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A Capacity Modelling Study of Diverging Areas in Urban Tunnels Under Intelligent Connected Environments

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ABSTRACT

With the advancement of connected automated vehicles (CAVs), their increasing presence in traffic flows is expected to reshape road capacity. In urban tunnels, diverging areas are essential for traffic efficiency and safety. However, existing research has mainly focused on merging and diverging areas in expressways and arterial roads, with limited attention to urban tunnel environments. To address this gap, this study proposes a capacity estimation method for the diverging areas in urban tunnels under an intelligent connected environment. A simulation framework was developed to analyse key influencing factors under different CAV penetration rates. Then, a capacity estimation model was established using a multivariate nonlinear fitting approach and was validated through SUMO simulation experiments. The results indicate that: (1) penetration rate, diversion ratio and deceleration lane length are key parameters influencing capacity; (2) a CAV penetration rate of 0.5 marks a threshold beyond which deceleration lane length has little impact; and (3) a case study using the Nanping Tunnel in Chongqing shows that the model's prediction error is within 5.29%. This study offers a targeted capacity estimation method for diverging areas in urban tunnels, aiding adaptive traffic control design and CAV deployment planning.

KEYWORDS

traffic engineering; capacity modelling; intelligent connected environment; diverging areas in urban tunnel; influencing factors.

1. INTRODUCTION

As a critical functional zone for traffic flow redistribution, urban tunnel diverging areas are characterised by frequent lane changes, deceleration manoeuvres and vehicular weaving conflicts [1]. These phenomena can lead to intensified lane-changing disputes, traffic flow instability, reduced operational efficiency, as well as increased risks of congestion and safety incidents [2]. With the progressive advancement of intelligent and connected vehicle technologies, connected automated vehicles (CAVs) are emerging as the predominant trend in future mobility systems. Consequently, conventional traffic patterns are transitioning into mixed traffic flows comprising both CAVs and human-driven vehicles (HDVs) [3]. Under such conditions, capacity is subject to coupled influences from multiple factors. Understanding its dynamic characteristics provides crucial support for both the planning of urban tunnel diverging areas and the development of CAV deployment strategies with associated traffic management measures.

In current studies on tunnel capacity, scholars primarily investigate two dimensions: factors influencing capacity and corresponding calculation methodologies. Research under conventional traffic conditions has centred on how road infrastructure, traffic composition and driving behaviours affect capacity. In intelligent connected environments with mixed traffic flows, research focuses on the effects of CAV penetration rates, vehicle platooning patterns and interactive control systems. Methodologically, existing research relies on three primary approaches: data-driven estimation, simulation modelling and theoretical analysis. Nevertheless, tunnel diverging areas, which are critical components of urban tunnel systems, remain underexplored in this context, with their capacity mechanisms poorly understood. A notable gap persists as current analyses predominantly examine individual factors in isolation, without addressing the multifactorial interactions that shape capacity in diverging areas.

This study focuses on the diverging areas in urban tunnels, analysing traffic characteristics and vehicle behaviour patterns under mixed traffic flow conditions. A capacity estimation model tailored for the diverging areas under intelligent connected environments is developed, and its validity is further verified using empirical data. The main contributions are as follows:

1) Key parameters of HDVs and CAVs were calibrated using the SUMO simulation platform to develop and validate a mixed traffic flow simulation model for the diverging areas in urban tunnels.
2) The evolution patterns of capacity under various factor combinations were explored from a multi-dimensional perspective, and a capacity estimation model was developed based on multivariate nonlinear fitting methodology.
3) The accuracy of the proposed model was validated through simulation experiments using empirical data.

2. LITERATURE REVIEW

2.1 Influencing factors on traffic capacity

Capacity is influenced by the coupling effects of multiple factors, including roadway geometry, traffic composition and human-vehicle interaction behaviour. Relevant studies can be broadly categorised into two areas: traditional traffic flow and mixed traffic flow under intelligent connected environments. In the context of conventional traffic flow, research has primarily focused on the effects of road infrastructure, traffic composition and driving behaviours on capacity. Calvi et al. [4] analysed the influence of ramp configurations and reported that reducing the number of exit lanes from two to one significantly decreases capacity. Chen et al. [5] investigated lane-changing behaviour in merging, diverging and weaving areas, concluding that frequent lane changes significantly reduce capacity and exacerbate congestion. Patkar et al. [6] observed that higher non-motorised vehicle presence markedly lowers capacity. Ghosh et al. [7] used microscopic simulation models to reveal how different driving behaviour patterns affect traffic flow characteristics and capacity. Yao et al. [8] further identified that reaction time and acceleration/deceleration behaviour of individual vehicles significantly impact capacity in mixed traffic flows. Under intelligent connected environments, studies have shifted focus to the influence of CAV penetration rates, vehicle platooning patterns and interactive control systems. Yao et al. [9, 10] investigated the effects of CAV platoon size and found that increasing the maximum platoon size can significantly improve capacity. Chen et al. [11-13] explored the relationship between CAV penetration rate and traffic density, revealing that critical density and maximum average flow rate are key factors affecting capacity. Sala et al. [14] demonstrated that platoon length exerts a notable influence on capacity. Guan et al. [15] found that the willingness of semi-autonomous vehicles to platoon, the penetration rate of fully autonomous vehicles and platoon size all significantly affect capacity. Ghiasi et al. [16, 17] employed Markov chain methods to analyse the relationship between the number of CAV-designated lanes and capacity, further revealing the impact of CAV deployment on overall traffic system performance.

2.2 Traffic capacity calculation method

Modelling approaches for estimating road capacity primarily include empirical estimation based on observed data, simulation-based modelling and theoretical derivation. Empirical estimation methods rely on statistical analysis of field data to capture capacity variations under different traffic conditions. Dhamaniya et al. [18] developed speed-flow equations for various vehicle types using field data and applied fundamental diagram theory to calculate arterial road capacity, offering a quantitative basis for capacity assessment. Wu et al. [19] constructed an integrated model covering diverging, merging and weaving segments, calibrating parameters with field data to estimate capacity across configurations. With advancements in computing technology, microscopic traffic simulation has gained traction in capacity analysis due to its ability to simulate long-term traffic dynamics. Mohan et al. [20] optimised parameters of a VISSIM simulation model using genetic algorithms and analysed network capacity under varying traffic conditions. To improve the generalisability of models, theoretical derivation methods have been proposed based on traffic flow theory and factor analysis. Liu et al. [21] proposed a dynamic capacity estimation framework suitable for real-time urban traffic management by integrating fundamental diagrams with multidimensional traffic state variables. Yu et al. [22] derived flow–density relationships under different CAV penetration rates using traffic equilibrium theory, establishing a capacity model for signalised intersections in mixed traffic environments. Qin et al. [23] developed a capacity model for secondary roads under mixed traffic through mathematical derivation and investigated optimisation strategies for homogeneous and heterogeneous platoon control involving CAVs and HDVs. Fu et al. [24] employed the Greenshields traffic flow model and a lane-specific calibration approach to compare the capacity of freeway tunnels with adjacent segments, enabling a quantitative evaluation of expected tunnel capacity on expressways.

Diverging areas in urban tunnels occupy an important structural and functional position within urban transportation systems, with their research value reflected in aspects such as network transition efficiency, congestion bottleneck identification and traffic safety management. As tunnels are often considered critical and vulnerable components of the urban road network, diverging areas within tunnels frequently serve as transition nodes between different network hierarchies, playing a key role in route switching and traffic distribution, thereby directly affecting the overall accessibility and operational efficiency of the network. Due to significant spatial constraints in tunnels, these diverging areas are typically characterised by short deceleration lanes and limited manoeuvring space, making them prone to becoming congestion bottlenecks that restrict traffic flow. Moreover, diverging areas are also recognised as high-risk segments. Empirical studies from multiple countries have shown that accident rates near tunnel entrances, exits and transition zones are significantly higher than those on open roads [25–27], with the crash risk in diverging areas estimated to be approximately twice that of tunnel entrances [28].

In summary, although existing studies have made some progress in estimating the capacity of diverging areas, several limitations still persist. Current research efforts are primarily focused on typical merging and diverging areas of expressways and arterial roads, with insufficient attention paid to the capacity characteristics of urban tunnel diverging areas. The theoretical framework and empirical studies in this context are still underdeveloped. Most existing studies focus on individual or partial influencing factors, lacking systematic modelling approaches and adequate exploration of multi-variable coupling mechanisms. Existing capacity models are inadequate for capturing the complex traffic dynamics of urban tunnel diverging areas. Particularly in intelligent connected environments, there remains a lack of capacity modelling methods tailored to mixed traffic flow scenarios. These limitations hinder the in-depth evaluation of traffic performance and the formulation of effective optimisation strategies for urban tunnel operations.

3. SIMULATION MODEL DEVELOPMENT AND ANALYSIS

Figure 1 illustrates the overall workflow of simulation model development and analysis, comprising four main components. The first component involves defining the spatial scope of conventional urban tunnel diverging areas as a basis for subsequent investigation. The second component focuses on the construction of a simulation model based on the topological features and field data of the Nancheng Tunnel diverging area. Sensitivity analysis is conducted, and key behavioural parameters for both HDVs and CAVs are calibrated to ensure high-fidelity modelling. The third component analyses the operational characteristics of mixed traffic under varying CAV penetration rates and identifies a critical threshold at which traffic performance exhibits a significant change. The final component redefines the scope of urban tunnel diverging areas under intelligent connected environments to ensure the scientific validity and applicability of the study.

