Analysis and Initial Observations on Varying Penetration Rates of Automated Vehicles in Mixed Traffic Flow utilizing SUMO

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***Abstract*—Understanding the effects of having automated vehicles in the future traffic scenarios is an important research topic that attracts a great deal of attention currently. The difficulty in studying this problem is the fact that real life measurement and testing of these scenarios can not be made as there are still a very small fraction of automated vehicles in the traffic. So analyzing and understanding the effects of mixed traffic requires extensive simulative analysis. In this paper we analyze this problem using real traffic data in combination with the open-source SUMO traffic simulation software. The traffic flow is modeled based on the measurement data from a section of the Austrian A2 motorway, while the effects of automated vehicles at various penetration rates is simulated and consequently some observation are made.**

***Index Terms*—Automated Vehicles, Mixed Traffic Flows, Traffic Management, Traffic Simulation, SUMO.**

I. Introduction

One of the biggest challenges in today's automotive research is automated driving. Nowadays, prototypes of automated vehicles (AVs) with advanced sensing technologies and intelligent control functions are being tested on public roads. Also all major OEMs are investing heavily on, and are already offering vehicles with, advanced driver assistance systems (ADAS) in their product lines that will eventually lead to AV functionalities. Therefore, it is a widely accepted fact that in the near future, AVs have to operate with conventional vehicles in the so-called mixed traffic. From the perspective of traffic management, it is important to understand the potential problems with such mixed traffic, particularly the capacity change as a result of introducing AVs at different penetration rates.

Much research has been dedicated to impact assessment of adaptive cruise control (ACC) systems on traffic flow efficiency, particularly focusing on the network capacity. It is widely recognized that increasing the penetration rate of the vehicles equipped with ACC does not necessarily lead to significant traffic capacity improvements, and in certain situations (e.g. with large time headway) it can even worsen the network capacity. To achieve capacity benefits, the time headway settings must not be too conservative [1], [2]. Davis analyzed the effect of adaptive cruise control in mixed traffic near on-ramps. He proposed a cooperative merging for ACC vehicles and stated that under a moderate on-ramp traffic flow, mixed traffic with 50% ACC compared to the flow of all conventional vehicles can produce 20% improvement in the throughput [3]. Furthermore, Shladover et al. extended ACC into Cooperative Adaptive Cruise Control (CACC), where they examined the implications of varying market penetration rate of ACC/CACC on freeway capacity through micro-simulation. They claimed that application of ACC has a little effect on freeway lane capacity, while CACC can substantially increase the capacity at a moderate to high CACC market penetration [4]. To model more realistic automated driving functionalities, Kerschbaumer et al. developed a longitudinal and lateral controller for automated driving and coupled them with VISSIM [5], [6]. Based on this, the effects of automated driving functions on the traffic flow of the Austrian motorway network were investigated . The different simulation scenarios showed that the higher level of automation and penetration rate of AVs bring bigger positive effects on traffic capacity [7], [8], which contradicts the observations in this work. The target in several other studies was also to evaluate whether (connected) AVs or even autonomous vehicles have positive impacts on the road infrastructure capacity [9], [10], [11], [12].

To the best of our knowledge, in most of the relevant research work in this field, the modeling of conventional vehicle flow was not derived from real traffic flow data, which leads to a lack of reality. While lane-change and cut-in behavior is frequently observed near on-ramps and off-ramps in real traffic, the lane change behavior of manual driven (i.e.,

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conventional) and automated vehicles was not treated with high importance in the existing literature. In this paper we tackle both of this problems using real traffic measurement data and also taking into account the lane change behavior analysis in modeling the traffic flow.

The tool SUMO (Simulation of Urban MObility) was opted for the microscopic traffic simulation. It is an open source, multi-modal traffic simulation package that can reproduce realistic traffic flow models in simulation scenarios [13]. It provides high flexibility for modeling conventional and automated driving in any traffic scenario and is also convenient for further investigating the control measures for the traffic scenario at hand.

Main contributions of this work are:

- Calibration and validation of traffic flow model in SUMO from the statistical viewpoint, based on real traffic measurements;
- Tuning of the traffic flow model for lane-change behavior of conventional vehicles and specification of AV's lane change mode;
- Impact analysis of different penetration rates of AVs on the road capacity using the realistic traffic flow model, which indicated that the more conservative time headway of AVs compared to human drivers is the main cause of capacity reduction.

