Hindawi
Journal of Advanced Transportation
Volume 2024, Article ID 6170743, 22 pages
https://doi.org/10.1155/2024/6170743

Research Article

Cost Analysis of Vehicle-Road Cooperative Intelligence Solutions for High-Level Autonomous Driving: A Beijing Case Study

Guangyu Zhu, [1,2] **Fuquan Zhao**, [1,2] **Haokun Song**, [1,2] **and Zongwei Liu** [1,2]

[1] *State Key Laboratory of Automotive Safety and Energy, Tsinghua University, Beijing 100084, China*
[2] *Tsinghua Automotive Strategy Research Institute, Tsinghua University, Beijing 100084, China*

Correspondence should be addressed to Zongwei Liu; liuzongwei@tsinghua.edu.cn

Received 20 July 2023; Revised 25 October 2023; Accepted 3 January 2024; Published 23 January 2024

Academic Editor: Peng Hang

The development of the vehicle-road cooperative intelligence can effectively resolve the current technical impediment and cost quandary associated with high-level autonomous driving. Nevertheless, the intelligent infrastructure entails initial deployment costs and ongoing energy consumption and maintenance costs, necessitating a comprehensive and quantitative analysis of the costs of intelligent infrastructure and the corresponding changes in comprehensive costs. The cost evaluation model for the cooperative intelligent system is designed in this paper, considering the corresponding intelligent infrastructure layout scheme for different road types within the technical framework. The intelligent configuration and corresponding cost transfer from roadside to vehicle side under the synergy effect is also analyzed. Using Beijing as a case study, the results indicate that the deployment of intelligent infrastructure will effectively reduce acquisition and usage costs of high-level intelligent vehicles and achieve a greater "reuse" effect by serving more intelligent connected vehicles (ICVs). Compared to the vehicle intelligence, collaborative intelligence will reduce cumulative total costs by more than ¥200 billion from 2023 to 2050, even with the inclusion of intelligent infrastructure's costs.

1. Introduction

Autonomous driving has become a significant factor influencing the development of the automotive industry. On the basis of fundamental autonomous driving capabilities, intelligent vehicles can replace humans in driving tasks. It not only provides passengers with a safer and more comfortable driving experience but also increases travel efficiency [1–4], saves energy, and reduces emissions [5–7] and traffic accident rates [8–10]. Chinese consumers have the highest level of acceptance of self-driving technology in the world [11]. In China, the penetration rate of L2 autonomous passenger vehicles with combined assisted driving functions has reached 34.5% in 2022 [12]. Intelligent vehicles represent the leading strategic position of future automobiles in terms of product form and key technologies. The Chinese government is actively promoting the development of intelligent vehicles. The research presented in this paper is set against this background. However, autonomous driving is still in its early stage of development. The primary autonomous driving is gradually maturing and becoming commercialized, while intermediate and advanced autonomous driving remains dominated by trials and regional demonstrations. To address the technical challenges faced by intermediate and advanced autonomous driving, as well as the cost barrier to large-scale commercial implementation, ICVs powered by the latest information and communication technologies have been recognized globally as the future direction of automotive development [13, 14]. Intelligent infrastructure can offer more extensive sensing data for vehicles, broadening the range and capability of vehicle sensors, improving safety, and resolving technical issues encountered in vehicle intelligence, such as sensing blind spots, beyond-the-horizon challenges, extreme weather, and an array of "perceptual long-tail" problems. This can also decrease the performance demands of vehicle-side sensing equipment. By providing a global path planning and decision optimization for ICVs, it can tackle challenges in mixed traffic scenarios, such as autonomous driving games, significantly reducing the need for vehicle-side computing power. Lowering the costs for vehicle intellectualization will contribute in increasing the adoption rate of intermediate and advanced intelligent vehicles. Currently, a growing number of countries and companies are emphasizing the route of vehicle-road cooperative intelligence [15]. The intelligent transportation infrastructure will be pivotal for ICVs' evolution. To address the current industrial constraints, the schematic design and deployment of intelligent transportation infrastructure should correspond with the needs of ICVs. Simultaneously, the deployment and operation of intelligent transportation infrastructure necessitate substantial and ongoing expenditures. A quantitative analysis of the cost of intelligent transportation infrastructure and the corresponding changes of comprehensive costs is necessary for national or local decisions to upgrade intelligent transportation infrastructure.

Currently, most related researches are focusing on the functions and technologies involved in intelligent transportation systems at the micro level [16–19], but few scholars have quantified and analyzed the cost of intelligent transportation infrastructure and the resulting changes in the total cost to society. Chang proposed the roadside sensing configuration method, the vehicle fusion planning method, and the control method from the perspective of an intelligent networked cloud control system and simulated and verified using the actual vehicle platform [17]. Wan et al. reviewed research on queue control-related communication architectures, communication protocols, traffic models, and control methods, with application scenarios involving traffic flow optimization, dynamic queuing, and queue control [19]. Other scholars have explored the deployment methods corresponding to the characteristics of intelligent roadside devices, such as communication environments, roadside units, and sensors [20–26]. Liu et al. analyzed the demand for 5G base-station RSUs and outlined their technological architecture and fundamental functions, based on the development trend of the 5G and cellular vehicle-to-everything (C-V2X) network [21]. Zhang investigated the optimization problem of network layout under the vehicle-linked sensor network architecture model and solved the optimal network layout scheme with the lowest deployment cost [22]. Fu et al. examined the efficient solution problem of spatial arrangement of cameras for area coverage and proposed a probability-based binary particle swarm optimization technique to optimize both the number of sensors and the spatial arrangement scheme [24]. Zhan et al. investigated optimal sensor placement for multitype sensor assignment on highways [25]. Liu et al. examined the cost of various upgrading paths and deployment schemes for intelligent transportation infrastructure in two scenarios: open city road and closed highway [27]. Therefore, researches on the cost of intelligent transportation infrastructure and the corresponding changes of comprehensive social costs can, therefore, close the current research gap in industry and academia and assist governments and policy makers in making decisions regarding the intelligent upgrading of transportation infrastructure. The construction of intelligent transportation infrastructure is frequently city-based. Cities, especially first-tier cities, have a large car population and road usage intensity; the deployment of intelligent infrastructure will generate greater social benefits and amortize its costs through greater "reuse" of large-scale fleets. With 685 million motor vehicles, Beijing ranks first among Chinese cities [28], and it is also the most congested city in China [29]. Intelligent transformation of transportation is required to address the city's safety, congestion, environmental, and energy problems.

To fill the current research gap, this paper evaluates the total cost of transportation infrastructure to achieve an intelligent upgrade. The cost of fleet intelligence and total social cost are compared and analyzed under two scenarios: collaborative intelligence and vehicle intelligence. First, the architecture of the vehicle-road cooperative intelligent system is established as the theoretical basis. Then, the cost evaluation model for the vehicle-road cooperative intelligent system is designed, which includes the submodels of roadside and vehicle side. Based on the characteristics of various road types, the corresponding scheme of intelligent transportation infrastructure is designed. The logic and principles of intelligent configuration and cost transfer from the vehicle side to the roadside under the synergy effect are qualitatively and quantitatively described, respectively. When combined with characteristic parameters of fleet and road in a specific city, the model can output the comprehensive costs of vehicle side and roadside. This study takes Beijing as an example. These costs include the deployment and operational costs at roadside, as well as the acquisition and usage costs of intelligent configurations on the vehicle side. The corresponding results can provide some cost references and directional recommendations for city managers to help them make decisions on the deployment of intelligent infrastructure. The cost evaluation model of vehicle-road cooperative intelligent system designed in this study is also applicable to other cities.