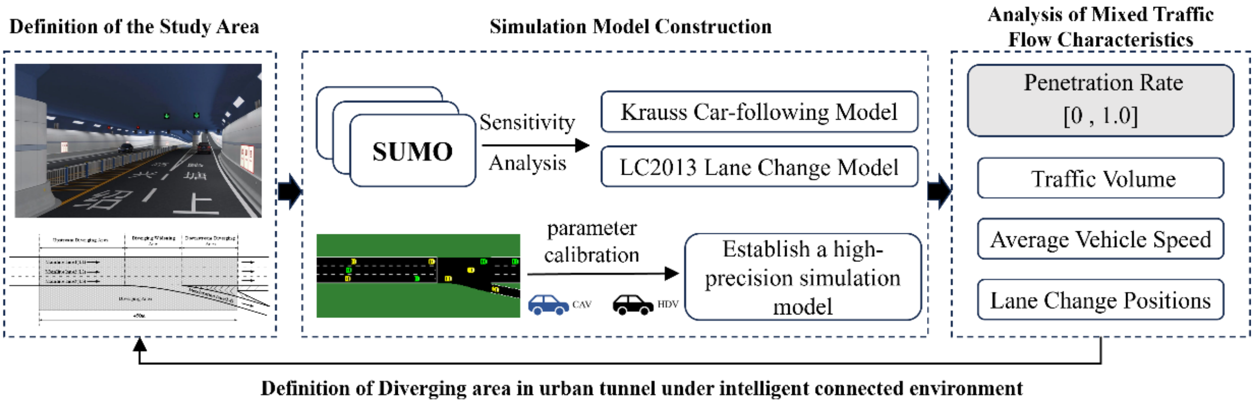


Figure 1 – Capacity modelling and simulation process for urban tunnel diverging areas

3.1 Definition of the study area

Currently, there are no established standards defining the spatial extent of diverging areas in urban tunnels. This study defines the urban tunnel diverging area as a 450-metre continuous segment extending upstream from the point where the exit ramp connects to the mainline tunnel, encompassing all lanes of the mainline section [29]. The spatial extent of the defined diverging area is schematically illustrated in *Figure 2*.

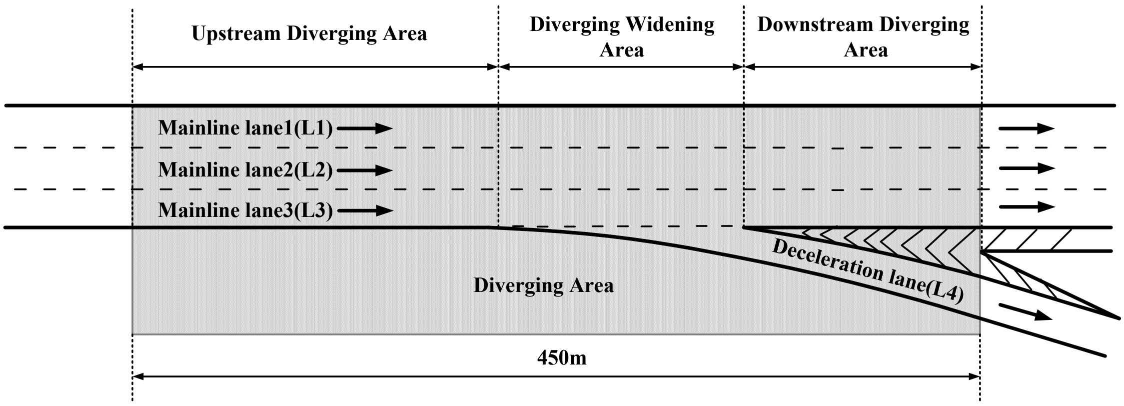


Figure 2 – Schematic diagram of the diverging areas in an urban tunnel

3.2 Simulation model construction

A simulation model was constructed based on the topological structure and observed traffic data of the diverging areas in the Nancheng urban tunnel in Chongqing. Sensitivity analysis is then conducted to identify the key parameters influencing the simulation. Subsequently, behaviour parameters of CAVs and HDVs are calibrated according to the identified results, ensuring that the model outputs fall within an acceptable margin of error when compared with field observations, thereby enhancing the model's credibility.

Sensitivity analysis

In this study, SUMO is used as the microscopic traffic simulation platform. The diverging area within the Nancheng urban tunnel in Chongqing was selected as a representative case study. The mainline's upstream and downstream sections each consist of two lanes, while the exit ramp comprises a single lane with dashed lane markings throughout. Based on this configuration, a static simulation model of the diverging area in the Nancheng Tunnel was developed, incorporating key input parameters such as traffic volume, vehicle composition, desired speed and diversion ratio, as illustrated in *Figure 3*.

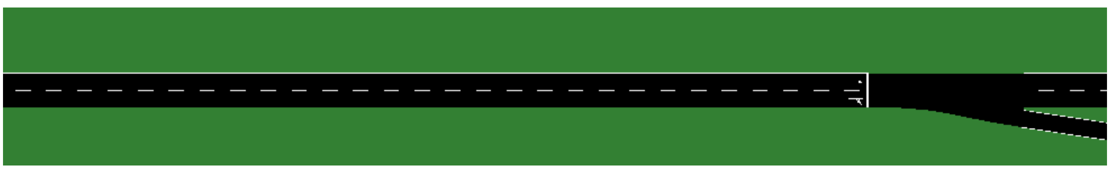


Figure 3 – Static simulation model of the diverging areas in Nancheng Tunnel

Prior to the sensitivity analysis, the upstream input traffic volume on the mainline corresponding to the capacity of the tunnel diverging area must be determined. Accordingly, the speeds of the mainline and ramp are set to the Nancheng Tunnel's design values of 60 km/h and 40 km/h, respectively, while all other parameters remain at their default settings. A capacity test is then conducted. The results indicate that the diverging area reaches its maximum capacity when the upstream input volume reaches 3700 pcu/h. Therefore, in the subsequent sensitivity analyses, the mainline upstream input traffic volume is fixed at this value.

This study adopts the default Krauss car-following model and the LC2013 lane-change model in SUMO as the basis for sensitivity analysis. The Krauss model [30] is a stochastic car-following model based on safe distance and driver anticipation. It calculates the safe speed that a following vehicle should maintain at each time step according to the relative distance and speed to the preceding vehicle, while incorporating driver behaviour uncertainty under the constraint of collision-free operation. This model is well-suited for urban traffic scenarios with rapidly changing conditions. The LC2013 model [31] determines lane-change behaviour at each simulation step by integrating incentive conditions and safety constraints. It makes lane-change decisions based on a vehicle's planned route and its current and surrounding traffic states, while also considering the acceleration and deceleration of both the subject and adjacent vehicles to ensure safe and effective manoeuvring. This makes it particularly applicable to confined environments with frequent lane changes, such as diverging areas in urban tunnels.

The analysis employs the single-factor control variable method, where each target parameter is systematically varied while all others are held constant. The downstream traffic volume and average speed within the diverging area serve as evaluation metrics to assess the impact of each parameter on the simulation results. The results of the sensitivity analysis are presented in *Table 1*.

Table 1 – Comparative results of sensitivity analysis

Parameter		**Range**	**Number of values**	**Maximum traffic flow (pcu/h)**	**Minimum traffic flow (pcu/h)**	**Difference ratio**	**Maximum speed (km/h)**	**Minimum speed (km/h)**	**Difference ratio**
Mingap	Minimum gap	[1.0, 3.0]	5	3343	3180	5.88%	51.88	50.90	1.89%
accel	Acceleration	[2.2, 3.6]	8	3243	3111	4.07%	51.77	50.69	2.09%
decel	Deceleration	[3.5, 5.5]	5	3295	3134	4.89%	51.91	50.76	2.22%
emergencyDecel	Emergency deceleration	[7, 11]	5	3218	3218	0.00%	51.30	51.30	0.00%
sigma	Driver's reaction time	[0.00, 1.00]	5	3485	2899	16.81%	53.78	47.37	11.93%
tau	Desired headway	[0.5, 1.3]	9	3670	2826	23.00%	53.06	50.87	4.13%
lcStrategic	Lane change strategic	[0.0, 3.0]	7	3218	3022	6.09%	52.56	35.24	32.95%
lcCooperative	Lane change cooperative	[0.0, 1.0]	6	3219	1600	50.30%	51.34	18.22	64.51%
lcSpeedGain	Lane change speed gain	[0.0, 2.0]	5	3222	3165	1.77%	51.70	46.26	10.52%
lcKeepRight	Lane change keep right	[0, 4]	5	3222	3213	0.28%	51.70	51.30	0.77%
lcLookaheadLeft	Lane change lookahead left	[0.0, 3.0]	7	3220	3212	0.25%	51.48	51.30	0.35%
lcAssertive	Lane change assertive	[0.25, 2.00]	8	3228	3136	2.85%	52.09	44.03	15.47%

The test results indicate that parameters such as desired speed, Mingap, sigma, tau, lcStrategic, lcCooperative, lcSpeedGain and lcAssertive have a significant impact on the simulation model. In contrast, other parameters exhibit relatively minor effects, with the difference ratio consistently remaining below 5%. Therefore, the key parameters influencing the simulation model of the diverging areas in urban tunnels are identified as: Mingap, sigma, tau, lcStrategic, lcCooperative, lcSpeedGain and lcAssertive.

