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Research Article

Macroscopic Experiments on Coexistence of Autonomous Vehicle Behavior on Various Heterogeneous Traffic Conditions

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Automated vehicles (AVs) are likely to bring paradigm shift in the future of transportation and in the transformation of urban space as they could reduce traffic accidents, energy consumption, and pollution while also lowering congestion expenses. To provide meaningful insights, there is a substantial need for investigation into the macroscopic evaluation of various evolutions of AVs using several measures of effectiveness. The main focus of this study is to evaluate the macroscopic operational impacts of AVs in terms of their driving logics, automation levels, and roadway type, all of which are adopted based on their passenger car unit (PCU) factors at various penetration rates, in order to assess the coexistence of AVs with heterogeneous traffic. The daily vehicle hours travelled, daily vehicle kilometers travelled, sum of delays on links, speed variation, and sum of vehicle volumes on links are used as measures of effectiveness parameters based on outputs of PTV Visum scenario manager. The results of the various scenario combinations depicted an overall improvement with advancement of driving logics, automation levels, and roadway types for each studied parameter. For instance, for better roadway condition with the motorway scenario and at higher AV penetration, the cautious driving behavior negatively affects the network performance, whereas favorable improvements are observed for the parameters of the normal and aggressive driving behaviors. Decision makers could make use of the insights obtained from the results to further shape the AV deployment aspects and extend the study considering infrastructure AV-readiness along with AV communication systems.

1. Introduction

Vehicles with a certain level of automation to aid or replace human control are known as automated vehicles (AVs). They are projected to reduce traffic accidents, energy consumption, and pollution while also lowering congestion expenses. AVs are likely to bring paradigm shift in the future of transportation and in the transformation of urban space. It is expected that the proportion of AVs would gradually increase in the near future, which initially coexist with conventional vehicles (CVs) under mixed traffic condition [1–4]. Although there are still many unanswered questions regarding the precise effects of AVs on energy and the environment, it is generally acknowledged that at increasing AV penetration, a substantial net decrease in greenhouse gas emissions can be achieved [5–8]. The heterogeneous blend of AVs and CVs will undoubtedly have a substantial impact on traffic performance. The role AVs could play in future transportation should continuously be investigated to build trust between the road user and the possible impacts of the technology.

Levels of automation range from no driving automation (level 0) to complete automation (level 5, which is commonly defined as fully autonomous, self-driving, or driverless vehicles). Advanced driver assistant system (ADAS) technology defines the levels 0 to 2, whereas levels 3 to 5 are classified as high-level automatic driving systems. The advanced automated driving system (ADS) functions (i.e., levels 3 to 5, which are referred to as highly autonomous vehicles (HAVs)) of automated driving technology are expected to have a significant impact on future urban mobility. AVs with integrated communication systems and network technologies to accomplish intelligent information transfer, exchange, and sharing between vehicles and the environment are referred to as connected and automated vehicles (CAVs). HAVs have the potential to change future mobility patterns since they can complete the entire dynamic driving task (DDT) and include crash mitigation and avoidance capabilities as part of their ADS feature [2, 9, 10].

By the late 2020s, level 5 autonomous vehicles are expected to be commercially available and legal in some areas, but they will be expensive and have limited performance at first [11]. Market forecasts predicted that the share of HAV and CAV in new car sales will rise from around 10% in 2025 to around 50% in 2035 [12]. Despite the change in the parameters of mobility patterns as a result of AVs and the expected change in transportation efficiency, stakeholders should be mindful regarding the directions of congestion and social equity as the market penetration increases progressively. The adoption of AV and its impact on changes in travel demand will be influenced by country-specific context factors created by national policy [13]. Modelling tools should predict the impact of AV technology on transportation networks and passenger choices to help decision makers understand the impact of AV technology on regional plans [14]. Shared AV fleets could have a positive influence, such as reducing the number of vehicles and requirement of parking places on the road, where on-street parking could be avoided completely [15, 16]. With the presence of massive autonomous mobility on demand, it has been found that journeys previously done by private car can be replaced by shared AVs; the modal share of walking, public transportation, and bicycle is also expanding [17, 18]. Overall, AVs are thought to have a lot of potential for improving the capacity, traffic flow stability, and efficiency of today's transportation networks [19, 20].

The transition from low AV penetration to 100% AVs will take time, and this will most likely gradually happen by including progressive mix of human-driven cars and AVs with varying levels of automation and automation generations. Vehicles having only one automation feature, such as adaptive cruise control (ACC) or connected/cooperative adaptive cruise control (CACC), are commonly investigated in traffic simulation studies of AVs. Articles on the topic of AVs usually contain speculations and opinions due to a lack of precise data and information about the new technology [21, 22]. There is a substantial need for investigation into the macroscopic evaluation of various evolutions of AVs using multiple measures of effectiveness to provide relevant insights for policymakers, vehicle manufacturers, transportation mode operators, and urban planners. This study uniquely integrates the investigation of the operational effects of AVs in terms of their driving logics, automation levels, and roadway types, which are adopted based on their PCU factors at various penetration rates, in order to assess the coexistence of AVs with heterogeneous traffic. The macroscopic traffic simulation environment for AVs is still in very active development stage, which is being monitored and maintained on a regular basis with several research projects. The macroscopic AV evaluations are primarily concerned with determining changes in specified traffic performance parameters on links of large transportation network.

2. Literature Review

With the limited information on how AVs will behave, there are numerous techniques to incorporating their driving behavior into traffic simulation models. Simulation studies of AVs frequently assume one type of automated vehicle and that all AVs behave similarly. To deal with the uncertainties related to how different generations of automated vehicles will behave and which combinations of different generations of automated vehicles are likely to coexist at different stages of the transition period, traffic simulation investigations of AVs must use an organized and systematic approach [21]. Apart from SAE international's main rationale for classification of AVs based on the driver's intervention and attentiveness [9], the European project CoEXist on the simulation and modelling of the coexistence of conventional cars and AVs along with developers of traffic flow models considers vehicle capabilities based on their driving logics as classification criteria. Accordingly, the driving logics in the CoEXist project include the rail safe, cautious, normal, and aggressive/all-knowing behaviors. Rail safe driving logic imitates the behavior of a train on tracks (the vehicle follows a predetermined course) while maintaining sufficient safety distance, which could suit closed or low-speed environments. The cautious driving logic calculates gaps precisely and merges only when they are satisfactory, and it is not reliant on other vehicles or the infrastructure for communication or cooperation as in the rail safe behavior. In the cautious driving logic, the vehicle acts like a human driver, with the extra capability of monitoring distances and speeds of other vehicles, as a result of its various sensors. This driving logic may necessitate the use of communication and cooperation devices among vehicles. Vehicles with all-knowing driving logic can maintain smaller gaps for all maneuvers with flawless awareness and anticipation of the surroundings, as well as the behavior of other road users. Such driving logic allows for cooperation with other AVs that have communication and cooperation capabilities [3, 21, 23, 24].