2. Cost Evaluation Model for Vehicle-Road Collaborative Intelligent System

2.1. Architecture of Vehicle-Road Collaborative Intelligent System. With the aid of C-V2X and 5G communication technologies, collaborative intelligence is built on vehicle intelligence and fully utilizes the benefits of roadside perception, edge computing, cloud server, and networks. Through the cooperative efforts of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I, mainly referring to various types of road equipment and facilities, such as weather detectors, state monitoring equipment, traffic guidance, and control facilities), vehicle-to-network (V2N, mainly referring to map platforms, traffic management platforms, travel service platforms, etc.) and vehicle-to-pedestrian (V2P), it can realize complex environment perception, decision optimization, and collaborative control, which contributes to achieving advanced autonomous driving ultimately.

The cloud platform, roadside infrastructure, ICVs, communication network, and resource platform are the five core components of the collaborative intelligent system. Figure 1 depicts the architecture of the key connecting pieces between each component. In this study, intelligent infrastructure is characterized as a combination of the cloud platform, roadside infrastructure, communication network, and resource platform. The communication network connects various nodes of the system. The wide interconnection and high-performance transmission can be realized through the application of uniform standardization mechanisms. ICVs, roadside infrastructure, and digital resource platform are connected to the cloud platform. The cloud platform uniformly utilizes the perception results of ICVs and roadside infrastructure as well as data from resource platforms. Through real-time hierarchical perception fusion on the cloud of each level, it provides real-time data required for the operation of a wide range of collaborative applications. The overall performance of vehicle movement and traffic operation can be optimized by constructing multiobjective and multitask planning technology for collaborative applications. It can also optimize the allocation of system computing resources to guarantee the safety and performance of collaborative applications serving vehicle and traffic optimization. The ICVs can also directly connect to the roadside infrastructure and other ICVs, which contributes to sensing, planning, and decision-making at vehicle side. The subsequent cost evaluation methodology will be theoretically based on this system architecture.

2.1.1. Cloud Platform. Edge, regional, and central clouds make up the cloud platform. The regional and central clouds typically serve the city or province and mainly run quasi-real-time collaborative applications, such as overall traffic guidance at the regional/city level. The edge cloud typically serves the street or district and primarily runs real-time collaborative applications, such as rapid multiple perception fusion.

2.1.2. Roadside Infrastructure. It consists of different kinds of roadside sensors, mobile edge computers (MECs), roadside units (RSUs), intelligent signal lights, and other traffic-control systems.

2.1.3. Communication Network. A communication network connects various nodes of traffic participants, roadside infrastructure, and cloud platforms by combining wired and wireless communication technologies on the basis of a standardized communication mechanism. In order to realize real-time data collection and transmission as well as instruction update and transmission (such as real-time acquisition of HD map information to assist vehicle positioning), the reasonably deployed 5G base stations will provide low latency and large bandwidth communication capability. At the same time, the direct wireless communication between OBU and RSU can function as an efficient addition to 5G communication, resolving the issue of a blocked or unstable 5G signal.

2.1.4. ICVs. To improve vehicle intelligence and realize optimized driving performance, ICVs connect to cloud platforms, roadside infrastructure, and other ICVs, share vehicle-side data, and use the output of intelligent infrastructure for assisted driving or autonomous driving.

2.1.5. Resource Platform. It consists of high definition (HD) maps, weather data, traffic management data, and other elements.

2.2. Model Framework. In this section, the cost evaluation model of the vehicle-road cooperative intelligent system is built, as shown in Figure 2. The characteristic parameters of various road types, the population, and penetration of each type of intelligent vehicle, the cost and energy consumption of intelligent configurations, and intensity of usage are the inputs. With the full deployment of the intelligent infrastructure, the intelligent configuration will transfer from the vehicle side to the roadside due to the synergy effect. In the model, an optimized vehicle-road cooperative system scheme is designed, which includes the intelligent schemes of vehicle side and roadside. The final output is the deployment and operational costs of the intelligent transportation infrastructure and the acquisition and usage costs of fleet intellectualization. The specific cost evaluation submodels of intelligent transportation infrastructure and fleet intellectualization are described in Sections 2.2.1 and 2.2.2, respectively.

2.2.1. The Cost Evaluation Submodel of Intelligent Infrastructure. The cost evaluation submodel for intelligent infrastructure has been designed, as shown in Figure 3. The model considers urban expressways, urban main roads, urban secondary roads, motorways, class-1 highways, class-2 highways, and class-3 highways, a total of seven different road types. Additionally, urban large intersections, urban small intersections, suburban large intersections, and suburban small intersections were also identified. Different road types and intersection types possess distinct characteristics and demands for roadside intelligent configurations. For instance, highways are closed roads with relatively simple road scenarios, in contrast to urban main roads or secondary roads, which are open roads that present more complex scenarios. Corresponding roadside intelligence schemes have been developed for each road type and intersection type, taking into account the design service capacity of the roads as well as the complexity of road scenarios. These schemes encompass specific sensing, communication, and computing schemes, as detailed in Tables 1 and 2. The roadside intelligent configurations involved are 5G macro stations, 5G micro stations, RSUs, vision sensors, millimeter-wave radar, LiDAR, edge cloud servers, central cloud servers, intelligent signal machines, timing servers,

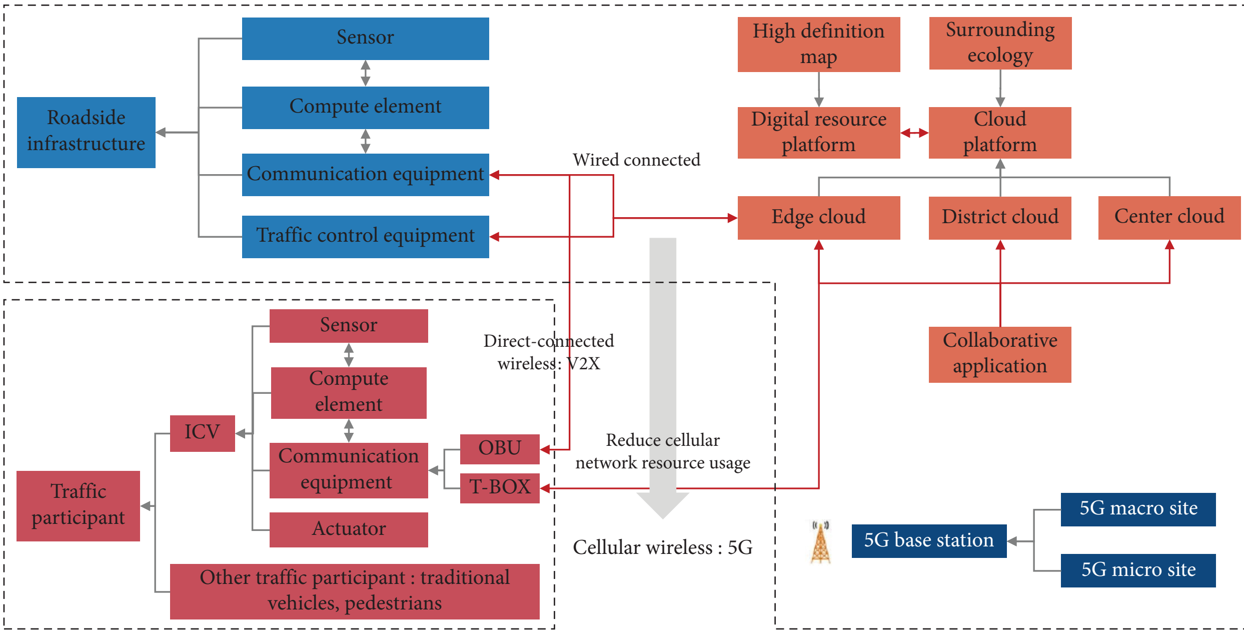

Figure 1: Architecture of vehicle-road collaborative intelligent system.