Construction of the HDVs simulation model

HDVs depend on driver vision and onboard systems, lacking direct communication capabilities. In simulating vehicle following behaviour, the Krauss car-following model is commonly used, while lane-changing behaviour is represented by the LC2013 lane-change model. By inputting foundational data into the simulation software and continuously adjusting and optimising the model parameters, the simulation outputs are calibrated to align with actual observational data within an acceptable error range. This process completes the parameter calibration of the HDV model. The calibration results are shown in *Table 2*.

Table 2 – Calibration results of critical parameters for HDVs

Model	Parameter	Default value	Calibrated value	Definition
Krauss car-following model	Mingap	2.5	2.50	Minimum gap
	sigma	0.5	0.30	Driver's reaction time
	tau	1.0	1.89	Desired headway
LC2013 lane-change model	lcStrategic	1.0	0.50	Strategic lane change behaviour of vehicles
	lcCooperative	1.0	0.60	Cooperative lane change behaviour of vehicles
	lcSpeedGain	1.0	3.00	Speed gain after lane change
	lcAssertive	1.0	3.00	Willingness to accept smaller front and rear gaps in the target lane during lane change

Traffic volume, speed and lane change positions were selected as evaluation metrics to compare the optimised simulation data of HDVs with observed data. The simulation was conducted for 3600 seconds with a time step of 0.5 seconds. Under both congested and free-flow conditions, the traffic volume error of the optimised model did not exceed 2.90%, the speed error remained within 3.29%, and the distribution of lane change positions closely aligned with the observed data. Compared to the default model, this optimised model more accurately captures the operational characteristics of HDVs in the diverging areas in urban tunnels, demonstrating significantly improved performance.

Construction of the CAVs simulation model

The primary distinction in car-following behaviour between CAVs and HDVs lies in the advanced driver assistance systems (ADAS) typically installed on CAVs. When operating within the maximum communication range, CAVs function under the cooperative adaptive cruise control (CACC) mode [32, 33]. If the lead vehicle lacks communication capabilities, the system switches to the sensor-based adaptive cruise control (ACC) mode [1, 34]. Accordingly, this study adopts the ACC/CACC car-following model in SUMO to simulate the car-following characteristics of CAVs. The LC2013 lane-change model is likewise employed for CAVs, with its parameters calibrated to reflect the dynamics of an intelligent connected mixed traffic environment. The specific parameter settings are presented in *Table 3*.

Table 3 – Calibration results of critical parameters for CAVs

Model	Parameter	Default value	Calibrated value	Definition
ACC car-following model	Mingap	2.5	2.0	Minimum gap
	tau	1.0	1.1	Desired headway
CACC car-following model	Mingap	2.5	2.0	Minimum gap
	tau	1.0	0.6	Desired headway
LC2013 Lane change model	lcStrategic	1.0	2.5	Strategic lane change behaviour of vehicles
	lcCooperative	1.0	1.0	Cooperative lane change behaviour of vehicles
	lcSpeedGain	1.0	1.0	Speed gain after lane change
	lcAssertive	1.0	2.0	Willingness to accept smaller front and rear gaps in the target lane during lane change

The effectiveness of the simulation model for the intelligent connected environment is evaluated by comparing the optimised model with the baseline model using default parameter settings. The simulation duration is set to 3600 seconds with a time step of 0.5 seconds. The traffic density on a single lane is varied from 10 vehicles/km to 80 vehicles/km, in increments of 10 vehicles/km. Data from the time window between 1800 and 2400 seconds are selected as the analysis sample. Under different traffic densities, the optimised model improves speed and throughput while decreasing delay, better capturing mixed traffic dynamics in urban tunnel diverging areas.

3.3 Analysis of mixed traffic flow characteristics

Traffic volume

To examine the impact of the CAV penetration rate on traffic flow in the diverging areas, a series of simulation experiments was conducted with CAV penetration rates p set to 0, 0.2, 0.4, 0.6, 0.8 and 1. The resulting volume–density fundamental diagram for the diverging areas is presented in *Figure 4*, where the x-axis represents the single-lane traffic density.

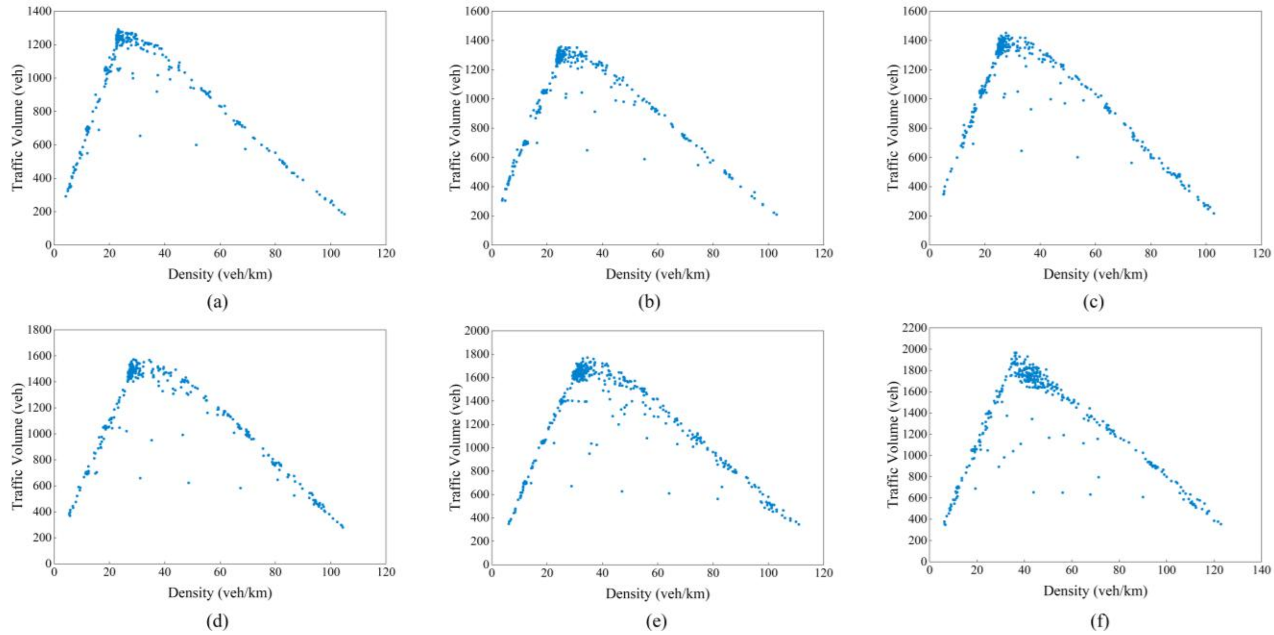


Figure 4 – Basic flow-density diagram under different penetration rates: (a) p = 0; (b) p = 0.2; (c) p = 0.4; (d) p = 0.6; (e) p = 0.8; (f) p = 1.0

As the CAV penetration rate increases, the maximum traffic flow in the diverging areas exhibits a clear upward trend. When the penetration rate is 0, the traffic capacity is approximately 1290 vehicles per hour (veh/h). As the penetration rate increases to 0.4, the capacity rises to 1452 veh/h, representing a 12.6% improvement. When the penetration rate reaches 1, the capacity further increases to approximately 1967 veh/h, corresponding to a cumulative increase of 52.4%. These results suggest that during the initial stages of intelligent connectivity, the effect of CAV penetration on capacity enhancement is relatively limited. However, in the later stages, the increasing proportion of CAVs leads to a substantial improvement in traffic capacity.

Average vehicle speed

To examine the impact of CAV penetration rate on the average vehicle speed in the diverging areas, the penetration rate was varied from 0 to 1 in increments of 0.1. The average vehicle speed during peak hours corresponding to each penetration rate is presented in *Figure 5*.

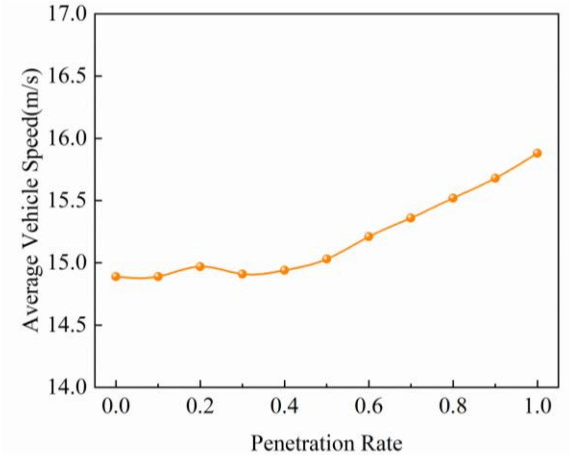


Figure 5 – Average vehicle speed under different penetration rates

As the CAV penetration rate gradually increases from 0 to 1, the average vehicle speed during peak hours exhibits an overall increase of 6.65%. A slight decline in average speed is observed when the penetration rate ranges between 0.2 and 0.3. However, once the penetration rate reaches 0.5, the speed improvement becomes significantly more pronounced, displaying a near-linear upward trend. These findings suggest that at low penetration rates, variations in the proportion of CAVs have a limited impact on average speed. In contrast, when the penetration rate reaches 0.5, average speed increases substantially with further rises in penetration rate, identifying 0.5 as a critical threshold for noticeable speed improvement.

Lane change positions

To examine the impact of CAV penetration rate on lane change positions, a statistical analysis of the lane change distribution of CAVs during peak hours was conducted across various penetration rates. The results are presented in *Figure 6*.