This paper is structured as follows: first the traffic measurement data from an Austrian test site is described in Section II. Then in Section III, the setup and tuning of the traffic flow model in the SUMO open-source traffic simulator is explained. Again in Section IV, SUMO based automated vehicle models used in the mixed flow analysis with various penetration rates is described. Finally, the analysis results are presented in Section V and consequently, the main observations are stated in Section VI.

II. Road Measurement Data from the Austrian Test Site

A per vehicle data was collected at two kilometric points (169,897; 172,275) separated by 2,378 meters on the Austrian three-lane motorway A2 "Süd Autobahn" in the direction from Vienna heading to Klagenfurt nearby Graz, as illustrated in Fig. 1.

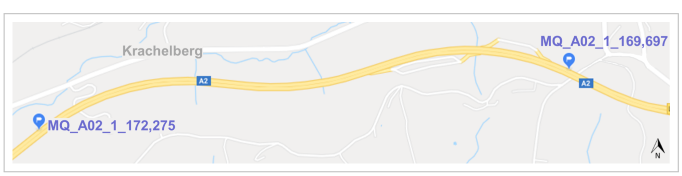

Fig. 1. The investigated motorway segment with gantry location indications.

Each sensing point contains a per lane information measured between November the 2^{nd}, and December the 2^{nd} of the year 2018 by the Austrian toll operator ASFINAG. The measurement includes data from a total of 31 days, during which the speed limit in the measurement region was reduced to 100 km/h due to compliance with pollution control restrictions. In the provided data set, per vehicle information includes the following variables among others:

- Entry timestamp (the time at which the vehicle reached the sensor in milliseconds);
- Vehicle type (passenger vehicle, motorcycle, truck, trailer, etc.);
- Speed (vehicle velocity in kilometers per hour);
- Vehicle length (in decimeters);
- Occupancy (the time the sensors was covered by the vehicle in milliseconds);
- Net time gap (the time gap in between two successive vehicles in milliseconds).

The traffic spatial density "$\boldsymbol{\rho_s}$" was then calculated using the occupancy information, where the percentage of the occupied time "***O***" from the total evaluated period is regulating "$\boldsymbol{\rho_{max}}$" that is the bumper to bumper density using the following relationship

$$\rho_s = O \ . \ \rho_{max} = O \ . \ \frac{N(T)}{\sum\limits_{t \le t_n < t+T} l_n} = \frac{O}{L} \tag{1}$$

where "***N(T)***" denotes the total number of vehicles passing at a period of time "***T***", "$\boldsymbol{l_n}$" indicates the length of the n^{th} vehicle passing at the same period, and "***L***" is the resulting mean length.

This calculation method serves only as a punctual estimation of the spatial density at each sensing point as it is bound to the assumption of a constant velocity of the vehicles during the averaging process [14].

III. Flow Modeling Based on SUMO

In order to ensure a high level of resemblance between the real traffic measurement data and the simulated traffic model, we utilize an optimization process that enables the parametrization of the SUMO car-following and lane-changing models. The process is based on the "San Pablo Dam" calibration approach [15], where vehicles are calibrated by comparing their simulation travel time to the real one. This approach was previously used to calibrate the car-following model alone in the existing literature, while it is adapted in this study to also include the lane changing behavior in the tuning process. This optimization task was achieved through the work-flow diagram illustrated in Fig. 2.

This process can be divided into two major steps. The first step aims to set the simulation environment (primary setup) and initial conditions based on the traffic characteristics and statistical analyses of the information provided by ASFINAG through the system mentioned in Section II. Then in the second step, the focus is on the calibration and validation of the most

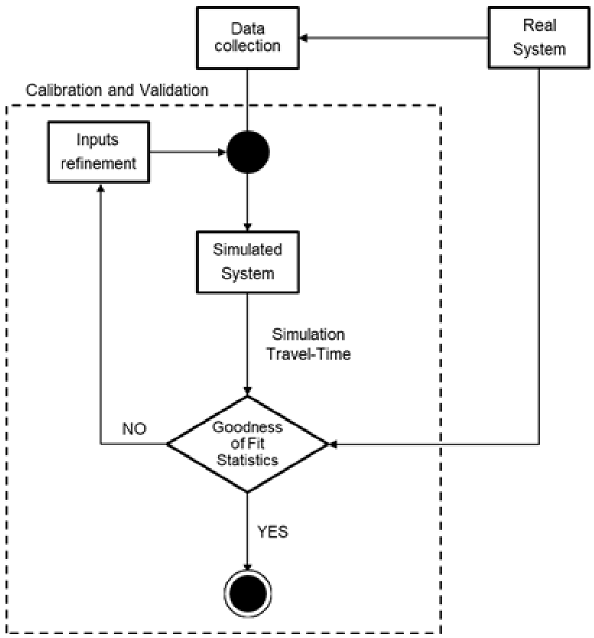

Fig. 2. Calibration/Validation work-flow.

influencing parameters of the driver models in the SUMO traffic simulator.