Integrating AVs into macroscopic travel demand model necessitates volume-delay functions (VDFs) that take into account AV's share and features to determine the travel times of links and turns within the road network. Usually, a demand model uses a collection of VDFs and assigns different VDF to different types of roads and intersections. The travel time on links is determined by multiplying the free flow travel time by a VDF factor, which depends on the volume-capacity ratio. The concept of passenger car units (PCUs) is used to represent the connection between volume and capacity, where capacity and vehicle volumes are converted into passenger car equivalents. Presuming that

AVs differ from CVs in terms of performance and that this performance is also affected by the type of road environment, the PCU concept must be extended to AVs as well as intersections and roadway types [25–28]. The roadways could be urban street, arterial, and motorway, where public roads with at least one traffic signal every 3.22 km characterize urban streets. There is no clear demarcation between car traffic and pedestrian and bicycle traffic on urban streets, whereas physical barriers or medians separate bicycle and pedestrian traffic from vehicle traffic in arterial roads. The main function of an arterial road is to move traffic from collector roads to freeways or expressways, as well as between metropolitan areas, with the best quality of service possible. An arterial road is a high-capacity urban road that ranks below freeways/motorways (roads with physical barrier between directions) on the road hierarchy in terms of traffic volume and speed [25, 29, 30]. The framework for AV impact analysis in macroscopic level could involve scaling up the derived network capacities (affects the PCU) through the network macroscopic fundamental diagram (MFD) with microscopic simulation experiments. Then, the effects on PCUs are identified and the PCU functional relationships are estimated with statistical methods. Finally, the PCU functional relationship is used as input to the VDFs of macroscopic demand models to forecast impacts on network performance in macroscopic simulation experiments [31–33].

The majority of AV research focuses on assessing the effects of increased mobility and changes in transportation system efficiency. At higher penetration rate and assumed random PCU values for AVs, a macroscopic study on the effect of AVs depicted that a reduction of 8.41%, 1.61%, and 37.87% can be achieved for travelled daily hours, travelled daily kilometers, and total network delay, respectively, whereas the speed could increase by 4.08% [34]. Another study in Budapest found that with a conservative estimation technique and 100% AV penetration, 1–2 billion hours of operating time can be saved in 15 years and 20–30% of average trip travel time can be reduced [35]. An agent-based transport simulation model that considered the effects of AVs on modal share, waiting time, additional vehicle miles travelled, AV fleet utilization, travel time, and travel distance revealed that AVs have varying degrees of influence on different groups of people, as evidenced by the modal share changes [36].

The topic of traffic analysis, modelling, and simulation is a well-developed field, with various simulators accessible. By using simulation tools, various attempts have been made to explore the effects of AVs on traffic performance. The currently available traffic analysis, modelling, and simulation techniques are not fully sufficient for assessing the driving behaviors of CAV and HAV, due to the gap in simulating vehicle interconnectivity with other vehicles or the infrastructure (V2V or V2X), deficiency of data for parameter calibration, and so on [2]. PTV Visum [34, 35, 37], MATSim [36, 38–40], and Aimsun [31, 41] are among the developing macroscopic traffic simulation tools used by traffic analysts to investigate various AV features.

3. Materials and Methods

The adopted methodology in this study estimates the impacts of autonomous vehicle behaviors on various heterogeneous traffic conditions using macroscopic traffic simulation experiments. The approach entails progressively changing the AV driving logics and automation levels based on their PCU in PTV Visum 2020.00-14 scenario manager. The traffic performance indicators that are investigated on the road links include vehicle hours travelled, vehicle kilometers travelled, overall delays, travel speed, and volume, which are analysed considering private transport (PrT) systems.

3.1. Basis for Scenario Development. In each of the driving logics (cautious, normal, and all-knowing) and SAE automation levels, the study utilizes derived PCU factors on various roadway types (urban street, arterial, and motorway) for successive penetration rates (see Table 1). For each specific scenario, the roadway condition in the network is idealized to be uniform hypothetically. The penetration rates in the Visum scenario management are based on different combinations of autonomous vehicle driving logics and SAE levels according to their PCU (10%, 20%, 30%, 40%, 60%, 80%, and 100%), which considers close increment at lower penetrations. The PCU values represent the AV capability based on the driving logics and automation level. For each generated scenario, the procedure sequence is carried out by integrating the driving logics, roadway type, automation level, and progressive penetration rates.

PCU indicates how much of an impact a particular mode of transportation has on traffic variables when compared to a single regular passenger car. Each scenario is established by defining the proportion of AVs in the demand matrix for specified penetration rates. Accordingly, a total of 99 scenarios were developed for the combinations of AV driving logics, roadway types, and SAE automation levels.

In the base/do-nothing scenario (with no AVs), basic settings such as OD (origin-destination) demand matrix for AVs, transport system mode for AVs, demand segment, and so on were defined for facilitating the creation of modifications on other scenarios. The matrix multiplication factors for the original PrT data matrix are defined at each penetration rate (in each scenario modifications) for the new shares with progressive AVs and CVs in the network. Then, the proportions are adjusted with a matrix formula procedure prior to the assignment procedure. After arranging modifications and developing each scenario, the PrT assignment procedure is conducted based on equilibrium assignment concept to study the effects on the network considering the selected performance parameters. The equilibrium assignment undertakes an iterative procedure, which consumes a huge simulation time until balanced state (equilibrium) is achieved. The goal of the assignment is to find the optimal route for each trip while spending the lowest costs on transportation.

Table 1: Recommended PCU factors for AV driving logics at different roadway types and automation levels [27, 34, 35].