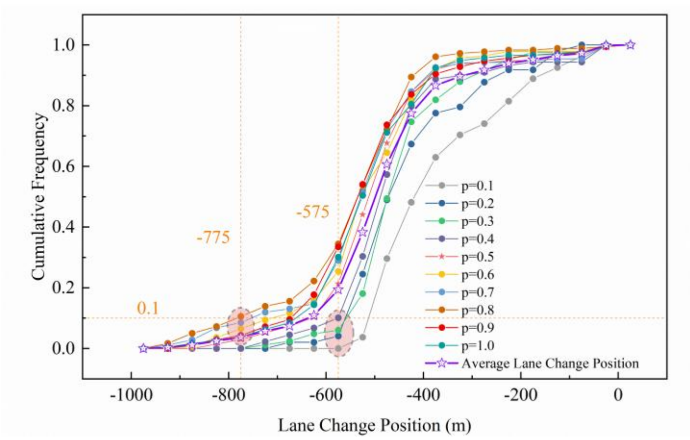


Figure 6 – Distribution of CAV lane change positions under different penetration rates

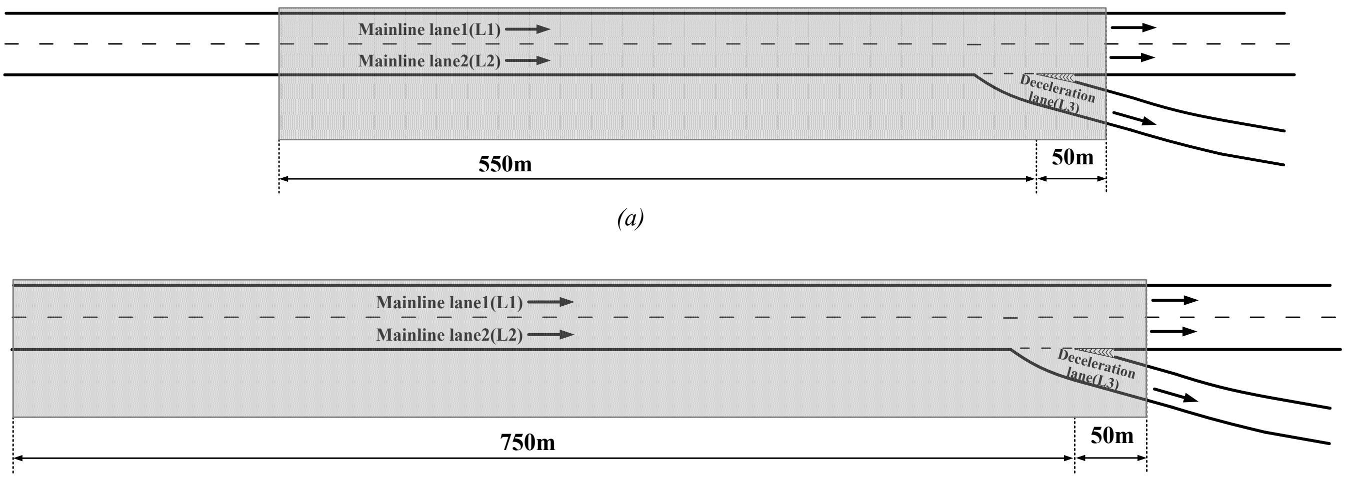
To analyse the distribution of CAV lane change positions, the 0.1 quantile of the cumulative frequency was used as a reference line. The horizontal coordinate corresponding to this quantile was identified as the starting position for 90% of CAV lane changes, serving as an indicator of overall lane change behaviour and trends. Furthermore, based on the lane change position distribution curves at various penetration rates, an average lane change position distribution curve was generated. As shown in the figure, this average curve closely aligns with the distribution curve at a penetration rate of 0.5. Notably, a significant shift in lane change positions is observed once the penetration rate reaches 0.5. Therefore, a penetration rate of 0.5 is identified as a critical threshold for conducting a more detailed analysis of lane change position distribution.

When the penetration rate is below 0.5, CAV lane change positions are relatively close to the diverging point, with 90% of CAVs changing lanes approximately 550 metres upstream. This is primarily due to the high proportion of HDVs in the mixed traffic flow at low penetration rates, which significantly interferes with the lane-changing behaviour of CAVs. In contrast, when the penetration rate is greater than or equal to 0.5, 90%

of CAVs perform lane changes around 750 metres upstream of the diverging point. This shift occurs because CAVs become the dominant vehicle type in the traffic stream once the penetration rate reaches 0.5, allowing them to initiate lane changes earlier when conditions permit.

3.4 Definition of diverging area in urban tunnel under an intelligent connected environment

A comprehensive analysis of mixed traffic flow characteristics, average vehicle speed and lane change positions reveals that the spatial extent of the diverging areas in intelligent connected environments varies with the CAV penetration rate. Consequently, it is necessary to redefine the boundaries of the diverging areas. Based on the observed lane change behaviour of CAVs under different penetration rates, a revised delineation standard is proposed for urban tunnel diverging areas in intelligent connected environments. Specifically, when the penetration rate is below 0.5, the diverging areas extend from 550 metres upstream to 50 metres downstream of the diverging point. When the penetration rate is 0.5 or higher, the upstream boundary expands to 750 metres, while the downstream boundary remains at 50 metres. These expanded areas also include the deceleration lanes and the outermost two lanes of the mainline, as illustrated in *Figure 7*.



(b)

Figure 7 – Study areas of the diverging areas in urban tunnel under an Intelligent connected environment: (a) p < 0.5; (b) p ≥ 0.5

4. CAPACITY MODEL CONSTRUCTION

By considering the road characteristics and traffic features of urban tunnel diverging areas, multiple factors that potentially influence capacity are initially identified. Under varying CAV penetration rates, the effects of these factors on capacity are analysed, allowing for the identification of the primary influencing variables. Additionally, a bivariate and multivariate coupling analysis is performed to uncover the interaction mechanisms between the influencing factors and their functional relationships with capacity. Ultimately, a capacity model is developed, capturing the multivariable nonlinear characteristics of the system.

4.1 Analysis of influencing factors under different penetration rates

Six influencing factors, including penetration rate, deceleration lane length, diversion ratio, mainline lane count, ramp lane count and lane width, are selected to explore the impact of each factor on capacity under varying penetration rates. Based on the defined research range of the diverging areas in urban tunnels within the intelligent connected environment, as established in Section 3.4, a simulation model is developed. Each factor is then tested under different penetration rate conditions, while all other parameters are maintained at their default values.

1) The first analysis focuses on the penetration rate, and the simulation results concerning its impact on capacity are presented in *Figure 8*.

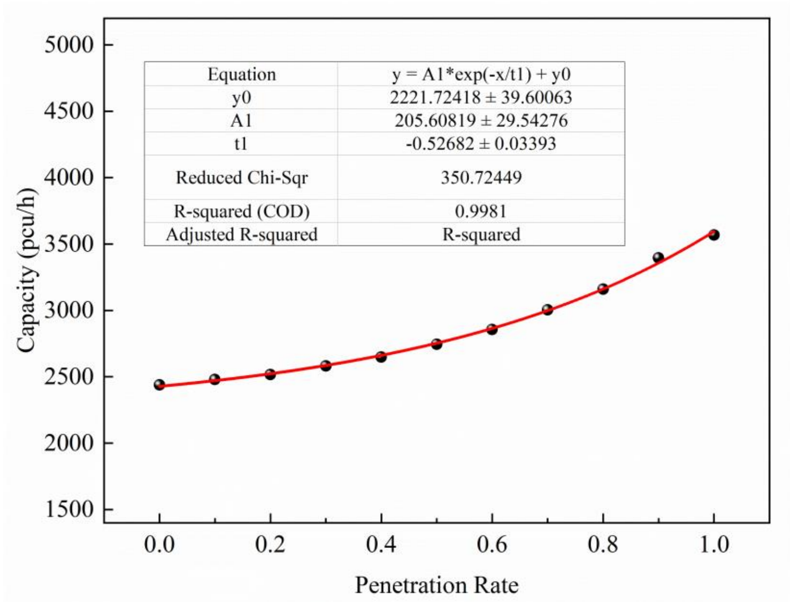
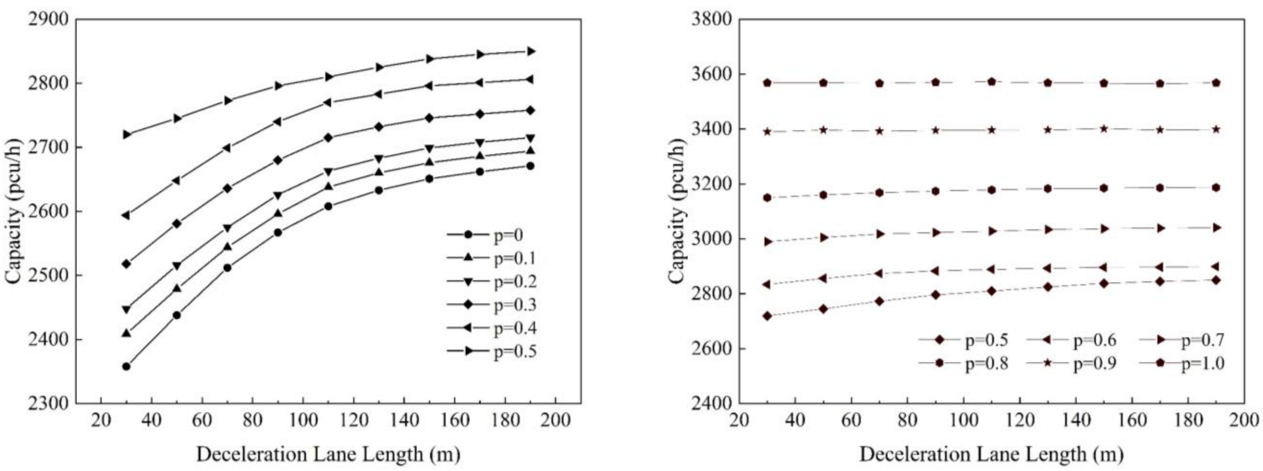


Figure 8 – Simulation results of penetration rate

The fitting analysis reveals an exponential growth relationship between the two. When the penetration rate rises from 0 to 1, capacity increases by approximately 46.3%. When the penetration rate rises from 0.5 to 1, capacity increases by approximately 30.0%. These results demonstrate that the penetration rate significantly impacts the capacity of the diverging areas in urban tunnels, with the effect becoming more pronounced as the penetration rate increases.