A. Traffic characteristics

During the whole recording period, a total of 857,747 vehicles passed through the first sensing point. This traffic flow is composed of different vehicle types illustrated in Fig. 3.

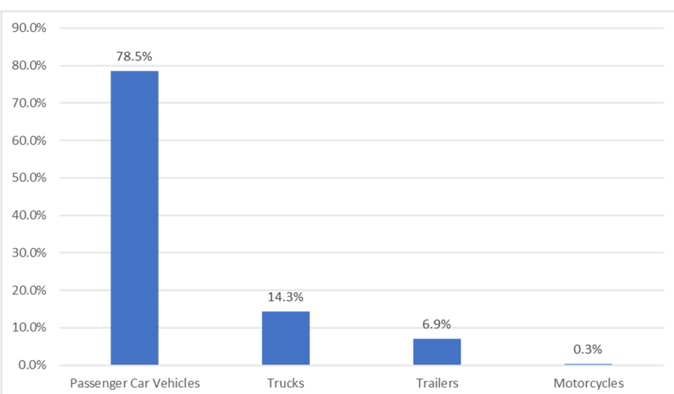

Fig. 3. Traffic composition based on the recorded traffic data.

As it is appropriate to mention here that the data aggregates contain a more detailed classification where the trucks class covers all of delivery vans, buses, cars with trailers and two axle trucks. Also trailers class contain lorries and articulated vehicles (vehicles with more than three axles). These different vehicle types behave in dissimilar manners and as a result, the related vehicular flows must be converted to passenger car equivalent (PCE) rates where the Highway Capacity Manual (HCM) was used as a reference to adjust the flow characteristics. Level of Service (LOS) thresholds were also applied to regulate the studied road segments by a density measure. These levels describe the quality of service under which this road segment operates by evaluating the inter-vehicle distances and how they vary, thereby quantifying how dense the traffic is. This also enables an evaluation of the freedom of maneuver and the respective levels of comfort the drivers experience within this traffic stream [16].

Considering the calculated adjusted flow rates per hour per lane and their respective occupancy-based densities, a primary analysis was performed to locate the most critical conditions and the traffic characteristic they happened within. It is important to mention that the measurement data collected contained gap periods where the sensors were most probably deactivated. This is the reason why some parts in the very right of the speed-flow diagram illustrated in Fig. 4 are far away from the others, which is due to the abnormal decrease/increase of the flow.

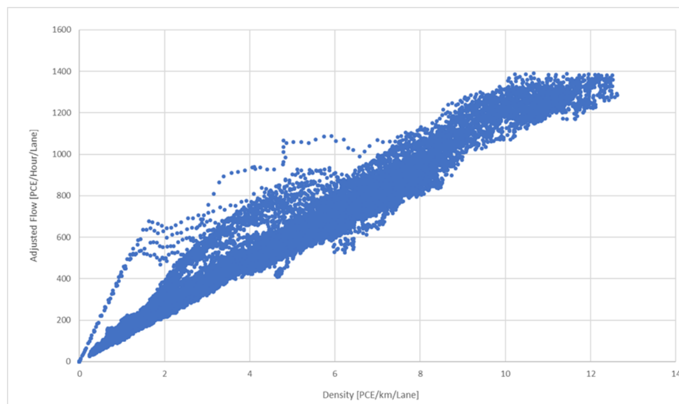

Fig. 4. Speed-Flow diagram.

The highest recorded flow was on a Monday morning, more precisely on November the 5^{th}, 2018 at 06:23:59 am with a value of 1391 passenger car equivalent per hour per lane. On the other hand, the peak density took place on November the 19^{th}, 2018 at 07:20:59 am, where nearly 38 vehicles (12.63/lane) occupied one kilometer of the analyzed track.