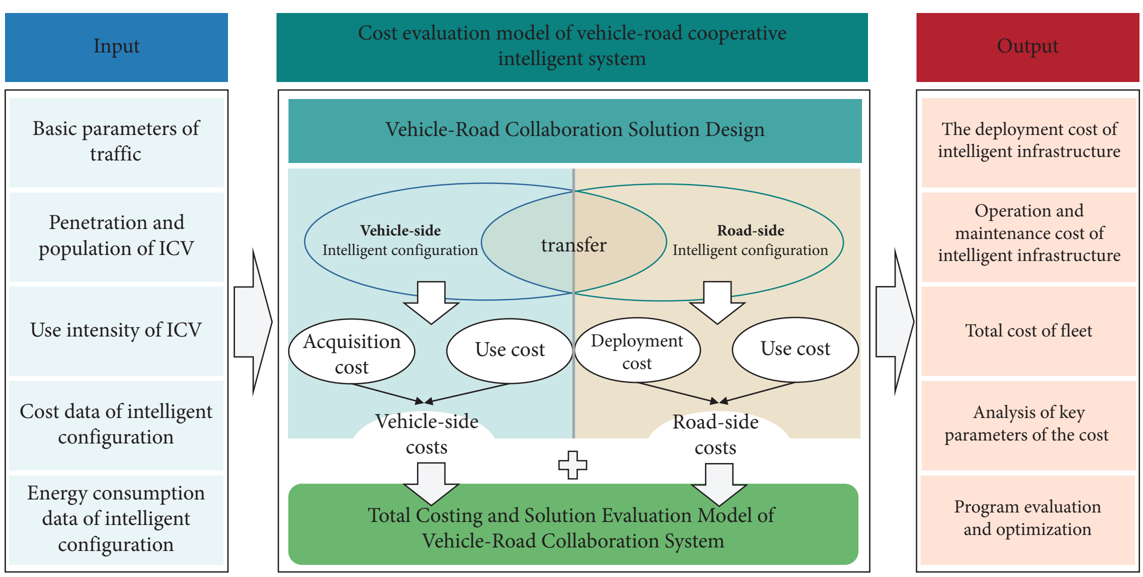

Figure 2: Cost evaluation model of vehicle-road cooperative intelligent system.

and auxiliary equipment such as brackets and power distribution equipment.

(1) Data. In Table 3, we present the cost, power, and performance parameters for roadside intelligent configurations. Our group has established the cost database of these facilities [27, 30]. Currently available or upcoming transportation infrastructure with satisfying performance is selected. Detailed functional parameters and associated costs can be sourced from manufacturers' websites, product manuals, or research reports.

In developing the deployment logic for intelligent devices within the cost evaluation submodel of intelligent transportation infrastructure, factors such as average traffic flow and the complexity of road scenes were taken into consideration. We also reviewed several related studies [20–27] to determine the deployment density of roadside intelligent configurations for each road type and each intersection type in the city, as displayed in Tables 1 and 2, separately. Detailed explanations of the corresponding intelligent infrastructure solutions can be found in the Appendix.

(2) Communication Infrastructure. The construction level of the current communication infrastructure varies between urban and suburban roads. In Beijing, urban roads have

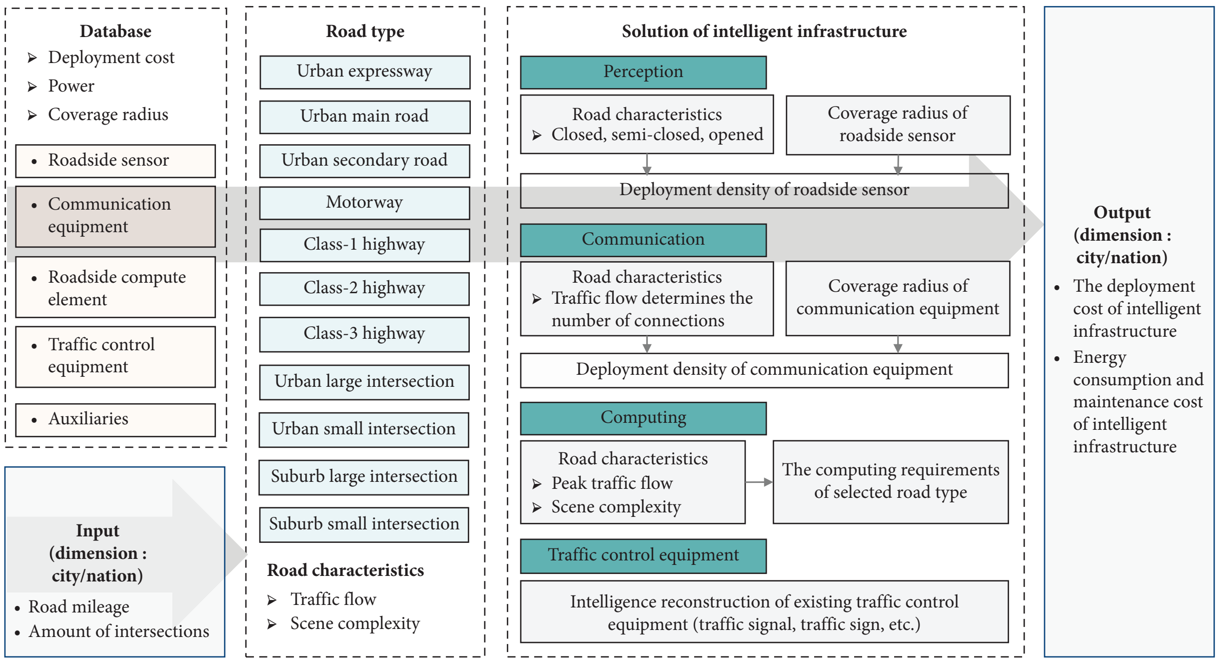

Figure 3: Cost evaluation submodel of intelligent transportation infrastructure.

largely achieved 5G signal coverage. To enhance the 5G network's coverage and accessibility, 5G micro base stations need to be paired in urban expressways, urban main roads, and urban secondary roads. On the other hand, motorways and highways, which serve as transportation arteries connecting the city's core regions, are often situated in areas with fewer economic activities and lower population densities. For these roads, it is essential to deploy both 5G macro and micro base stations to guarantee the 5G network's coverage and accessibility. The intersection deployment schemes adhere to this same design rationale.

(3) Roadside Perception. The solution primarily considers the average traffic flow and the complexity of scenes across various road and intersection types. Urban main and secondary roads have complex environments due to heavy traffic and a mix of participants, especially during peak hours. Given the sensing range limitations of roadside sensors, it is crucial to integrate a denser array of cameras, millimeter-wave radars, and Lidars to minimize blind spots. On the other hand, motorways and urban expressways are more controlled environments with simpler scenarios and singular traffic participants. This allows for a reduced deployment density of roadside sensing devices. The perception scheme at intersections largely depends on their size, with larger intersections equipped with more sensing equipment to ensure complete coverage.

(4) Roadside Computing Platform. The approach for roadside computing is chiefly influenced by the average traffic volume. Urban expressways, main roads, and motorways experience higher traffic volumes and, therefore, demand more robust roadside computation. In these areas, the edge computing unit is tasked with serving a larger number of ICVs at each time step. The deployment logic for roadside computing at different intersections adheres to this same design rationale.