2) Simulation analysis of deceleration lane length was conducted under different penetration rate conditions, with the specific results shown in *Figure 9*.

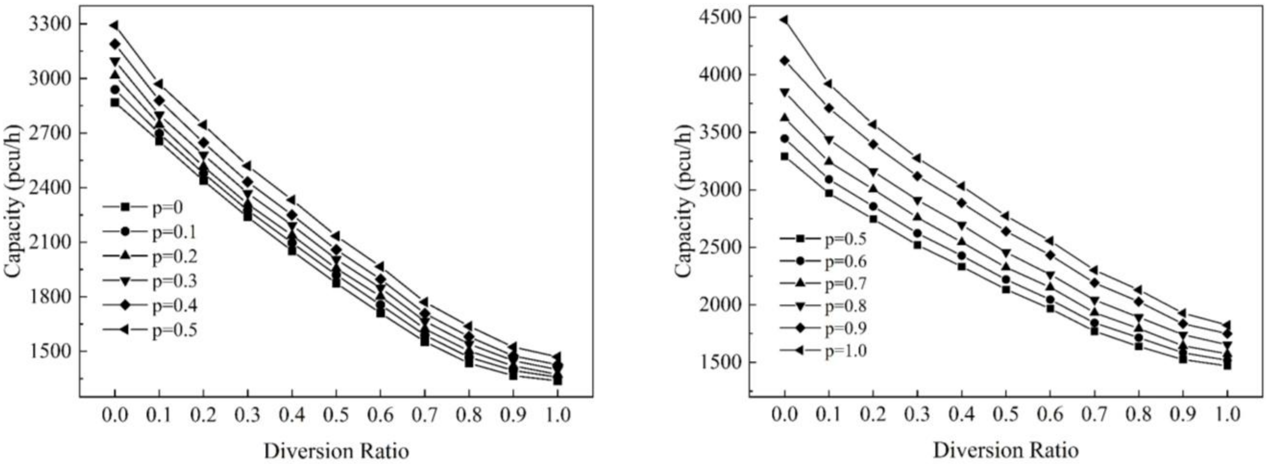


(a) *(b)*

Figure 9 – Simulation results of deceleration lane length: (a) p ≤ 0.5; (b) p≥0.5

As shown in the figure, when the penetration rates are 0 and 0.5, increasing the deceleration lane length from 30 m to 190 m results in capacity improvements of 13.3% and 4.8%, respectively. When the penetration rate falls within the range of [0.5, 1], optimising the deceleration lane length significantly improves the capacity of the diverging areas. However, its impact is relatively limited under high penetration rate conditions.

3) Simulation analysis of the diversion ratio was conducted under different penetration rate conditions, with the specific results shown in *Figure 10*.



(a) *(b)*

Figure 10 – Simulation results of diversion ratio: (a) p ≤ 0.5; (b) p≥0.5

As shown in the figure, the diversion ratio has a significant impact on the capacity of the diverging areas, and the degree of its influence gradually weakens as the diversion ratio increases. Specifically, when the penetration rates are 0 and 1, as the diversion ratio increases from 0 to 1, the capacity of the diverging areas decreases by 53.4% and 59.3%, respectively, indicating that the diversion ratio significantly affects the capacity of the diverging areas. When the penetration rate is 0, as the diversion ratio increases from 0 to 0.5, the capacity decreases by 34.6%, and as the diversion ratio increases from 0.5 to 1, the capacity decreases by 28.6%, indicating that the effect of the diversion ratio on the capacity weakens as it increases.

4) Simulation analyses were conducted for the number of mainline lanes, ramp lanes and lane width under different penetration rate conditions, with the specific results shown in *Figure 11*.

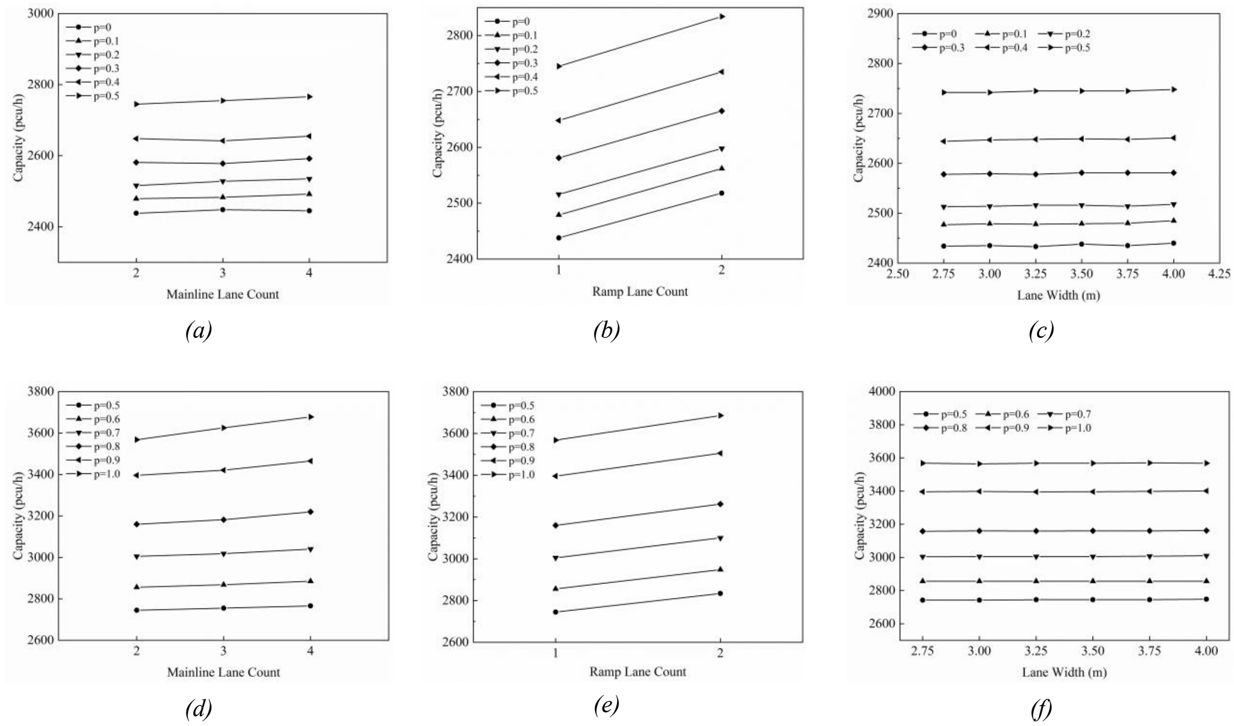


Figure 11 – Simulation results of main lane count, ramp lane count and lane width: (a) p ≤ 0.5, (b) p ≤ 0.5; (c) p ≤ 0.5; (d) p ≥ 0.5; (e) p ≥ 0.5, (f) p ≥ 0.5

As shown in the figure, the increase in mainline lane count, ramp lane count and lane width has a limited impact on the capacity of the diverging areas in the urban tunnel. Specifically, under varying penetration rates, even though the mainline lane count, ramp lane count and lane width increase, the capacity of the diverging areas remains largely stable, showing no significant improvement trend. Therefore, penetration rate, diversion ratio and deceleration lane length are identified as the key influencing factors for the capacity of the diverging areas in an intelligent connected environment.

4.2 Factor combination analysis

Two-factor surface-fitting analysis

1) Penetration rate – diversion ratio

To comprehensively analyse the joint effect of penetration rate and diversion ratio on the capacity of the diverging areas, a three-dimensional surface plot is constructed to illustrate their relationship. The optimal fit results are obtained using a function fitting method. The experimental results are shown in *Figure 12*.