According to these results, the analyzed motorway section operated only under LOS A, B, and C throughout the studied period. The road capacity was never reached, and consequently not all traffic states were observed in the data. However, for the purpose of traffic calibration, the collected peak periods were then studied further to calculate travel time and mean speed values over the driven path, by comparing the entry time-stamp of each vehicle at the mentioned sensing points.

As no vehicle tracking information was provided with the measurement data, the exact travel time and space mean speeds were not directly deduced from the ASFINAG data. Nevertheless, to determine their values a comparison was made between the peak hours data collected at the two sensing points, where the distance in-between is already known. This comparison took into account each vehicle's length, and velocity as it passed through the first measurement location. A temporary travel-time was then calculated and used to point the middle of a twenty seconds interval where the next sensing point data were analyzed to locate the presence of a vehicle with the same characteristics.

B. Models calibration and validation

The calibration and validation of simulation models are two very related tasks, where the former emphasizes on adjusting the model inputs so that its outputs are aligned to the real measurement data, while the latter assesses the degree of similarity and its reliability, or more precisely to what extent the model replicates the reality [17]. The applied method uses a linear-approximations based algorithm to minimize an objective function and a set of constraints or limitations that are bound to be positive. Such processes provide a good fit only when they are near the current simplex. To ensure that, the linear program also estimates a radius where the solutions must lay within. This radius decreases with each iteration thereby shaping a trust region for the approximated values [18]. Furthermore, the initial estimations and constraints used were guided by the collected data means and deviations where possible. If not, the default values and the specified definition range by SUMO [19] for each parameter were employed.

Human driver model:
When aggregated data are used to calibrate the traffic micro-simulation models, the results are always bound to a limited behavioral influence. It is therefore important to mention that SUMO sub-models used hereafter are already founded on a strong theoretical background, as they have been developed to mimic the driver's behavior as realistic as possible, based on different motives that are assessed and controlled by a set of rules and parameters. These values are defined according to real measures, or are adapted to a certain data set and assumptions that may vary under different circumstances and scenarios. As a result, a re-adaptation is more than necessary to ensure a good replication of the studied reality [15], [20].

During this study, the default car-following model proposed by SUMO is used (Stefan Krauss model), where the parameters mentioned in Table I (taken from [19]) were calibrated for each vehicle type.

TABLE I
CAR-FOLLOWING MODEL PARAMETERS

Attribute	**Description**
accel	The vehicle's acceleration ability
decel	The vehicle's deceleration ability
Sigma	Driver imperfection
tau	The desired minimum time headway
minGap	Minimum space to the leader back
SpeedFactor	The vehicles speed multiplicator (based on lane speed limit)
SpeedDev	SpeedFactor deviation

Alternatively, for the lane changing behavior modeling, an analysis assessing the sensitivity of the calibration output (Travel-Time) regarding the model's parameters was firstly made to assess the effectiveness of the adapted approach. This sensitivity analysis was performed using the open source Python library "SALib" that enables a black box examination of the model, where a set of inputs can be generated by a variety of sample functions that are bound to the number of inputs, their range of definition, as well as the intended number of trials. The library enables then to calculate the respective sensitivity indexes based on the resulting model outputs by utilizing an analyze function. Table II represents the results of this analysis, where each attribute denotes the willingness to perform a lane change due to a certain reason or under a specific condition. The first-order index "S1" refers to the local effect of an input on the output variance (without considering its interaction with the other inputs), and "ST" is the total sensitivity index that includes interactions as well [21].

The performance of this lane changing model was previously studied in [22], where its parameters were examined in order to select the ones with the highest influence on the vehicle's lane changing behavior. This study showed that the parameter "lcAssertive" is the one accounting for most of the lane changing variance, along with a minor contribution of the "lcSpeedGain" parameter. Hence, the applied calibration approach is credible and could be used in order to replicate the desired behavior according to the results shown in Table II where "lcAssertive" generated a total sensitivity index of 68.69%.

TABLE II
LANE CHANGING PARAMETERS

Attribute	**Description**	**S1**[%]	**ST**[%]
lcStrategic	Lane changing to avoid a dead-end lane	0.0	0.0
lcCooperative	Lane changing to facilitate other vehicles' lane change	0.0	0.0
lcSpeedGain	Lane changing to gain speed	19.18	29.51
lcKeepRight	Lane changing due to regulatory obligations	8.43	20.64
lcAssertive	The desire to accept lower front and rear gaps on the target lane when executing a lane change	54.24	68.69

The results of this analysis reflects mainly the features of the measurement data used in the calibration process, as neither on-ramp nor off-ramp flows were collected or included in the study. Therefore, the process could not be sensitive to such behaviors or motives to perform lane changes.