Description	Main scenario categories	PCU factor
Combinations of driving logics and roadway types	Urban street with cautious behavior (US_C)	1.32
	Urban street with normal behavior (US_N)	0.85
	Urban street with aggressive behavior (US_A)	0.79
	Arterial road with cautious behavior (Art_C)	1.26
	Arterial road with normal behavior (Art_N)	0.81
	Arterial road with aggressive behavior (Art_A)	0.76
	Motorway with cautious behavior (Mw_C)	1.20
	Motorway with normal behavior (Mw_N)	0.77
	Motorway with aggressive behavior (Mw_A)	0.73
SAE automation levels	SAE automation level 1 (SAE_1)	0.98
	SAE automation level 2 (SAE_2)	0.95
	SAE automation level 3 (SAE_3	0.90
	SAE automation level 4 (SAE_4	0.80
	SAE automation level 5 (SAE_5)	0.65

3.2. Case Study. Budapest, Hungary's capital city and the country's political, administrative, industrial, and commercial hub, is Central Eastern Europe's largest metropolitan area. The city is leader in Central Eastern Europe in terms of implementing transport management organizational schemes, with responsibility for the integration of various means of transportation as well as the development of organizational capacity for the execution of sustainable policies. The road network in the city is around 4,500 km long having 4 metro lines, 5 suburban railway lines, 276 bus lines, 30 tram lines, and 5000 licensed taxis. There are 1870 number of public transport vehicle operations in each day, which are serving the 5 million daily trips in the city. Buda and Pest, the city's two halves, are located on opposite sides of the Danube River and are joined by a number of bridges. In Budapest, there are 408 passenger cars per 1000 residents, whereas in Pest County, there are 460 based on 2021 census and vehicle fleet data of the Hungarian Central Statistical Agency (KSH). By 2030, the strategic plan aims to increase public transportation share from 45% to 50%, reduce passenger car share from 35% to 20%, increase walking from 18% to 20%, and cycling from 2% to 10% compared to the baseline situation in 2014 [42, 43].

In 2015, a single traffic model called Unified Transport Model of Budapest (EFM) was created for examination of future transport investments in the capital and agglomeration effects (see Figure 1). The model is developed based on huge data (updated every 5 years) in PTV Visum, which is progressively maintained and owned by the Budapest Transport Center (BKK Zrt.). The strategic model is well-suited for long-term transportation strategic studies, examining the effects of significant traffic engineering and regulatory interventions, examining projects spanning at least 2-3 districts with significant traffic reorganization, and investigating complex, multi-mode infrastructure interventions.

The Unified Transport Model (UTM) is built on a complex system of many different data sources, including traffic count data, area descriptive data, infrastructure data describing traffic characteristics, and other external data sources. The main elements of the model include data warehouse (contains results of traffic counts and other external data source records, like loop detector data), transport demand model (individual and public transport, taxi, bicycle, and freight traffic matrices appearing in Budapest and its agglomeration), network model (keeping datasets of transport links of road, rail, and cycling infrastructure elements and public transport connections ready for computer programs) and area model (boundaries of the EFM modelling area with the place where the transport needs originate). The authors developed the macroscopic hypothetical scenarios based on the calibrated and validated EFM base model.

4. Results and Discussion

The measures of effectiveness considered in this study include the daily vehicle hours travelled, daily vehicle kilometers travelled, sum of delays on links, sum of average vehicle speed on links, and sum of vehicle volumes on links. The results of each parameter were compiled based on definition of scenario indicators in scenario manager. The selected output parameters are analysed for private transport (PrT) transport system.

In each scenario, the results are compared in terms of the percentage changes relative to the base scenario, which has 0% AV penetration. The base/do-nothing scenario is based on the original Budapest EFM base model with 1.0 PCU for the passenger car class, which is accordingly modified in all other scenarios based on the proportion of AV penetrations.

4.1. Evaluation of Daily Vehicle Hours Travelled. In this evaluation, the percentage changes in the daily hours travelled are compared among the three driving logics for each roadway types (see Figure 2). At progressive penetration rates, the scenarios with driving logics of cautious, normal, and aggressive are compared with the base scenario. Accordingly, the percentage change in sum of daily vehicle hours travelled increased up to 6.22% for cautious behavior, while it reduced for the normal and aggressive behaviors by up to 2.92% and 3.51%, respectively. For instance, at 100% penetration when all links are idealized as motorways, the absolute change with the base scenario depicted

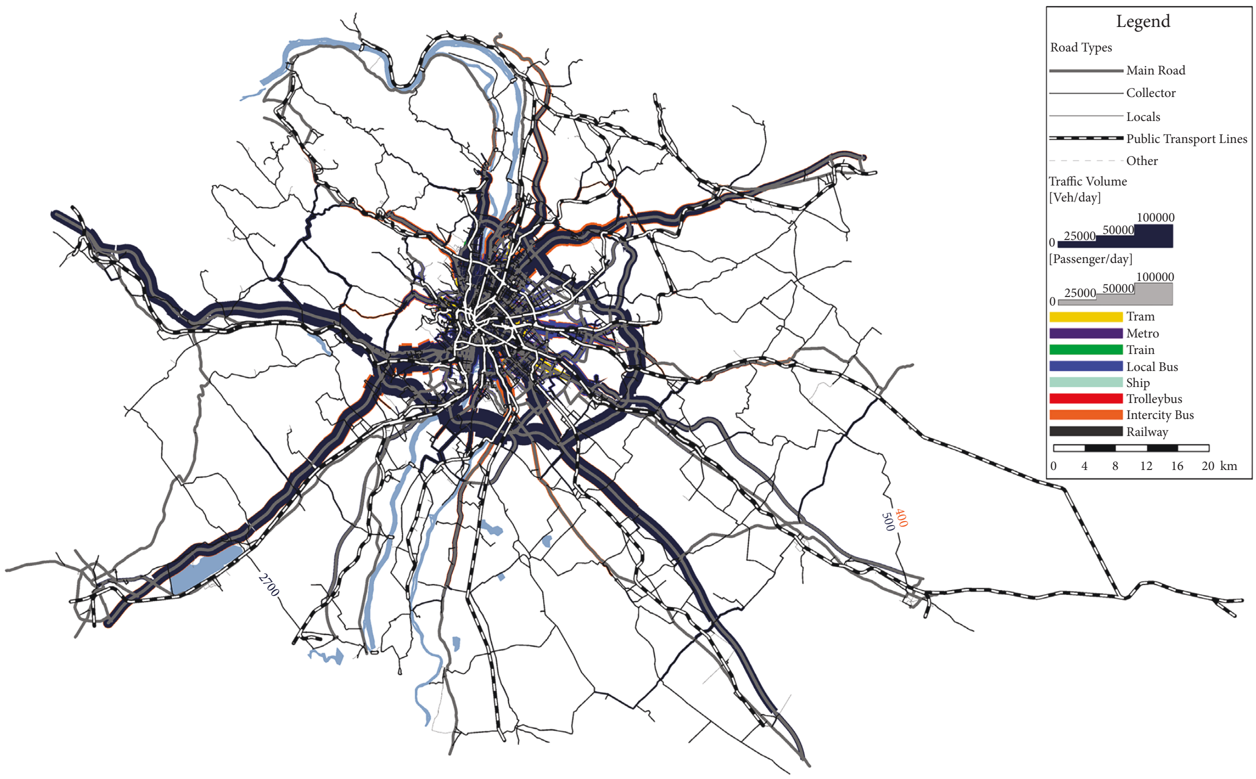
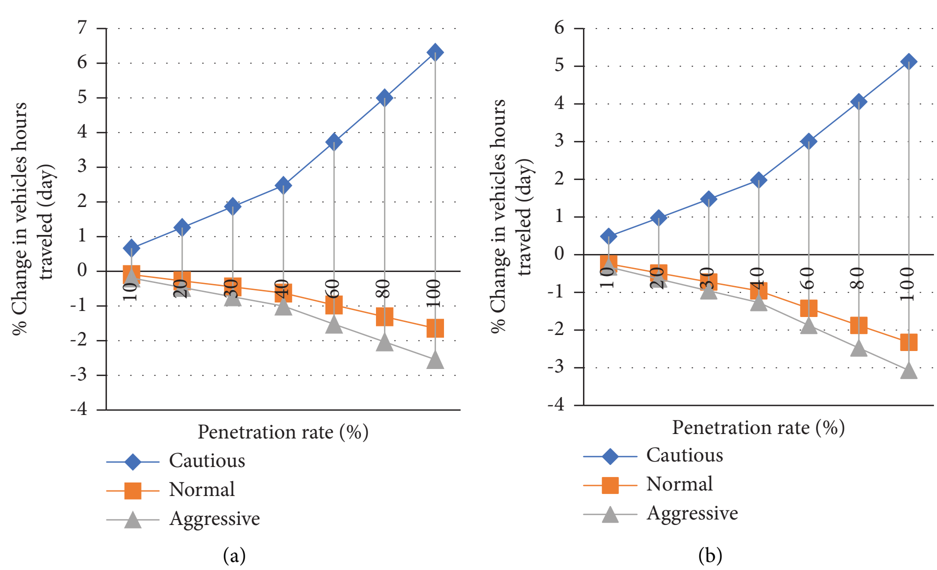