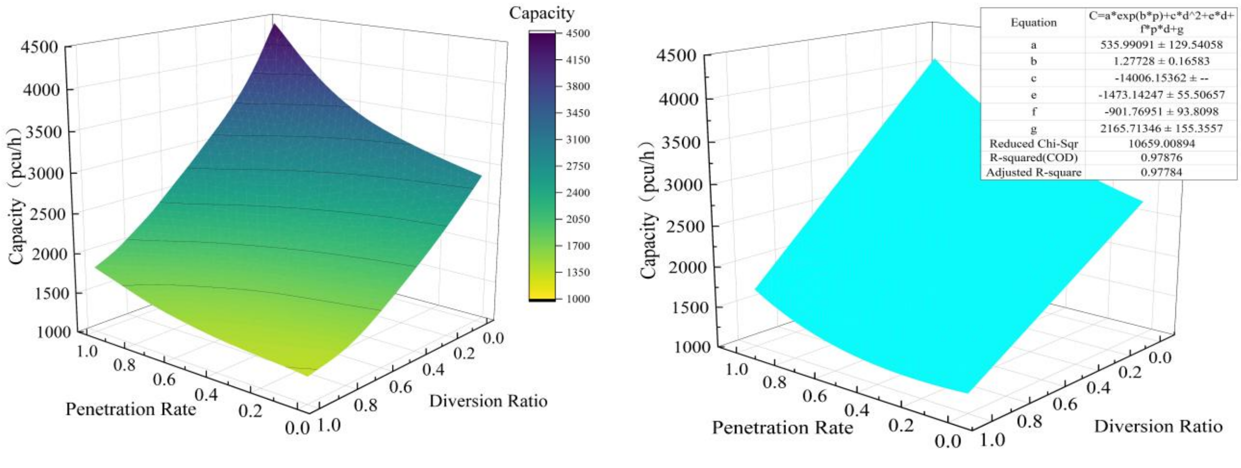


Figure 12 – Experimental results of the combination of penetration rate and diversion ratio: (a) traffic capacity surface diagram; (b) fitting surface diagram

The fitting results indicate that under the joint influence of penetration rate and diversion ratio, the capacity (C) shows an exponential growth relationship with penetration rate (p), while it follows a quadratic function with diversion ratio (d). This suggests that in the early stages of intelligent connectivity, the improvement in capacity due to an increase in penetration rate is relatively limited. However, with the maturity of intelligent connected technology, capacity can be increased by up to 50% in the mid-to-late stages. Furthermore, an increase in the diversion ratio weakens the positive effect of the penetration rate on capacity, indicating that while the deepening of intelligent connectivity significantly promotes the improvement of capacity, it is constrained by changes in the diversion ratio.

2) Penetration rate – deceleration lane

Based on the analysis of the impact of deceleration lane length on capacity in Section 4.1, three-dimensional surface plots are generated to represent the relationship between penetration rate and deceleration lane length for conditions where penetration rate is less than 0.5 and greater than or equal to 0.5. For cases where the penetration rate is greater than or equal to 0.5, a fitting function is applied, and the optimal fitting results are selected. The results for the combination of penetration rate and deceleration lane length are shown in *Figure 13*.

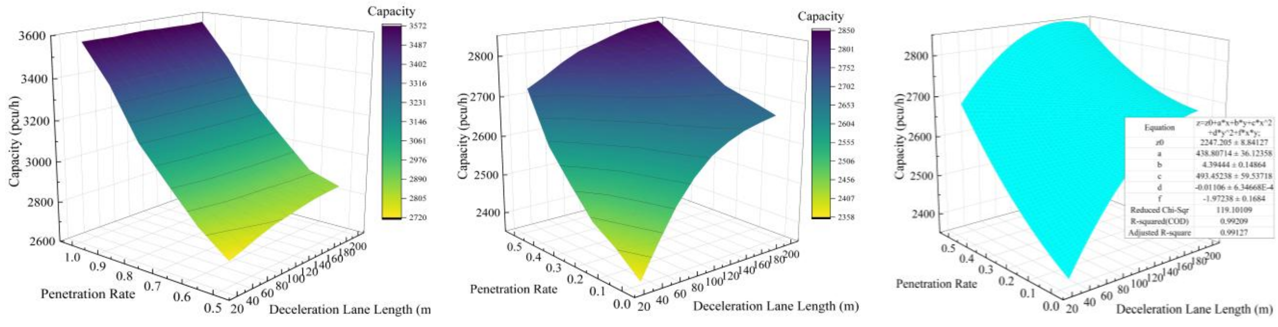


Figure 13 – Experimental results of the combination of penetration rate and deceleration lane: (a) traffic capacity surface plot (p < 0.5); (b) traffic capacity surface plot (p ≥ 0.5); (c) fitted surface plot (p < 0.5)

The fitting results indicate that under the combined effect of penetration rate and deceleration lane length, when the penetration rate (p) is less than 0.5, the capacity (C) exhibits a quadratic relationship with both penetration rate (p) and deceleration lane length (L). Both an increase in penetration rate and a deceleration lane length lead to an improvement in capacity. In low penetration rate scenarios, the impact of deceleration lane length on capacity enhancement is more pronounced. However, when the penetration rate reaches 0.5 or higher, the influence of deceleration lane length on capacity gradually diminishes, especially when the penetration rate exceeds 0.8, at which point its impact becomes negligible.

3) Diversion ratio – deceleration lane length

The combined effect of the diversion ratio and deceleration lane length on capacity is represented in a three-dimensional surface plot, with the optimal fitting results obtained using a function fitting method. The experimental results are shown in *Figure 14*.

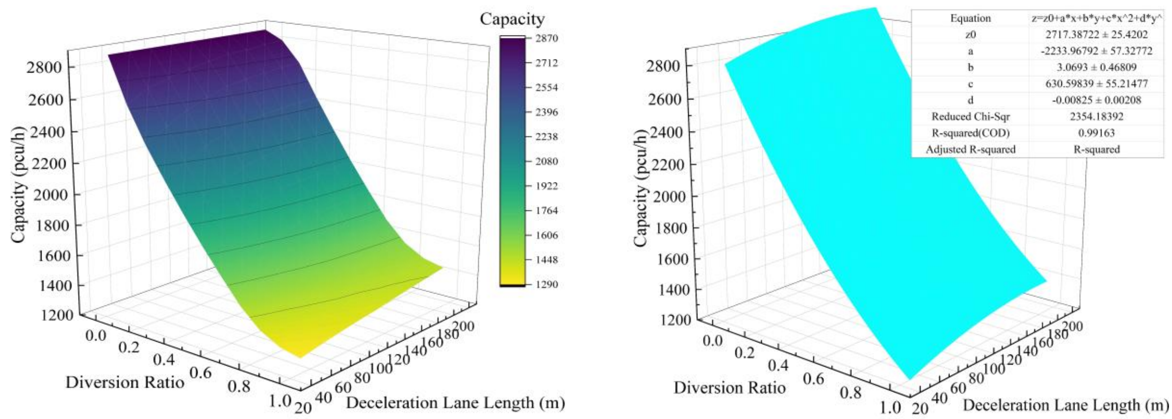
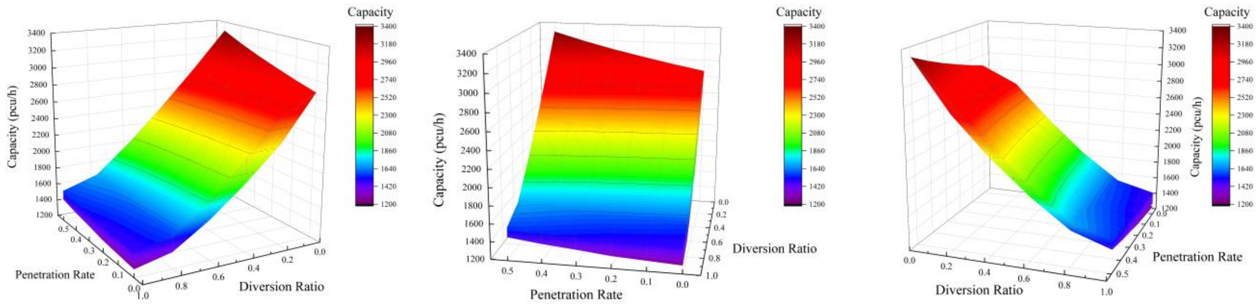


Figure 14 – Experimental results of the combination of deceleration lane length and diversion ratio: (a) traffic capacity surface diagram; (b) fitting surface diagram

The fitting results indicate that under the combined effect of diversion ratio and deceleration lane length, capacity (C) exhibits a quadratic relationship with both diversion ratio (d) and deceleration lane length (L). For the diverging areas in urban tunnels, increasing the deceleration lane length can enhance capacity to a certain extent, particularly when the diversion ratio is high, where the improvement in capacity is particularly significant.

Multifactor combination analysis

A multi-factor coupling analysis was conducted on the primary influencing factors (penetration rate, diversion ratio and deceleration lane length) affecting capacity when the penetration rate is less than 0.5. Using the SUMO simulation platform, a surface plot was created to represent the coupling effects of these three major factors on capacity (*Figure 15*). In the figure, the X-axis represents the penetration rate (p), the Y-axis represents the diversion ratio (d), and different height levels correspond to various deceleration lane lengths (L), ranging from 30 m at the lowest level to 190 m at the highest, with increments of 20 m per height level. This plot illustrates the impact of the penetration rate and diversion ratio on capacity under different deceleration lane length conditions.



(a) *(b)* *(c)*

Figure 15 – Surface plot of traffic capacity under the interaction of multiple factors: (a) viewpoint 1; (b) viewpoint 2; (c) viewpoint 3

Under fixed conditions of penetration rate (p) and deceleration lane length (L), the capacity (C) decreases as the diversion ratio (d) increases, reaching its minimum value when $d = 1.0$. This suggests that the relationship between d and C may follow a quadratic function. Additionally, when the diversion ratio (d) and deceleration lane length (L) are held constant, the capacity (C) increases as the penetration rate (p) rises, reaching its maximum value when $p = 1.0$. However, under multi-factor coupling conditions, the exact form of the relationship between p and C cannot be directly determined. It is speculated that these two variables may exhibit either an exponential or quadratic relationship. Meanwhile, as the deceleration lane length (L) increases, the capacity (C) shows a gradual upward trend, but the rate of increase in adjacent surfaces diminishes as L increases, suggesting that the relationship between L and C may also follow a quadratic function.