(5) The Deployment Cost of Intelligent Infrastructure. The deployment cost of roadside intelligent solutions corresponding to each road type is calculated, using the cost of roadside intelligent configuration, as shown in the following equation:

$$\text{Cost}_{r,\text{deploy}} = \sum_{i=1}^{i=10} \text{Density}_{r,i} \times \text{cost}_i, \quad (1)$$

where $\text{Cost}_{r,\text{deploy}}$ is the deployment cost of intelligent infrastructure for per mile road type r, $r = 1, 2, 3, \ldots 11$ represents road types and intersections types mentioned above, cost_i is the cost of roadside intelligent configuration i, $i = 1, 2, 3, \ldots 10$ represents roadside intelligent configuration introduced before, and $\text{Density}_{r,i}$ is the deployment density of roadside intelligent configuration i for per mile road type r.

(6) The Operational Cost of Intelligent Infrastructure. The operational cost of roadside intelligent scheme corresponding to each road type is calculated, which consist of energy consumption cost and maintenance cost, as shown in the following equation:

$$\text{Cost}_{r,\text{operating}} = \sum_{i=1}^{i=10} \text{Density}_{r,i} \times (\text{ecr}_i \times \beta_i + \text{maintain}_i), \quad (2)$$

where $\text{Cost}_{r,\text{operating}}$ is the operational cost of intelligent transportation infrastructure for one kilometer of road type r; ecr_i, β_i, and maintain_i are the power, usage characteristics,

Table 1: Roadside intelligence schemes of various road types.

Deployment density (km)	Motorway	Class-1 highway	Class-2 highway	Class-3 highway	Urban expressway	Urban main road	Urban secondary road
5G macro site	2	2	2	2	0	0	0
5G micro site	5	5	5	5	5	5	5
RSU	5	5	5	5	5	10	10
Vision sensor	20	20	20	20	20	40	40
Millimeter-wave radar	20	20	20	20	20	40	40
LiDAR	10	10	10	10	10	20	20
Edge computing server	20	20	10	5	20	20	10
Auxiliaries	5	5	5	5	5	10	10

Table 2: Roadside intelligence schemes of various intersection types.

Deployment density (unit)	Urban large intersection	Urban small intersection	Suburb large intersection	Suburb small intersection
5G macro site	0	0	1	1
5G micro site	4	1	4	1
RSU	1	1	1	1
Camera	16	8	16	8
Millimeter-wave radar	16	8	16	8
LiDAR	8	4	8	4
Intelligent signal machine	4	4	4	4
Edge computing server	4	2	2	1

and maintenance costs of roadside intelligent configuration i, respectively. The usage characteristics β_i of all roadside intelligent configurations i take the value of 1, which means all facilities are in an open status throughout the day, to satisfy the security requirements of high-level autonomous driving. In the future, as technology advances, the equipment can adjust power in real-time based on changes in traffic flow to minimize energy consumption. And the usage characteristics β_i can be further optimized in the follow-up study. Considering the service life of facilities is around 10–15 years [30], maintain_i takes the value of 0.1 of the deployment cost cost_i.

The total cost of the roadside intelligence solution matching the road type r consists of the deployment and the operational cost as shown in equation (3). It serves as the basis for the subsequent calculation of the city's total cost to implement the intelligent upgrades of its transportation infrastructure.

$$\text{Cost}_r = \text{Cost}_{r,\text{deploy}} + \text{Cost}_{r,\text{operating}}, \tag{3}$$

where Cost_r is the total cost of intelligent infrastructure for one kilometer of road type r.

(7) The Acquisition and Renewal Cost of HD Map. HD maps serve as a crucial infrastructure for deploying intelligent vehicles, aiding in vehicle localization and path planning. The methods for collecting HD map data fall into two categories: professional equipment collection and crowdsourcing. Professional equipment collection involves using mapping vehicles fitted with specialized tools, including LIDAR, panoramic cameras, and high-precision inertial navigation systems. While this method offers superior map accuracy and reliability, it tends to be more costly and less efficient. On the other hand, crowdsourcing leverages affordable sensors in the existing intelligent vehicle fleet. These vehicles gather a vast amount of road data during their daily routes and incorporate it into HD maps. This method boasts real-time data updates, a wealth of data sources, and cost-effectiveness. However, its accuracy and reliability might not meet the standards necessary for advanced autonomous driving.

Currently, HD map construction primarily uses a blend of professional equipment acquisition and a crowdsourcing renewal approach. In scenarios involving vehicle intelligence, HD maps can only be refreshed through "crowdsourcing collection" carried out by the intelligent vehicle fleet.

Leveraging vehicle-road cooperative perception, the crowdsourcing renewal process for HD maps achieves both high accuracy and reliability. This is achieved by pairing it with fixed-point observations made by roadside perception equipment, allowing for updates within minutes. This approach not only shrinks the size of the required fleet but also addresses prevalent challenges in the HD map industry, such as maintaining map freshness and high costs. By referring to relevant reports and literature, combined with expert interviews, the integration of intelligent infrastructure will cut the renewal costs of HD maps down to one-seventh in vehicle intelligence scenario [31–34]. Table 4 presents the unit costs associated with HD map and their corresponding data sources.

The costs of HD map are calculated, which consist of acquisition cost and renewal cost, as shown in equations (4)–(6). The acquisition cost for an HD map is influenced by its per-unit price and the length of roads, whether in a city or broader country context. Additionally, the renewal cost for an HD map is contingent upon its renewal frequency.

$$\text{Cost}_{\text{map}} = \text{Cost}_{\text{map,acquisition}} + \text{Cost}_{\text{map,renewal}}, \tag{4}$$

$$\text{Cost}_{\text{map,acquisition}} = \text{UnitCost}_{\text{map,acquisition}} * \text{road\_mileage}, \tag{5}$$

$$\text{Cost}_{\text{map,renewal}} = \text{UnitCost}_{\text{map,renewal}} * \text{road\_mileage} * \text{Renewal\_Cycle}. \tag{6}$$

(8) The Characteristic Data of Various Roads in Beijing. The characteristic data of various roads in Beijing is crucial for transitioning from individual road intelligent deployment schemes to the comprehensive cost of intelligent transportation infrastructure at the city level. Several factors influence the size of the road network. Beyond city

Table 3: Performance parameters and costs of roadside intelligent configurations.

Classification	Facility	Product model	Performance or cost (unit)	Value
Communication	5G macro site	HUAWEI BBU5900	Coverage radius (km)	0.25
			Transmission rate (Mbps)	100
			Power (W)	3500
			Cost (¥)	250000
	5G micro site	HUAWEI 5G Lamp Site	Coverage radius (km)	0.1
			Transmission rate (Mbps)	100
			Power (W)	100
			Cost (¥)	30000
	RSU	DATANG Telecom DTVL3100-RSU	Coverage radius (km)	0.25
			Power (W)	10
			Cost (¥)	50000
Roadside sensors	Vision sensor	HAIKANG cd7087f/DS-2 V	Coverage (km)	0.2
			Power (W)	20
			Cost (¥)	990
	Millimeter-wave radar	Continent ARS 408–21 77 GHz	Coverage radius (km)	0.2
			Power (W)	12
			Cost (¥)	940
	LiDAR	HESAI AT128	Coverage radius (km)	0.2
			Power (W)	40
			Cost (¥)	6250
Roadside computing	Intelligent signal machine	Hisense SC3101	Cost (¥)	20000
	Edge computing server	HAIKANG MEC	Power (W/TOPs)	1
			Cost (¥/TOPs)	20
	Cloud computing center	No specific product information, referring to research reports	Power (W/TOPs)	0.5
			Cost (¥/TOPs)	10
Auxiliaries	Carrier equipment and power distribution equipment	No specific product information, referring to research reports	Cost (¥)	20000

Table 4: The acquisition and renewal cost of HD map.