Figure 1: Basic features of the Budapest EFM model in Visum 2020.00-14.



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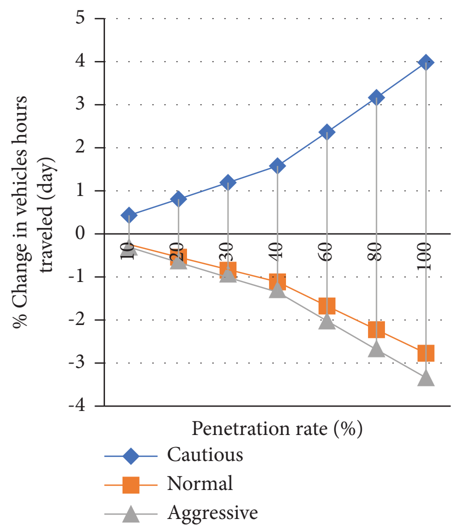


(c)

Figure 2: Percentage change in daily vehicle hours travelled for scenarios of (a) urban street, (b) arterial, and (c) motorway.

33,546.83 hrs of increase in the cautious behavior, while a decrease of 24,150.08 hrs and 29,007.61 hrs occurred in normal and aggressive driving logics, respectively, in a day.

With regard to each roadway type, the results depicted that the increase in percentage changes in the daily hours travelled of the cautious behavior reduced nearly by 1% (9,000 hrs) at higher penetration from urban street, arterial, and motorway types, respectively. Likewise, for the normal and aggressive behaviors, the reduction is a greater extent in percentage changes in the daily hours travelled when all the links are idealized as urban street, arterial, and motorway types, respectively. The trend of the results portrayed that more favorable outcome is achieved at lower PCU values and higher penetrations.

In case of SAE automation levels, more significant results are observed starting from automation level 3 (with higher penetration), which reduces the daily hours travelled by nearly 1% at 100% penetration (see Figure 3). However, at higher automation levels, the comparative change with the other SAE levels (at 100% penetration) decreases by 2.48% and 4.67% for automation levels 4 and 5, respectively. The difference daily vehicle hours travelled at 100% penetration reduces by 2.48% and 4.67% for automation levels 4 and 5, respectively. The absolute change with the base scenario at 100% penetration depicted 7,939.92 hrs, 20,472.99 hrs, and 38,588.5 hrs for automation levels 3, 4, and 5, respectively.

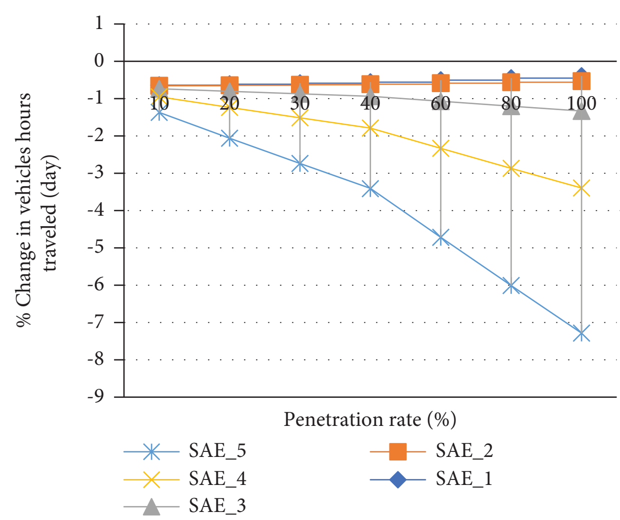


Figure 3: Percentage change in daily vehicle hours travelled based on SAE automation levels.

4.2. Evaluation of Daily Vehicle Kilometers Travelled. On the basis of the comparison of the AV driving behaviors with the do-nothing scenario, the results of the percentage change in sum of daily vehicle kilometer travelled increased up to 1.04% for cautious behavior, while it reduced for the normal and aggressive behaviors by up to 0.55% and 0.65%, respectively (see Figure 4). At 100% penetration, when links are idealized as motorways, the absolute change with the base scenario depicted 305,166.33 km increase in the cautious behavior, while a decrease of 244,899.95 km and 289,462.10 km occurred in normal and aggressive driving logics, respectively.