4.3 Construction of the capacity model under different penetration rates

Construction of the capacity model for a penetration rate of less than 0.5

When the penetration rate (p) is less than 0.5, the factors influencing capacity include the diversion ratio, penetration rate and deceleration lane length. Two hypothetical models are constructed to describe their relationships. Model 1 assumes that the capacity (C) follows a quadratic relationship with the penetration rate (p), as shown in *Equation 1*. Model 2 assumes that the capacity (C) follows an exponential relationship with the penetration rate (p), as expressed in *Equation 2*.

$$C = ap^2 + bd^2 + cL^2 + fpd + gdL + hp + id + jL + k \tag{1}$$

$$C = l\,e^{\{mp\}} + n\,d^2 + o\,L^2 + q\,d\,L + r\,d + s\,L + t \tag{2}$$

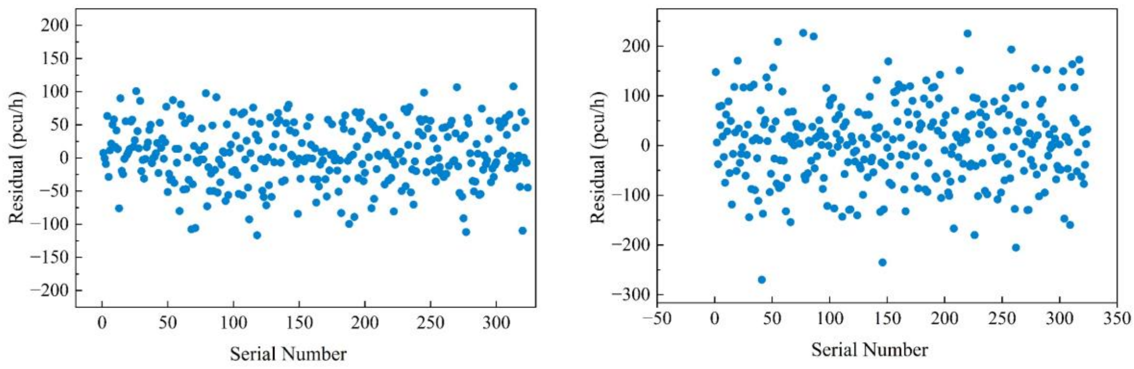
In the equations, C represents the actual capacity of the diverging areas in an urban tunnel, d is the diversion ratio, with a value range of [0, 1], p is the penetration rate, with a value range of [0, 0.5), L is the deceleration lane length and e is the natural constant. The coefficients a, b, c and f are the regression coefficients.

The traffic capacity data obtained from the multi-factor coupling experiment were substituted into the hypothesised models, and the unknown parameters in *Equations 1–2* were fitted using multivariate nonlinear regression. The resulting model regression coefficients are shown in *Table 4*.

Table 4 – Regression coefficients of the model ($p < 0.5$)

Model	**Parameter**								
1	a	b	c	f	g	h	i	j	k
	234.821	721.825	-0.006	-507.887	0.258	584.496	-2305.787	2.217	2772.311
2	l	m	n	o	q	r	s	t	l
	-126.122	-1082.942	721.825	-0.006	0.258	-2432.759	2.217	2960.98	-126.122

Using the coefficient of determination (R^2) and the sum of squared residuals as indicators of the goodness of fit, Model 1 and Model 2 have R^2 values of 0.994 and 0.981, respectively. Moreover, Model 1 exhibits a smaller sum of squared residuals, indicating a better fit. *Figure 16* shows the residual distribution of traffic capacity for both models. The difference between the calculated and actual traffic capacities is relatively smaller for Model 1, further confirming its higher fitting accuracy for the actual traffic capacity.



(a) *(b)*

Figure 16 – Residual distribution of the model (p < 0.5): (a) Hypothetical Model 1; (b) Hypothetical Model 2

Therefore, under the condition that the penetration rate (p) is less than 0.5, Hypothetical Model 1 is selected as the model for actual traffic capacity.

$$C = 234.82p^2 + 721.83d^2 - 0.006L^2 - 507.89pd + 0.258dL + 584.496p - 2305.79d + 2.22L + 2772.31 \quad (3)$$

In the equation, C represents the actual traffic capacity of the diverging areas in the urban tunnel; d is the diversion ratio, with a range of [0, 1]; p is the penetration rate, with a range of [0, 0.5); and L is the deceleration lane length.

Construction of the capacity model for a penetration rate of not less than 0.5

When the penetration rate p is greater than or equal to 0.5, the factors influencing traffic capacity include the diversion ratio and penetration rate. Two hypothetical models are constructed to describe the relationship between them. Model 1 assumes that the traffic capacity C has a quadratic polynomial relationship with the penetration rate p, as shown in *Equation 4*; while Model 2 assumes that C follows an exponential relationship with p, as shown in *Equation 5*.

$$C = ap^2 + bd^2 + fpd + gp + hd + i \quad (4)$$

$$C = je^{\{kp\}} + ld^2 + mpd + nd + o \quad (5)$$

In the equations, C represents the actual traffic capacity of the diverging areas in the urban tunnel; d is the diversion ratio, with a range of [0, 1]; p is the penetration rate, with a range of [0.5, 1]; e is the natural constant; and a, b, f, etc., are the regression coefficients.

The unknown parameters in *Equations 4–5* were fitted using multivariable nonlinear regression. The obtained model regression coefficients and their corresponding confidence intervals are shown in *Table 5*.

Table 5 – Regression coefficients of the model (p ≥ 0.5)

Model	**Parameter**					
Model 1	a	b	f	g	h	i
	964.935	1090.967	-1370	599.026	-2193.24	2727.6
Model 2	j	k	l	m	n	o
	1108.836	0.92	1090.967	-1370.642	-2192.758	1510.385

Using the coefficient of determination (R^2) and the sum of squared residuals as indicators of the goodness of fit. The results show that both models have an R^2 value of 0.998, with Model 1 having a slightly smaller residual sum of squares, indicating slightly better fitting performance. *Figure 17* illustrates the distribution of residuals for both models, and the boxplot further confirms that the difference between the fitted values and actual capacity is smaller for Model 1, demonstrating better performance.

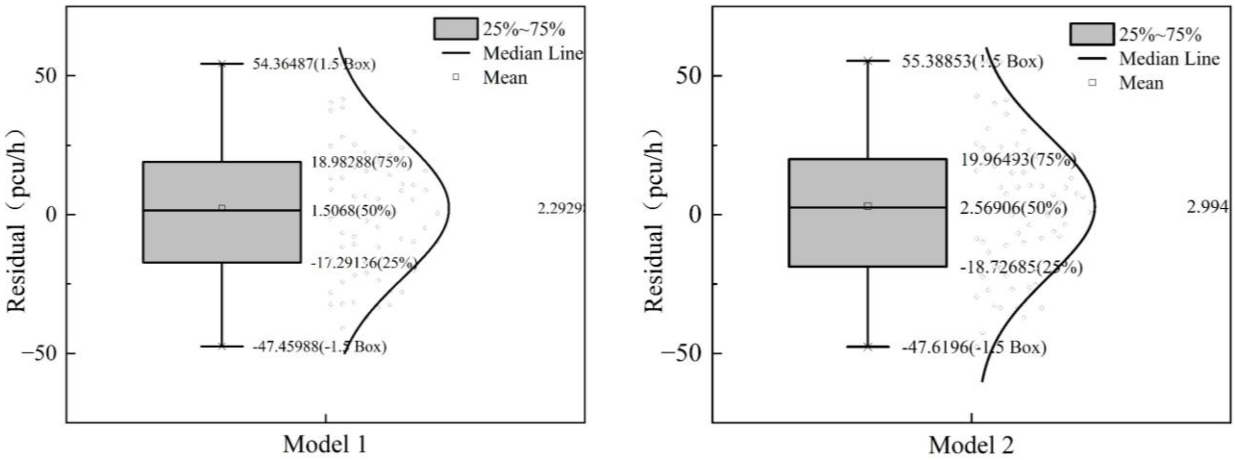


Figure 17 – Residual distribution of the model (p ≥ 0.5): (a) boxplot of Hypothetical Model 1; (b) boxplot of Hypothetical Model 2

Therefore, under the condition that the penetration rate $p \geq 0.5$, Hypothesis Model 1 is selected as the actual capacity model.

$$C = 964.94p^2 + 1090.97d^2 - 1370pd + 599.03p - 2193.24d + 2727.6 \quad (6)$$

In the equation, *C* represents the actual capacity of the diverging areas in the urban tunnel; *d* is the diversion ratio, with a range of [0, 1]; *p* is the penetration rate, with a range of [0.5, 1].