Classification	Unit cost (¥)	Source
Map acquisition cost-professional equipment collection	31142/km	DeepMap [31]
Map acquisition cost-crowdsourcing collection	11.61/km	Mapper.ai [32]
Map renewal cost-crowdsourcing collection (vehicle intelligence scenario)	0.077/km	1v15 [33]
Map renewal cost-crowdsourcing collection (vehicle-road cooperative scenario)	0.011/km	[33, 34]

management's planning and transportation infrastructure policies, the level of intelligence in both vehicles and transportation infrastructure impacts road capacity. Consequently, a city with higher urban travel demands might be adequately served by a consistently sized or even smaller road network. It is important to note that our study does not account for future variations in the size of Beijing's road network. The distance of each road type is obtained from "Beijing Transport Development Annual Report (2021)," as indicated in Table 5 [35]. Owing to the absence of specific statistical data for different types of intersections in Beijing, we estimate the ratio of urban large intersections, urban small intersections, suburban large intersections, and suburban small intersections to be 10 : 7 : 14 : 81. This estimation is based on the quantitative distribution of diverse road types. By integrating the characteristic data of Beijing's roads, the overall costs of intelligent transportation infrastructure can be determined using the cost-evaluation submodel designed for intelligent transportation infrastructure.

Table 5: The characteristic data of various road types in Beijing.

Classification	Value	Source
Motorway-distance (km)	1173.3	[35]
Class-1 highway-distance (km)	1368.7	
Class-2 highway-distance (km)	3995.8	
Class-3 highway-distance (km)	4118.7	
Urban expressway-distance (km)	390	
Urban main road-distance (km)	1020	
Urban secondary road-distance (km)	682	
Amount of intersections (unit)	9600	

2.2.2. The Cost Evaluation Submodel of Fleet Intellectualization. In this section, the cost evaluation submodel of fleet intellectualization is constructed, as shown in Figure 4. By identifying the vehicle-side intelligent scheme under the scenarios of vehicle intelligence and collaborative intelligence, the corresponding acquisition cost and usage cost are calculated. Factoring in the population and adoption rate of each type of intelligent vehicle in Beijing, the total cost of fleet intellectualization under these two scenarios is derived.

(1) The Substitution of Vehicle Perception under the Synergy Effect [36, 37]. High-dimensional perception from the roadside can provide a more encompassing view of the road, surpassing the perspective of individual vehicles, thus aiding advanced autonomous driving. It can also better satisfy the perception requirements for vehicle in terms of accuracy, time delay, and reliability. Furthermore, such high-dimensional perception from the roadside can take the place of redundant vehicle perception and serve as a backup to basic perception. Consequently, this results in a significant reduction in both acquisition and operational costs associated with the vehicle-side perception scheme.

(2) The Substitution of Vehicle Computing under the Synergy Effect [38, 39]. Roadside computing devices offer easy deployment and scheduling capabilities. Leveraging the abundant computing resources available roadside allows for effective sharing of computing power among vehicles, ensuring equitable distribution and optimal balancing of computational power across the system. On the other hand, in-vehicle computing devices have their limitations. They cannot be scaled up when faced with increased computational needs and cannot be downsized or reallocated when idle. Presently, many vehicles come pre-equipped with a large computing platform to accommodate potential future functionalities and software updates. This often leads to an unnecessary wastage of resources and consequently increased costs for the user.

(3) Data. Table 6 details the power and cost associated with intelligence configurations on the vehicle side. It outlines the primary, intermediate, and advanced intelligence schemes under the vehicle intelligence scenario as well as the advanced intelligence scheme for the collaborative intelligence scenario.

The current intelligence schemes of vehicles demonstrate greater differentiation due to the varying technical routes and capability levels of various companies. With reference to the primary, intermediate, and advanced intelligence scheme commonly adopted in the industry, as well as several published works [40, 41], typical vehicle intelligence schemes are presented, as shown in Table 6.

In the vehicle intelligence scenario, a higher level of intelligence in AVs necessitates the inclusion of more sensors to enhance sensing capability, additional computing units to increase computing power, and the use of dependable, low-latency actuators such as steering and braking. In the collaborative intelligence scenario, ICVs can interact with the intelligent transportation infrastructure in real-time via high-performance communication modules. This interaction allows them to access more comprehensive environmental information and reduces the demand for extensive perception and computing configurations within the vehicle itself. Simultaneously, roadside fusion perception and positioning information are correlated with the dynamic and static features of the vehicle. This correlation enables the acquisition of real-time and high-precision location information for vehicles, reducing the need for automatic positioning equipment on the vehicle side. On roads with

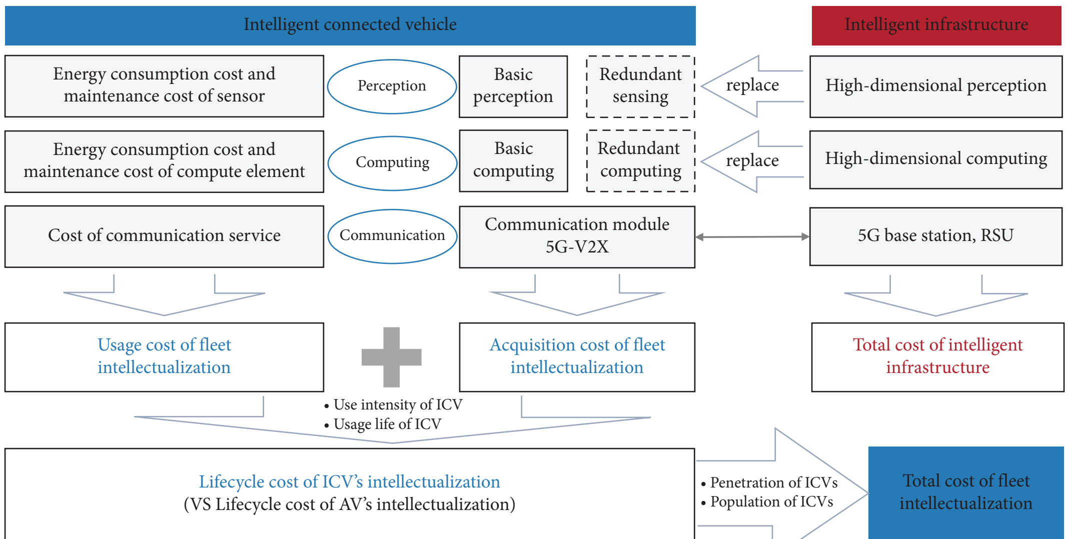

Figure 4: The cost evaluation submodel of fleet intellectualization.

fully deployed intelligent transportation infrastructure, ICVs can achieve advanced autonomous driving [34, 42], as previously described. Furthermore, due to their basic perception and computing configurations, ICVs can still achieve primary autonomous driving, even on roads without intelligent infrastructure coverage [34].

The expansion from intelligent vehicle schemes to fleet expenses at the city level depends on the characteristic data of fleet in Beijing, as illustrated in Table 7. The average use intensity of the fleet is influenced and constrained by many factors, including road mileage, road capacity, traffic restriction policies, convenience of other transportation modes, and epidemics. Changes in average utilization intensity in the future are not considered in our study. The average annual mileage and driving time are based on data in 2019 to exclude the impact of the epidemic.

(4) The Vehicle Sales and Market Penetration Data in Beijing. The quantity of intelligent vehicles in the future are calculated using the sales forecast data in Beijing and the survival law of vehicle, as shown in equation (7). The forecasted auto market sales in Beijing are primarily based on predictions by industry experts. The forecasted penetration rates of intelligent vehicles in Beijing are referenced from the "Intelligent Connected Vehicle Technology Roadmap 2.0" [45].

$$\mathrm{VS}_{v,y} = \sum_{j=y-l}^{y} \mathrm{Sales}_j \times \mathrm{PR}_{v,y} \times \mathrm{SR}_{y-j}, \tag{7}$$

where $\mathrm{VS}_{v,y}$ are the vehicle stocks of v type vehicles in the year y; $v = 0, 1, 2, 3, 4$ represent traditional vehicles, primary AVs, intermediate AVs, and advanced AVs and ICVs; l is the lifespan of the vehicle; Sales_j are the vehicle sales of Beijing in the year j; $\mathrm{PR}_{v,y}$ is the penetration rate of v type of vehicle in the vehicle sales in the year y; and SR_{y-j} is the survival rate of the vehicle in the $(y - j)$ th year (%).