The results showed that higher AV penetration on roadway types of urban street, arterial, and motorway reduced the increase in percentage changes of the daily kilometers travelled of the cautious behavior by an average of 77,713.63 km. Similarly, when all the links are idealized as urban street, arterial, or motorway types, the reduction in percentage changes in daily hours travelled increases for the normal and aggressive behaviors. The results also revealed that low PCU values and higher penetrations yielded more favorable results.

In terms of SAE automation levels, level 4 and 5 automations yield more significant results, reducing daily kilometers travelled by 207,861.98 km and 363,227.9 km, respectively, at 100 percent penetration,

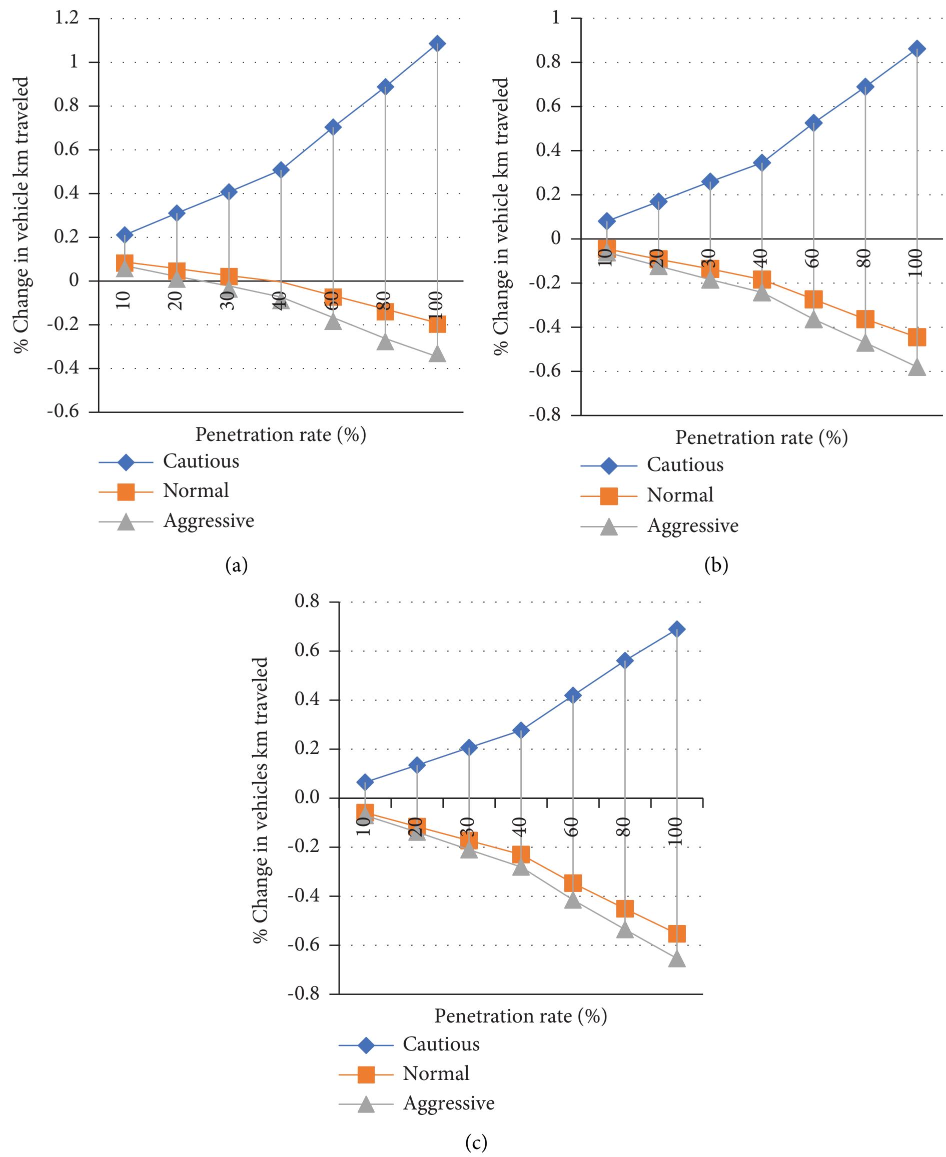


FIGURE 4: Percentage change in daily vehicle kilometer travelled for scenarios of (a) urban street, (b) arterial, and (c) motorway.

whereas level 3 automation yields a value of 80,522.13 km (see Figure 5).

4.3. Evaluation of Total Vehicle Delays. The introduction of AVs into the network has also impacted the vehicle delay significantly. When all links are idealized as motorways at 100% penetration, the absolute percentage change in total vehicle delay compared to the base scenario showed a 28,909.54 hrs increase in the cautious behavior, while a decrease of 21,029.75 hrs and 25,353.15 hrs occurred in the normal and aggressive driving logics, respectively (see Figure 6). The percentage change in total vehicle delays increased up to 33.44% for cautious behavior in urban street condition, while it reduced for the normal and aggressive behaviors by up to 15.9% and 19.17%, respectively, in motorway scenario. Higher AV penetration on urban street, arterial, and motorway roadway types reduced the increase in percentage changes of the total vehicle delay of the cautious behavior by an average of 7,657.6 hrs.

When it comes to SAE automation levels, the most significant results begin at automation level 3 (at greater penetration), which reduces the total vehicle delay by 5.16% at 100% penetration (see Figure 7). The comparative change in total vehicle delay at 100% penetration decreases by 13.46% and 25.66% for automation levels 4 and 5, respectively. For automation levels 3, 4, and 5, the relative change with the base scenario at 100% penetration is 6,829.48 hrs, 17,799.95 hrs, and 33,939.74 hrs, respectively.

4.4. Evaluation of Total Vehicle Speed. The percentage changes in travel speed due to AV implementations are compared among the three driving logics for each roadway type (see Figure 8). Accordingly, the percentage change in