Calibration and validation Criteria:
The calibration was proceeded using the Relative Root Mean Square Error (RRMSE) defined in (2) as a measure of closeness or proximity. The procedure was then repeated until the results converged to a certain threshold of accuracy that is regulated by the optimization function. The results are illustrated in Fig. 5, where the generated Kolmogorov–Smirnov test statistic was computed as 13%, which is interpreted in [23] as a very plausible fit.

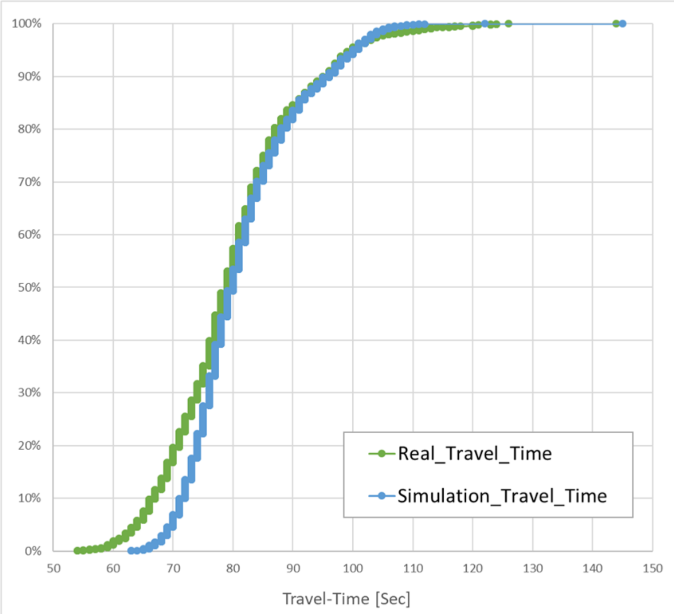

Fig. 5. Travel-Time Kolmogorov–Smirnov distribution.

However, for validating the calibration outputs, different time intervals were selected from the sensor data and the resulted parameters were tested for an RRMSE threshold of up to maximum 15% [24].

$$RRMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\frac{T_n^{sim} - T_n^{obs}}{T_n^{obs}}\right)^2} \tag{2}$$

where "$\boldsymbol{N}$" is the number of vehicles or time intervals, "$\boldsymbol{T_n^{sim}}$" refers to the simulation travel time of vehicle "$\boldsymbol{n}$" and "$\boldsymbol{T_n^{obs}}$" represents its observed counterpart. Finally, the parameters for the human driver model are shown here in Table III as a result of the whole calibration and validation process, where each vehicle type is represented by a group of parameters.

TABLE III
VALIDATED PARAMETERS

Attribute	Passenger Car	Motorcycles	Trucks	Trailers
accel	2.786	5.994	1.285	1.186
decel	7.424	9.848	3.820	4.013
Sigma	0.292	0.439	0.186	0.008
tau	1.001	1.038	1.775	3.471
minGap	2.377	2.506	2.136	2.181
SpeedFactor	1.193	1.073	1.043	0.866
SpeedDev	0.091	0.134	0.104	0.025
lcSpeedGain	0.887	1.0391	0.985	0.967
lcKeepRight	0.835	1.956	1.696	1.977
lcAssertive	1.616	1.057	1.001	1.157

IV. Automated Vehicle Models

Here we give the description of the automated vehicle models utilized for modeling the mixed traffic scenarios, again based on the SUMO simulation framework. The automated vehicles are modeled with a combination of a lane-changing and a car-following model, the details of which are given below.

A. *Lane-changing Model*

Automated vehicles are expected to differ from human lane-changing behavior due to the design of automated driving functions. LC2013 model from SUMO is adopted for simulation of automated lane-changing. The appropriate parameterization of the LC2013 model is referenced from [22], which mimics the automated lane-changing behavior in real life.