In order to compare the two scenarios under the same baseline, the forecasted penetration rates of intelligent vehicles in Beijing, whether it is under the vehicle intelligence scenario or the collaborative intelligence scenario, are based on the "Intelligent Connected Vehicle Technology Roadmap 2.0." It is assumed that users in both scenarios have the same willingness to purchase intelligent vehicles and will use them with the same intensity.

(5) The Cumulative Acquisition Cost of Fleet Intellectualization in Beijing. The annual acquisition costs of fleet intellectualization are calculated using equation (8), and the cumulative acquisition cost in Beijing from 2023 to 2050 is determined using equation (9). These calculations take into account the anticipated cost reductions associated with various intelligent configurations in the future.

$$\mathrm{cost}_{v,j} = \sum_{s=1}^{s=20} \left(\alpha_v \times \mathrm{cost}_{2023,s} \times \prod_{k=2023}^{j} \beta_{s,k} \right), \tag{8}$$

$$\mathrm{Cost}_{\mathrm{fleet,acquisition}} = \sum_{j=2023}^{y=2050} \sum_{v=1}^{v=4} \mathrm{Sales}_j \times \mathrm{PR}_{v,j} \times \mathrm{cost}_{v,j}, \tag{9}$$

where α_v is the intelligent scheme vector of the v type vehicle, $\beta_{s,k}$ is the cost reduction ratio of intelligent configuration s in the year k, and $\mathrm{cost}_{v,j}$ is the acquisition cost of intelligent configurations for the v type vehicle in the year j.

Intelligent configurations are at various stages of technological development and scale in different periods, resulting in different cost reduction ratios and unit costs. The average market price of these configurations in 2023 is used as the benchmark. Table 8 displays the cost reduction ratios for various intelligent configurations across different time periods.

Table 6: Parameters of intelligent configurations at vehicle side and various intelligence schemes.

	Facility	Classification	Cost (¥)	Power (W)	Disassembly of technical components of intelligent driving			
					Primary AV	Intermediate AV	Advanced AV	ICV
Communication	Communication module	4G-LTE	140	10	1	1	1	—
		5G-V2X OBU	5250	20	—	—	—	1
Perception	Camera	2-megapixel	220	10	4	5	4	4
		8-megapixel	625	15	2	2	1	2
		12-megapixel	990	20	—	—	2	—
	Millimeter-wave radar	Short-focus	510	5	4	4	4	4
		Long-focus	940	12	—	—	2	—
		4D-image	2090	20	—	—	1	—
	LiDAR	Semisolid	6250	40	—	—	3	—
		Solid	3750	35	—	—	—	—
Localization	High-precision localization	Submeter-class	2300	1	1	—	—	1
		Decimeter-class	7400	2	—	1	—	—
		Centimeter-class	13500	4	—	—	1	—
Computing	Central computing platform	Low compute	2000	100	1	—	—	1
		Middle compute	5000	400	—	1	—	—
		High compute	10000	1000	—	—	1	—
Actuator	Steering system	Electric-power-steering	1500	40	1	—	—	—
		Steering-by-wire	3500	70	—	1	1	1
	Braking system	Electric-power-braking	1200	50	1	—	—	—
		Braking-by-wire	2500	80	—	1	1	1

Table 7: The characteristic data of fleet in Beijing.

Classification	Value	Source
Vehicle lifespan (year)	15	[43]
Vehicle quantity (million)	6.85	[44]
Average annual distance traveled (thousand kilometer/vehicle/year)	12.168	[35]
Average annual driving time (h/vehicle/year)	488.675	

Table 8: The cost reduction ratio of various intelligent configurations.

Facility	Classification	Cost (¥) –2023	$\beta_{s,k}$ 2023–2030 (%)	$\beta_{s,k}$ 2031–2040 (%)	$\beta_{s,k}$ 2041–2050 (%)
Communication module	4G-LTE	140	2	2	1
	5G-V2X OBU	5250	5	3	1
Camera	2-megapixel	220	2	2	1
	8-megapixel	625	2	2	1
	12-megapixel	990	2	2	1
Millimeter-wave radar	Short-focus	510	2	2	1
	Long-focus	940	2	2	1
	4D-image	2090	5	3	1
LiDAR	Semisolid	6250	5	3	1
	Solid	3750	2	2	1
High-precision localization	Submeter-class	2300	5	3	1
	Decimeter-class	7400	5	3	1
	Centimeter-class	13500	5	3	1
Central computing platform	Low compute	2000	5	2	1
	Middle compute	5000	5	2	1
	High compute	10000	5	2	1
Steering system	Electric-power-steering	1500	5	3	1
	Steering-by-wire	3500	5	3	1
Braking system	Electric-power-braking	1200	5	3	1
	Braking-by-wire	2500	5	3	1

(6) The Cumulative Usage Cost of Fleet Intellectualization in Beijing. The usage cost of fleet intellectualization for the period from 2023 to 2050 is calculated, including the maintenance cost and energy consumption cost, as shown in the following equation:

$$\mathrm{Cost}_{\mathrm{fleet,usage}} = \sum_{y=2023}^{y=2050}\sum_{v=1}^{v=4}\mathrm{VS}_{v,y}\times\left(\mathrm{ecr}_v + \mathrm{maintain}_v\right), \quad (10)$$

where ecr_v is the annual energy consumption cost of the v type vehicle and $\mathrm{maintain}_v$ is the annual maintenance cost of the v type vehicle.

2.3. Scenario Design. In our study, Beijing is chosen as the case study, and the characteristic parameters of motor vehicle and various road types in Beijing are collected. Two scenarios, vehicle intelligence and collaborative intelligence, are selected to assess the comprehensive cost of implementing advanced autonomous driving under each scenario.

3. Results and Discussions

3.1. Annual Cost under the Vehicle Intelligence Scenario 2023–2050. In the vehicle intelligence scenario, intelligent vehicles rely solely on their own capabilities for sensing, decision-making, and execution, without support from intelligent transportation infrastructure. Figure 5 illustrates the forecasted annual incremental costs of fleet intellectualization in Beijing from 2023 to 2050.

3.1.1. Acquisition Cost. As depicted in Figure 5(a), the "climbing period" of incremental acquisition costs in fleet intellectualization from 2025 to 2035 corresponds to the growth of the penetration rate of intelligent vehicles in Beijing. It is projected that in 2035, the annual incremental acquisition cost of fleet intellectualization will reach ¥17.35 billion. Among these, intermediate AVs will account for 56.24% of the total acquisition cost, reaching its peak at ¥21.64 billion in 2045. The increase in the sales of intelligent vehicles will be more than offset by the reduced costs of intelligence due to advancements in key components and mass production. By 2050, it is anticipated that the annual incremental acquisition cost of fleet intellectualization will decrease to ¥20.45 billion. Advanced AVs will become the market mainstream, constituting 93.22% of the total acquisition cost.