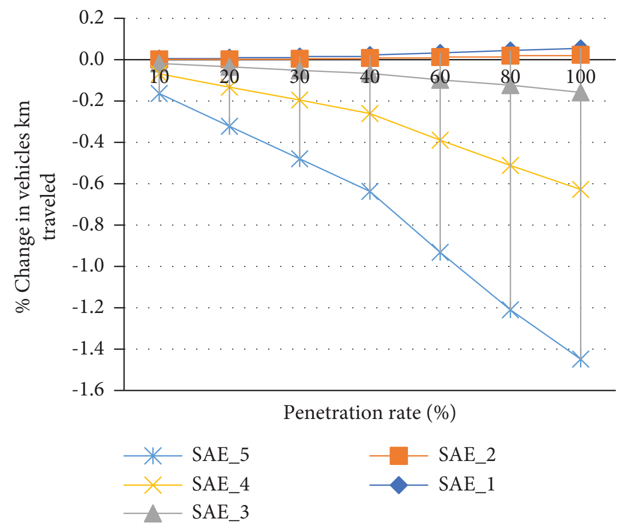
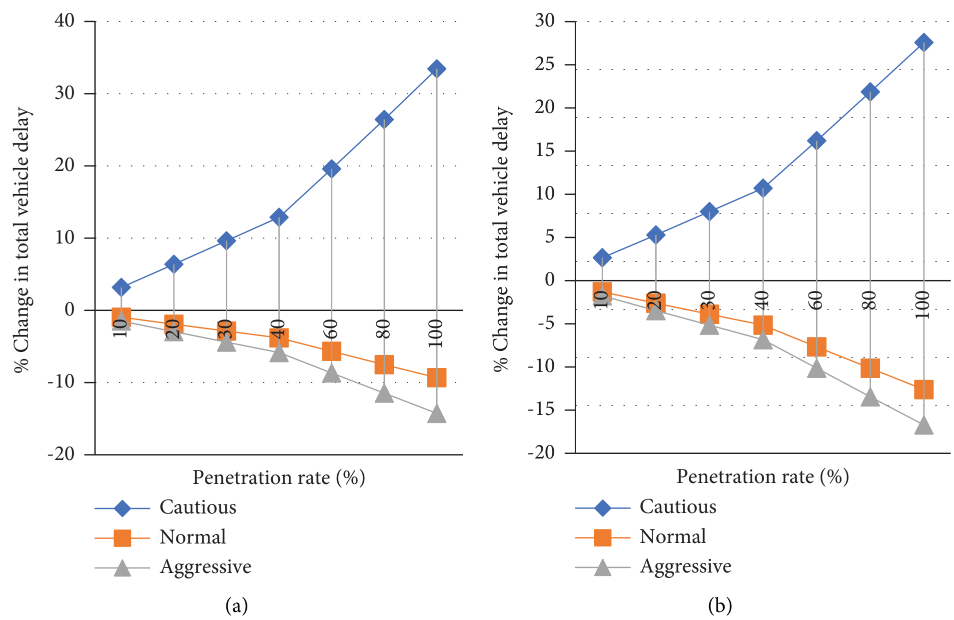


Figure 5: Percentage change in daily vehicle kilometer travelled based on SAE automation levels.



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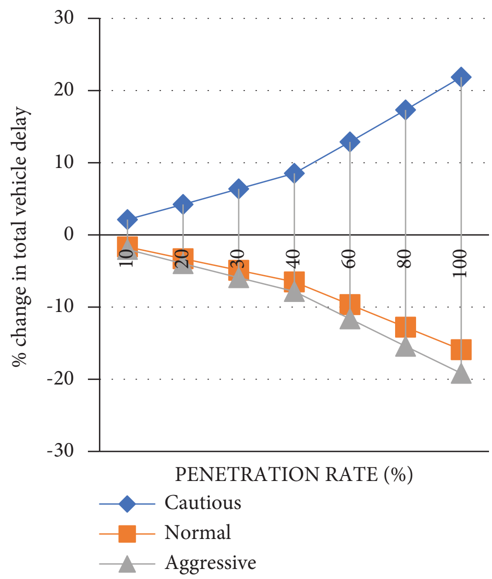

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Figure 6: Percentage change in total vehicle delay for scenarios of (a) urban street, (b) arterial, and (c) motorway.

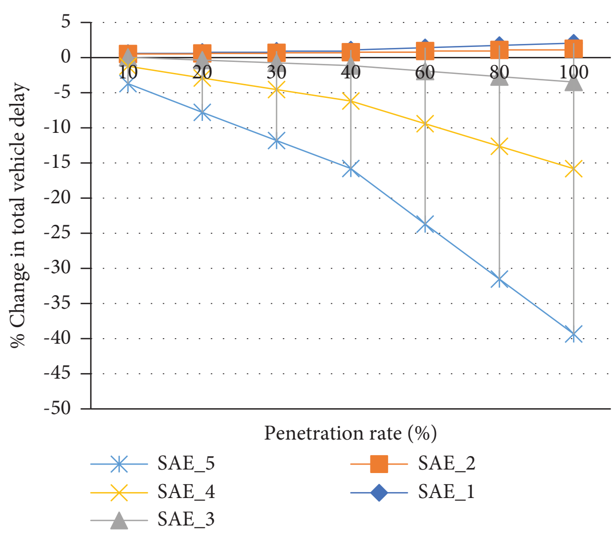

Figure 7: Percentage change in vehicle delay based on SAE automation levels.

the overall vehicle speed at 100% penetration has reduced up to 2.8% for cautious behavior, while it increased for the normal and aggressive behaviors by up to 1.46% and 1.76%, respectively.

At 100% penetration, SAE automation levels 4 and 5 improve the comparative change in the sum of average vehicle travel speed on links by 1.23% and 2.37%, respectively, while level 3 automation increases vehicle travel speed only by 0.46% (see Figure 9).

4.5. Evaluation Based on PrT Volume. The evaluation of PrT volume is made based on the output in terms of passenger car equivalence. All volume results based on absolute value comparison portrayed a progressive increase in volume in the cautious behavior, whereas the volume gradually decreased for the other driving logics (see Figure 10). At 100% penetration, the PrT volumes increase by 22.84% (28.51 million PCU) with cautious behavior under urban street roadway, while the volumes decrease by 12.11% (15.11 million PCU) and 14.68% (18.33 million PCU) under motorway scenario for normal and aggressive behaviors, respectively.

In case of SAE automation levels, similar volume reduction pattern is depicted with the progression of the penetration rate and automation level (see Figure 11). At 100% penetration, more significant results are obtained for SAE automation levels 3, 4, and 5, which reduce the PrT volume by 3.81%, 10.18%, and 19.84%, respectively.

4.6. Overall Assessment and Discussion. The pattern of aggregated studies in different regions predicted an inclusive increase in the vehicle miles travelled (VMT) ranging from 4 to 24%. For instance, at higher penetration, VMT increment assessments made in Stuttgart depicted 6% [25], 4% in Chicago [44], 4–8% in San Francisco Bay Area [45], 4–20% in Seattle Region [14], 4–24% in Atlanta [46], and 1.61% in Budapest [34]. Most of these studies considered activity-based modelling approach with control of assumption on capacity gains, reduction in value of in-vehicle time (VOT) for trips with AVs, reduction of operating costs, or removal of parking costs, which contribute to the result variabilities. Based the more disaggregated categories in this study, at 100% penetration, much higher percentage change in the daily hours travelled (6.22% for cautious, −2.92% for normal behavior, and −3.51% for aggressive behavior) is estimated on different roadways as compared to the percentage change in the sum of daily vehicle kilometer travelled (1.04% for cautious behavior, −0.55% for normal behavior, and −0.65% % for aggressive behavior).