B. *Car-following Model*

Advanced Driver Assistance Systems (ADAS) have been a focus of research in past decades. Adaptive cruise control (ACC) systems can be viewed as a benchmark ADAS function, as they have been heavily studied and are currently available on the market. To simulate the realistic longitudinal automated driving behavior, the ACC car-following model in SUMO is applied. The developed ACC control law in SUMO is explicitly divided into four modes [13]:

1) Speed control: the speed control mode aims to maintain the driver desired speed.
2) Gap-closing control: the gap-closing control algorithm enables the smooth transition from speed control mode to gap control mode.
3) Gap control: the gap control mode is designed to keep a constant time gap between the ACC-equipped vehicle and its predecessor.
4) Collision avoidance mode: the collision avoidance mode averts rear-end collisions when safety critical conditions prevail.

In case of parameterization, a distribution of time gap settings is adopted, which is more in accordance to the real field experiments [25]. The parameterization for the ACC model is obtained from [22].

V. Analysis Based on a Test Scenario

Here we present the results based on simulation analysis with varying penetration rates. The parameters for both the human driver model and the automated vehicle model, which were described previously, were implemented in SUMO. Each class was defined by a certain distribution, as these distributions were then used to generate different flows for these two classes. To examine the effects of introducing automated vehicles in the studied road segment, the penetration rate was increased by steps of 10% in each simulation run, as traffic flow and density were recorded and analyzed.

Fig. 6 illustrates the recorded flows and densities for each penetration rate with a specific shade, starting from a flow with human-only driver setup, indicated with the dark shade, ranging all the way up to a fleet composed only by automated vehicles, indicated with the light shade.

The effects of introducing automated vehicles on the traffic behavior start vaguely to be observed starting from LOS C (i.e., flow density >11) even at a relatively low penetration

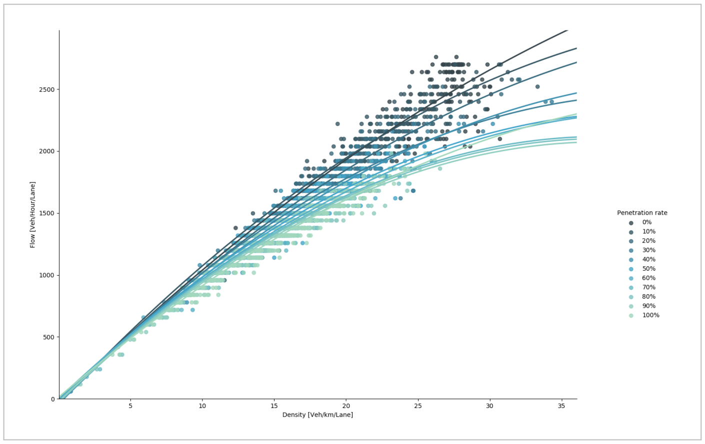

Fig. 6. Flow-density curves under different penetration rates of automated vehicles.

rate. This difference then grows as LOS D and E take place, where the critical flow is clearly decreasing as the penetration rate increases. However, when looking into the results of each run, one can observe that the peak flow has larger drops at some penetration rates compared to the others, even if the insertion of the AVs were increased by a fixed step.

The bottom line impact of the mixed traffic can be summarized as follows: As the penetration rate of the AVs increases, the flow decreases accordingly. So 0% penetration rate shows better flow rate compared to 10%, 20%.. etc. Nevertheless, when the motorway is only occupied by AVs, the critical flow is higher than the one observed at 70% penetration rate, as the contrast between vehicle behaviors due to mixed traffic is reduced. Also, even the most aggressive AVs use higher time headway when compared to a human driver's average headway. Humans drivers tend to take risks that AVs cannot tolerate due to safety reasons, which explains their more conservative behavior.

VI. Conclusions

In this paper we analyzed the modeling and tuning of SUMO traffic simulation models using real traffic measurement data to achieve a good matching of the arrival times of each vehicle. Then using this tuned traffic model we analyzed the objective effects of AVs at various penetration rates on the overall traffic flow characteristics. According to the current findings based on the SUMO simulation setup, where the traffic model is tuned to be similar to that of a measurement data taken from the Austrian A2 motorway in Graz, the maximum traffic flow rate decreases with increasing penetration rate of AVs. This result contradicts some literature utilizing alternative simulation tools [7], [8]. The reason for this contradiction is that the control logic for modeling of automated driving is different than what we used, and also that we utilized a tuned traffic model, which better reflects human driver behavior in a certain road segment.

In the future extensions of this work, control measure case studies will be performed to analyze the effects of individual speed advice, lane-change advice and dedicated lane advice for the automated vehicles. Such techniques will be implemented and tested to alleviate the traffic flow with a view to tackle such traffic scenarios expected in the decades to come.

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