3.1.2. Usage Cost. As depicted in Figure 5(b), particularly after 2025, as the population of intermediate AVs and advanced AVs increases, the inclusion of more sensing devices

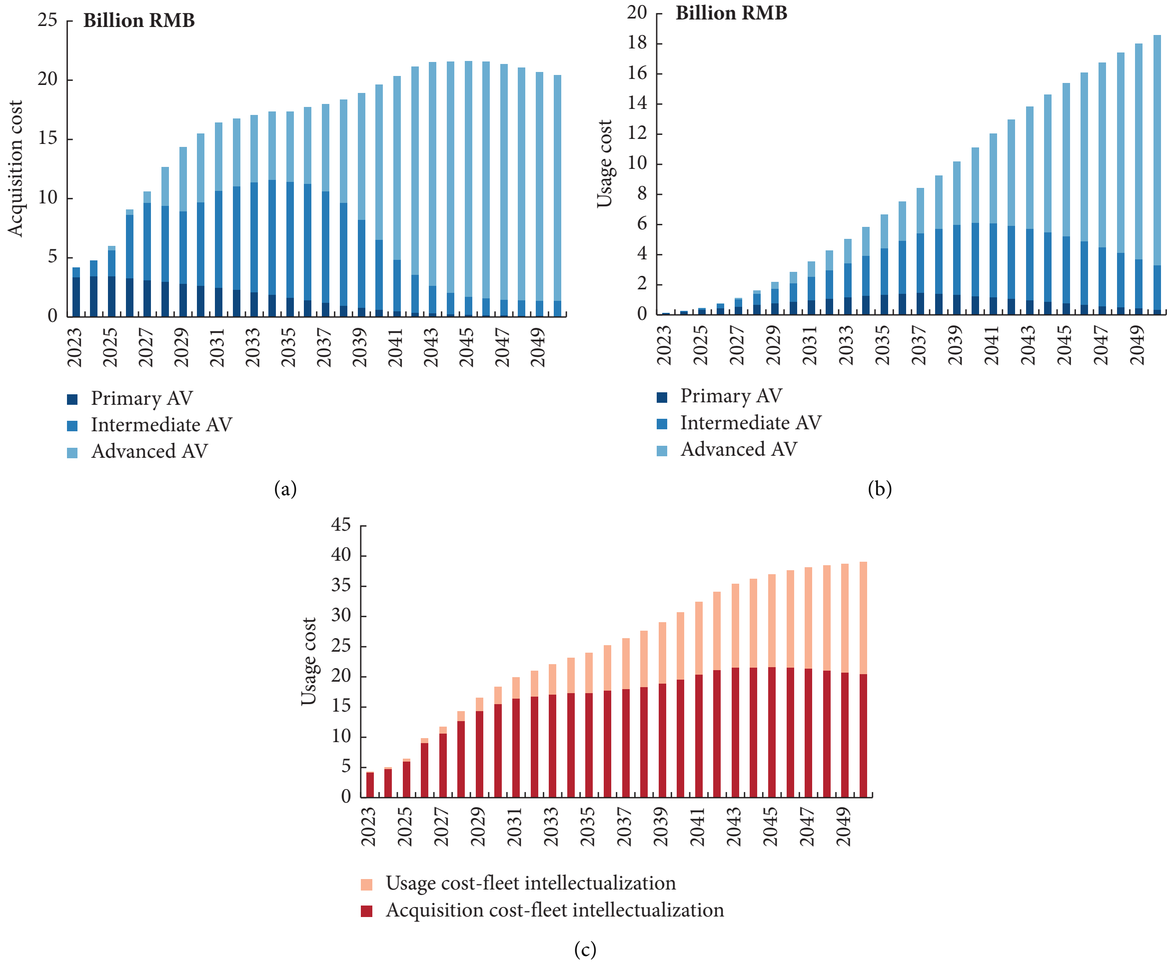

Figure 5: Annual incremental cost of fleet intellectualization. (a) Acquisition cost-fleet intellectualization. (b) Usage cost-fleet intellectualization. (c) Total cost-fleet intellectualization.

and additional computing power on the vehicle side will lead to higher energy consumption and maintenance costs. Consequently, there will be a significant increase in the incremental usage costs of fleet intellectualization. It is projected that, in 2035 and 2050, the annual usage cost of fleet intellectualization will amount to ¥6.65 billion and ¥18.58 billion, respectively. Interestingly, it is worth noting that the usage cost of fleet intellectualization in 2050 is roughly equivalent to the acquisition cost in the same year.

Overall, the increasing trend in comprehensive costs is evident under the vehicle intelligence scenario, as illustrated in Figure 5(c). It is projected that the total cost of fleet intellectualization will be ¥24.00 billion and ¥30.03 billion, respectively, with the usage cost of fleet intellectualization gradually representing a larger share of the total cost. Beijing is expected to pay a cumulative cost of ¥703.00 billion from 2023 to 2050 for fleet intellectualization.

3.2. Annual Cost under the Collaborative Intelligence Scenario 2023–2050. In the collaborative intelligence scenario, it is assumed that Beijing will complete the deployment of intelligent infrastructure from 2023 to 2024, thereby meeting the technical requirements for a vehicle-road collaborative intelligence system. The intelligent infrastructure will be put into use from 2025 onwards. ICVs, which synergize with intelligent transportation infrastructure, are expected to dominate the sales of intelligent vehicles due to their superior cost/performance ratio.

Under this scenario, society is responsible for covering the energy consumption and maintenance costs of intelligent transportation infrastructure, in addition to the acquisition and usage costs of fleet intellectualization. Figure 6 illustrates the annual incremental costs under the collaborative intelligence scenario from 2023 to 2050.

3.2.1. Acquisition Cost. As shown in Figure 6(a), the "climbing period" of incremental acquisition costs from 2023 to 2031 is also associated with the growth of the penetration rate of intelligent vehicles in Beijing, albeit at a much lower rate than the vehicle intelligence scenario. It is anticipated that the annual incremental acquisition cost of fleet intellectualization will reach its peak at ¥10.85 billion in 2032, which represents approximately 64.64% of the cost incurred under the vehicle intelligence scenario for the same