By comparing the fitting performance of the two models under different penetration rates, the results show that Hypothetical Model 1 yields smaller residuals and better goodness-of-fit at all penetration rate levels. Therefore, the actual capacity model of the diverging areas in the urban tunnel under the intelligent connected environment is constructed as follows:

$$C = \begin{cases} 234.82p^2 + 721.83d^2 - 0.006L^2 - 507.89pd + 0.258dL + 584.496p - 2305.79d \\ + 2.22L + 2772.31, & p \in [0,0.5) \\ 964.94p^2 + 1090.97d^2 - 1370pd + 599.03p - 2193.24d + 2727.6, & p \in [0.5,1] \end{cases} \quad (7)$$

In the equation, *C* represents the actual capacity of the diverging areas in the urban tunnel (pcu/h); *d* is the diversion ratio, with a value range of [0,1]; *p* is the penetration rate, with a value range of [0,1]; and *L* is the deceleration lane length (m).

To enhance the scientific rigour and robustness of the regression model, a multi-layered strategy was adopted to manage the effects of variable correlation during the modelling process. First, numerical analysis was conducted to quantify the relationships between candidate variables and diverging area capacity, allowing the identification of dominant variables and the reduction of potential multicollinearity risks. Second, a stepwise modelling approach was employed, progressing from single-variable to multi-variable coupling, with various functional forms designed to capture the nonlinear relationships among key variables. Finally, the model was comprehensively evaluated using metrics such as goodness-of-fit, residual distribution and confidence intervals of the regression coefficients to ensure strong explanatory power and parameter stability in the final model.

5. CASE STUDY

The validation of the capacity model is conducted using a diverging area of the Nanping Tunnel in Chongqing as the research subject. This diverging area adopts a direct diversion layout, with a deceleration lane length of 90 metres. Both the upstream and downstream sections of the mainline have three lanes, while the ramp is a single-lane facility. All lane boundary lines within the diverging areas are marked as dashed lines. The static simulation model of the Nanping Tunnel diverging areas is shown in *Figure 18*.

Figure 18 – Static simulation model of the Nanping Tunnel diverging areas

Based on the theoretical foundation established in Section 3.2 regarding the construction and calibration of the intelligent connected environment simulation model, the key parameters for HDVs and CAVs in the Nanping Tunnel diverging areas are calibrated. After completing the calibration, the CAV penetration rate is adjusted to simulate the actual operating conditions of the Nanping Tunnel diverging areas under varying penetration rates. The calibration results are presented in *Table 6*.

Table 6 – Key parameter settings for HDVs and CAVs

Model	Parameter	Calibrated value			Definition
		HDVs	CAVs (ACC)	CAVs (CACC)	
Car-following model	Mingap	2.50	2.0	2.0	Minimum gap
	sigma	0.40	-	-	Driver's reaction time
	tau	1.84	1.1	0.6	Desired headway
Lane-change model	lcStrategic	0.60	2.5	2.5	Strategic lane change behaviour of vehicles
	lcCooperative	0.60	1.0	1.0	Cooperative lane change behaviour of vehicles
	lcSpeedGain	3.00	1.0	1.0	Speed gain after lane change
	lcAssertive	2.50	2.0	2.0	Willingness to accept smaller front and rear gaps in the target lane during lane change

By calibrating the key parameters of HDVs and CAVs, and adjusting traffic volume, diversion ratio and other parameters based on observed traffic data, a simulation model consistent with the intelligent connected environment is developed. Furthermore, by controlling the CAV penetration rate, the actual operational conditions of the Nanping Tunnel diverging areas under varying rates are simulated.

The deceleration lane length of the Nanping Tunnel diverging areas is fixed at 90 metres, and a multi-factor combination experiment is conducted by adjusting the penetration rate of CAVs. The actual capacity of the tunnel diverging areas under the intelligent connected environment is obtained, and the corresponding capacity model values under different combinations are derived by substituting into *Equation 7*. The comparison between the model-calculated values and the actual capacity is presented in *Table 7*.

Table 7 – Comparison of calculated traffic capacity from the model and actual traffic capacity

Index	Deceleration lane length (m)	Penetration rate	Diversion ratio	Calculated traffic capacity (pcu/h)	Actual traffic capacity (pcu/h)	Error
1	90	0.0	0.24	2417	2449	1.31%
2	90	0.2	0.24	2519	2493	1.04%
3	90	0.4	0.24	2640	2544	3.77%
4	90	0.6	0.24	2775	2695	2.97%
5	90	0.8	0.24	3099	3046	1.74%
6	90	1.0	0.24	3500	3583	2.32%
7	90	0.0	0.21	2476	2452	0.98%
8	90	0.2	0.21	2581	2522	2.34%
9	90	0.4	0.21	2704	2589	4.44%
10	90	0.6	0.21	2851	2751	3.64%
11	90	0.8	0.21	3183	3023	5.29%
12	90	1.0	0.21	3593	3619	0.72%

As shown in the table, the error between the model-calculated values and the actual capacity does not exceed 5.29%, indicating that the capacity model developed in this study can accurately reflect the actual capacity of the diverging areas in urban tunnels under the intelligent connected environment.

6. DISCUSSION

Urban tunnels play a vital role in enhancing traffic efficiency and accessibility. By 2021, a total of 406 urban tunnels had been constructed across 86 cities in China. In typical Chinese designs, diverging areas within urban tunnels often feature two to three mainline lanes with a single-lane off-ramp, accompanied by short deceleration lanes and continuous dashed lane markings. Such configurations tend to induce concentrated lane-changing behaviour within a limited space, leading to increased traffic conflicts, reduced capacity and elevated operational risk. While previous studies have primarily focused on merging and diverging areas along expressways or conventional urban roads [5], this study targets diverging areas in urban tunnels. Based on the structural and operational characteristics of such areas, initial influencing factors were identified and further refined through simulation experiments and sensitivity analysis to determine the key variables, thereby improving the model's relevance and accuracy. Regarding the CAV penetration threshold, this study identifies a critical point at 0.5, beyond which traffic capacity patterns exhibit significant changes, providing a quantitative supplement to prior studies that only qualitatively discussed such nonlinear transitions [10, 11]. In response to the limitations of existing single-variable capacity models under connected environments [24], a segmented capacity estimation model was developed using a multi-factor coupling approach, enhancing both its applicability and predictive performance.

This study focuses on the diverging areas of urban tunnels, a critical yet previously underexplored component of urban transportation systems, and extends the applicability of existing capacity modelling approaches to complex and spatially constrained scenarios. Using the developed simulation model under intelligent connected environments, the scope of urban tunnel diverging areas was redefined with a CAV penetration rate of 0.5, identified as the threshold. The primary factors influencing capacity under such conditions were determined, and the capacity evolution characteristics were systematically analysed across different penetration rates, thereby enhancing the model's applicability to future traffic environments.

This study still has some limitations. The simulation analysis was conducted under relatively stable traffic conditions, without fully accounting for unexpected incidents, environmental disturbances or atypical driver behaviours. As a result, the evolution of traffic capacity under abnormal operating conditions thus remains insufficiently explored. Additionally, although behavioural parameters were calibrated and field data were used for validation to enhance the credibility of the simulation, the model still cannot fully reproduce the complexity of real-world vehicle interactions and microscopic behavioural responses.

This study also offers potential for further expansion. For instance, the current model's parameter calibration and fitting are based on a limited number of measured data samples. In the future, the calibration process could be further refined by increasing the sample size of the measured data, thereby improving the model's generalisation capability and accuracy. Furthermore, with respect to the impact mechanism of the intelligent connected environment on the capacity of urban tunnel diverging areas, future research could explore in greater depth the dynamic effects of V2X communication technology on traffic capacity and further uncover its underlying mechanisms. This would provide a more scientific foundation for practical traffic management and optimisation.

7. CONCLUSIONS

This paper proposes a method for capacity analysis and modelling of urban tunnel diverging areas based on the intelligent connected environment. The method employs SUMO simulation software to calibrate key parameters of CAVs and HDVs, constructs a hybrid traffic flow simulation model, and analyses traffic flow characteristics under different penetration rates. Subsequently, univariate analysis is performed to identify key influencing factors, followed by bivariate and multivariate coupling analyses to reveal the interaction mechanisms among the main factors. Finally, a multivariate nonlinear regression model of capacity is developed.

This method establishes a simulation model under the intelligent connected environment and analyses the characteristics of mixed traffic flow under varying penetration rates. The results indicate that traffic flow characteristics change significantly when the penetration rate reaches 0.5, which is thus set as the threshold for defining the research scope. On this basis, univariate analysis identifies the diversion ratio, penetration rate and deceleration lane length as the primary influencing factors. Further bivariate and multivariate analyses are conducted to examine their coupling effects, revealing that the impact of deceleration lane length becomes negligible when the penetration rate is below 0.5. Accordingly, capacity models are developed separately for scenarios with penetration rates below 0.5 and those equal to or above 0.5. The model is validated using the Nanping Tunnel diverging areas as a case study, with the error between the model predictions and actual measurements not exceeding 5.29%, thereby confirming the model's reliability and effectiveness.

The research findings provide valuable support for the deployment of intelligent connected vehicles and the traffic management of urban tunnel diverging areas. In a connected environment, identifying traffic flow characteristics under different penetration rates can serve as a basis for the phased deployment of intelligent connected vehicles [35, 36]. For example, when the penetration rate reaches a certain threshold and significant changes in traffic characteristics are observed, this can act as a critical point for large-scale vehicle deployment, assisting traffic managers in formulating differentiated deployment strategies to improve system performance [37]. Additionally, the construction of the capacity model can support the optimisation of diverging areas control strategies [38]. For instance, traffic managers can use the penetration rate levels and capacity model results to design parameters such as the diversion ratio and deceleration lane length in a way that enhances diversion efficiency and ensures operational safety [39].

ACKNOWLEDGEMENTS

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