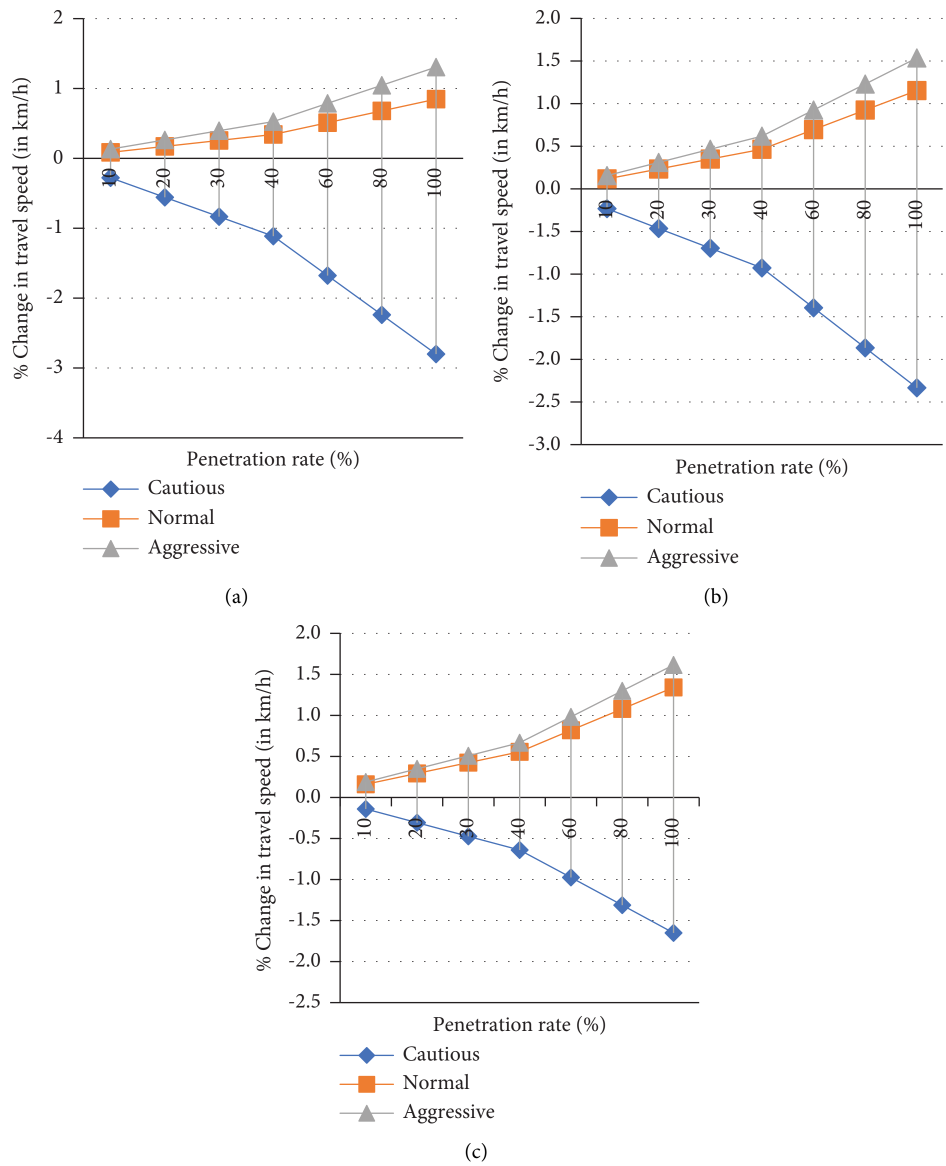

Figure 8: Percentage change in vehicle travel speed for scenarios of (a) urban street, (b) arterial, and (c) motorway.

A macroscopic study depicted a reduction in delay to reach 37.87%, which corresponds to a PCU value of 0.5 [34]. However, such random PCUs may not reflect realistic possible future scenario. For instance, the estimated PCU factor for SAE automation level 5 based on a practical study under the CoEXist project was estimated to be 0.65 [27]. At higher penetrations, the introduction of AVs could increase the total vehicle delays by 33.44% based on cautious behavior, while it reduces for the normal and aggressive behaviors by up to 15.9% and 19.17%, respectively. In SAE automation levels, the most significant results in reduction of the total vehicle delay are estimated at automation level 3 by 5.16%, level 4 by 13.46%, and level 5 by 25.66% at 100% penetration.

Moreover, the 4.08% speed improvement based on randomized PCU progression [34] has a similar trend with the speed results obtained in this study. The percentage change in the overall vehicle speed at highest penetration rates has reduced up to 2.8% for cautious behavior, while it increased for the normal and aggressive behaviors by up to 1.46% and 1.76%, respectively. On the other hand, for SAE automation levels 3, 4, and 5, the improvements in the relative vehicle travel speed are estimated to be 0.46%, 1.23%, and 2.37%, respectively. Implementation of automated driving could affect also the PrT volumes by 22.84% with cautious, −12.11% with normal, and −14.68% with aggressive behaviors, whereas the significant results obtained for the SAE automation levels are −3.81% for level 3, −10.18% for level 4, and −19.84% for level 5.

In comparison, this study stands out due to the integration of the evaluations on the operational effects of AVs in terms of their driving logics, automation levels, and roadway types to assess their coexistence with heterogeneous traffic, which supplements crucial inputs in understanding the combined impacts. More disaggregated categories of

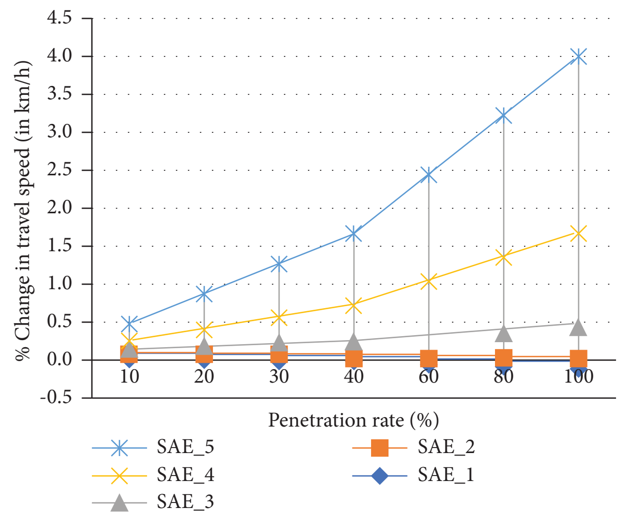

FIGURE 9: Percentage change in vehicle travel speed based on SAE automation levels.

