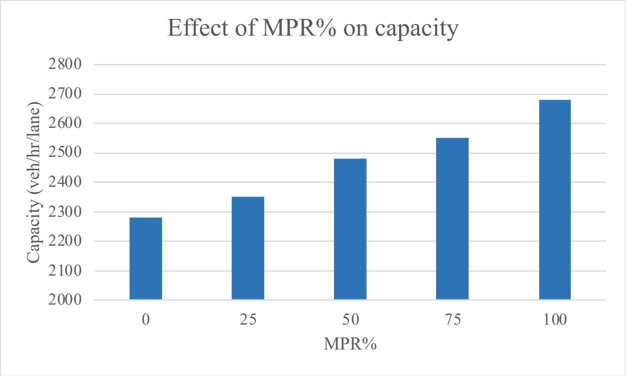

Fig. 2 Variation of capacity with respect to MPR %

4.2 Traffic density

As mentioned above, traffic density was used as the performance measure variable for evaluating traffic operation. Traffic density was measure throughout the simulation period at an interval of 10 minutes for each 10-m strips of the simulation section of the arterial. The whole stretch of road extends to about 1150-m. Fig. 3 shows the density heatmap for LOS-A, in which the x-axis shows the simulation time in multiples of 10 minutes for different MPR percentages and the y-axis shows the section of the road in multiples of 10m.

From the Fig. 3 it can be observed that better utilization of the space is being offered by the autonomy in vehicles. The reason is straightforward, which is the improved maneuverability, small reaction time and better understanding of the environment.
Apart from both extreme cases (fully AV traffic and fully RV traffic), one can see non-uniform density distribution which is due to the heterogeneity in the traffic caused by the coexistence of AVs and RVs at various parts of the midblock. At MPR levels near 50% Since AVs are unable to predict the intents of RVs before performing a maneuver resulting in isolated high-density areas. However, as reported in other studies, drivers who receive training may engage with AVs more effectively, and traffic flow may be improved [15].

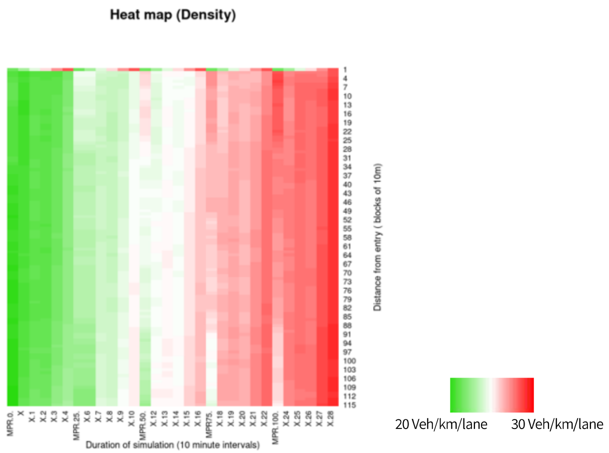

Fig. 3 Traffic density heatmap for different MPR % throughout the simulation time

4.3 Traffic speed

Speed was used as another performance metric to assess the efficacy of the operations in different scenarios. The speed of the vehicles on the arterial was studied by evaluating the average speed of each vehicle to traverse from start to end. A two-factor ANOVA (analysis of variance) with replication to accommodate multiple simulation results in each LOS was used in this study to analyze the effect on arterial speed.

Table 3 Results of ANOVA test (two factor with replication)

Source of Variation	SS	df	MS	F	P-value	F crit
Sample	67.078	3	22.359	121.520	0.000	2.758
Columns	1.878	4	0.470	2.552	0.048	2.525
Interaction	16.071	12	1.339	7.279	0.000	1.917
Within	11.040	60	0.184			
Total	96.068	79				

The analysis of variance test was conducted with average arterial speed from multiple simulations for each combination of LOS and MPR. Columns represent different penetration values and rows represent different LOS levels with replication. Results of the ANOVA test suggest that there is a statistical difference between the arterial speeds for different MPR values.

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