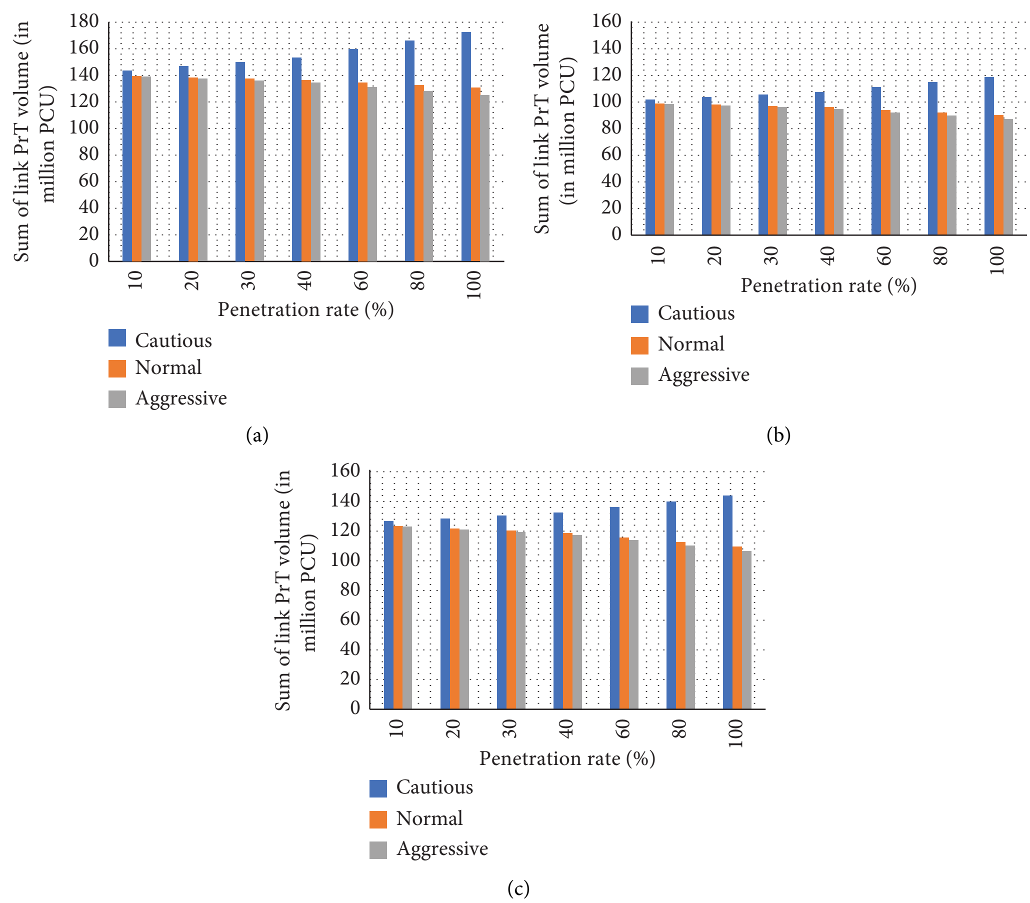

FIGURE 10: Sum of link PrT volume for scenarios of (a) urban street, (b) arterial, and (c) motorway.

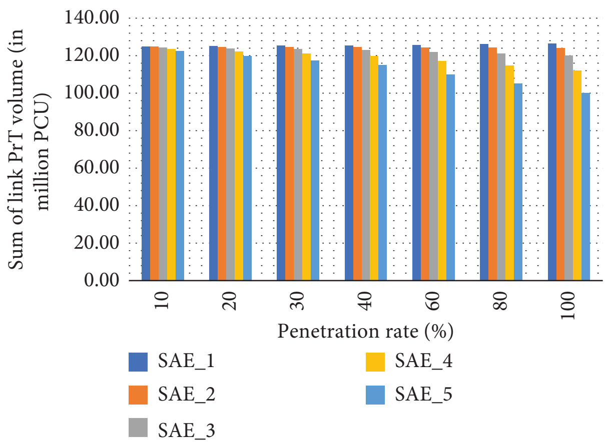

Figure 11: Sum of link PrT volume based on SAE automation levels.

critical importance are studied with several measures of effectiveness. Therefore, the findings show that, especially in the early stages of deployment with cautious behavior, the anticipated benefits of AVs for PrT users do not come without significant adverse effects brought on by increased road traffic.

5. Conclusions

In this study, the operational impacts of AVs have been investigated considering their driving logics, automation levels, and roadway types, which are accounted with their PCU factors at different penetration rates. The macroscopic traffic simulation experiments are conducted in PTV Visum 2020.00-14 scenario manager using the Budapest EFM model to evaluate the coexistence of AVs with the heterogeneous traffic. The evaluations are mainly focused on the assessment of the changes in the daily vehicle hours travelled, daily vehicle kilometers travelled, sum of delays on links, total speed variation, and sum of vehicle volumes on links.

There is an overall improvement in the network operational performance from cautious to aggressive driving behaviors and increase in penetration rate of AVs. The comparative study with the base scenario among the 99 combinations of scenarios depicted that the results of motorway scenario are much favorable than the urban street and arterial scenarios, which calls for more deeper investigation on AV-readiness of the infrastructure and its impacts on the network performance.

Therefore, AVs transformed the network performance in a very significant level, especially at higher penetrations, higher automation levels, better roadway conditions, and advanced driving logics. The results of this study could further be extended considering the AV-readiness of the various supply elements/infrastructure with different techniques and adoption of the communications among vehicles and the infrastructure with various logical contemplations.

The outcomes of the simulated scenarios can be used as a main basis for discussion of suitable steps to lessen negative effects with suitable countermeasures from policymakers and practitioners. There will be little favorable effects on road traffic during the early stages of AV deployment; for instance, if the general AV driving logic stays cautious, the network will experience worse traffic performance. Overall, it is important to carefully evaluate the trade-off and take equity into account while considering prioritized automation solutions in public transport along dedicated lanes or taking a risk with the PrT negative repercussions during the early implementation periods.

Data Availability

All data, models, and codes generated or used during the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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