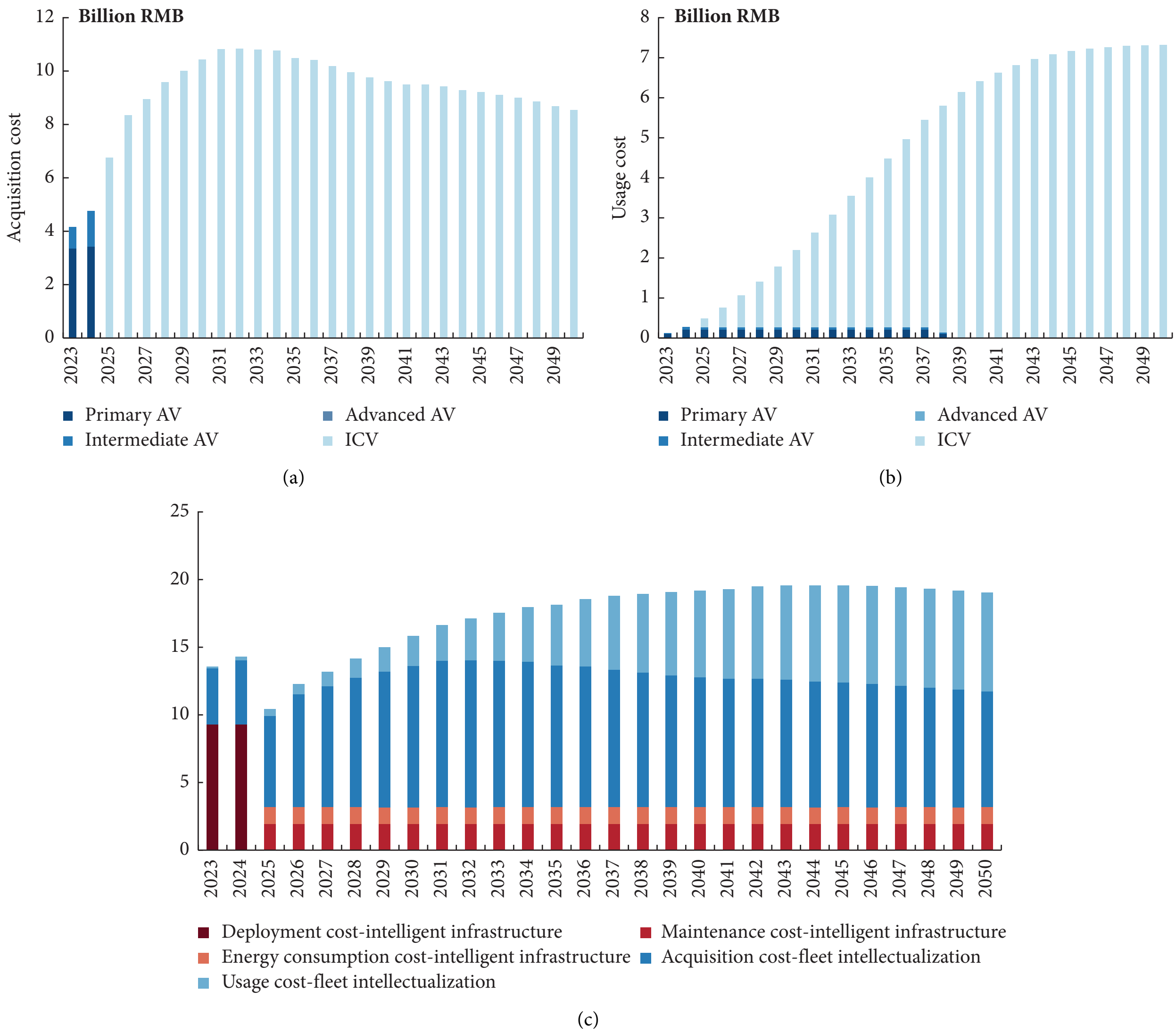

Figure 6: Annual incremental cost of collaborative intelligence system. (a) Acquisition cost-fleet intellectualization. (b) Usage cost-fleet intellectualization. (c) Total cost of collaborative intelligent system.

duration. Subsequently, the declining cost of fleet intellectualization can be attributed to technological advancements in key components and mass production. By 2050, it is expected that the annual incremental acquisition cost of fleet intellectualization will decrease to ¥8.55 billion, accounting for approximately 41.79% of the cost in the vehicle intelligence scenario over the same period.

3.2.2. Usage Cost. Illustrated in Figure 6(b), higher incremental usage costs are expected to occur from 2023 to 2045, aligning with the increasing number of ICVs. Beyond 2045, the annual usage cost of fleet intellectualization stabilizes at approximately ¥7.30 billion. This represents only about 40% of the usage cost under the vehicle intelligence scenario during the same period.

In the collaborative intelligence scenario, the deployment of intelligent transportation infrastructure in Beijing is scheduled to be completed between 2023 and 2024. However, due to the low penetration rate of ICVs in the early stages, society will continue to bear the costs of energy consumption and maintenance. During this period, the cost-effectiveness of the intelligent transportation infrastructure is relatively low. Starting in 2028, the collaborative intelligent system will have a lower total annual cost than the vehicle intelligence scenario, as shown in Figure 6(c). The cost-effectiveness of collaborative intelligence will increase as the penetration of ICVs continues to rise. A detailed comparison of the cumulative costs under the two scenarios and the cost breakdown for intelligent infrastructure is provided in Section 3.3.

3.3. The Comparison of Cumulative Costs in Two Scenarios 2023–2050. Based on the findings of Sections 3.1 and 3.2, Figure 7 illustrates a comparison of the cumulative social costs in Beijing from 2023 to 2050 under the two scenarios.

Between 2023 and 2050, the collaborative intelligence scenario is projected to yield total savings of ¥208.34 billion in the acquisition cost of fleet intellectualization and ¥111.16 billion in the usage cost of fleet intellectualization in Beijing

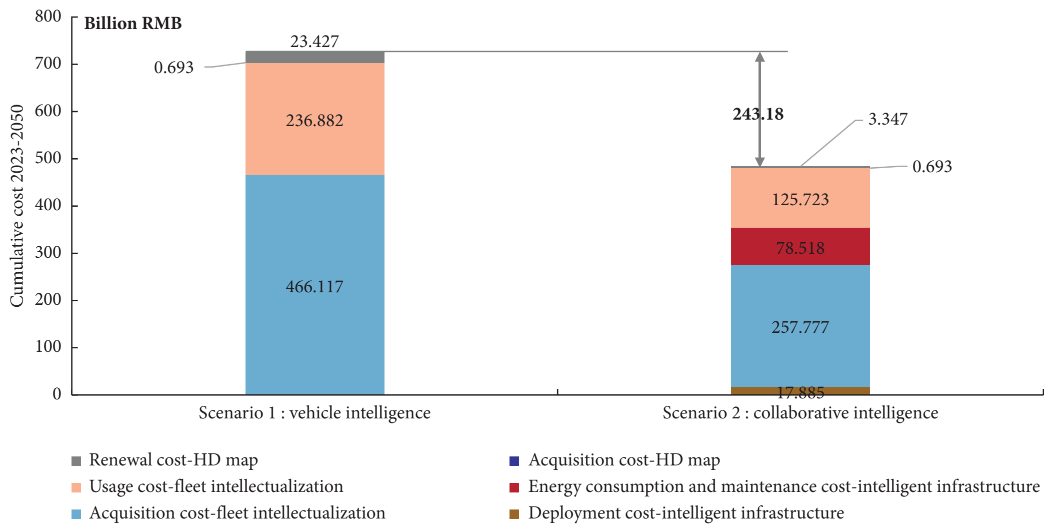

Figure 7: Comparison of cumulative cost in two scenarios 2023–2050.

when compared to the vehicle intelligence scenario. These savings are primarily shouldered by users. Regarding the cost of HD maps, the fleet scale for "crowdsourced maintenance" can be efficiently reduced through the vehicle-road cooperative awareness maintenance strategy. This strategy is expected to lower the overall renewal cost of HD maps by approximately ¥20.08 billion. Overall, the collaborative intelligence scheme is anticipated to reduce the total social cost by ¥243.18 billion from 2023 to 2050, factoring in the deployment, energy consumption, and maintenance expenses of intelligent transportation infrastructure in Beijing.

The deployment and energy consumption and maintenance costs of intelligent infrastructure across various road types in Beijing are shown in Figure 8. The total cost of deploying intelligent transportation infrastructure in Beijing amounts to ¥17.89 billion. Following the deployment, it becomes essential to regularly maintain and update the roadside sensing, communication, computing, and other intelligent equipment to ensure their proper operation. These operational activities also entail energy consumption costs. It is noteworthy that the cumulative cost of energy consumption and maintenance, which constitutes a substantial portion of the overall cost, is projected to reach ¥78.52 billion from 2025 to 2050. Figure 8 also provides a breakdown of the components contributing to the accumulated operational cost of intelligent infrastructure. The energy consumption cost associated with communication equipment is expected to account for approximately 68.2% of the total roadside energy consumption cost (¥32.00 billion) between 2025 and 2050. This is primarily due to the high energy consumption of 5G base stations deployed for road transportation. By around 2050, the energy consumption costs for roadside perception and roadside computing will have accumulated to ¥4.63 billion and ¥5.55 billion, respectively.

Furthermore, the deployment and operation of intelligent transportation infrastructure will introduce more industrial participants, benefiting a broader spectrum of stakeholders. The 5G communication network expands the scope of application scenarios. With the increasing penetration rate of ICVs, communication carriers stand to gain higher revenues from their users for communication services. Building upon the foundation of vehicle-road cooperative perception, HD map service providers can offer more accurate and reliable updates to HD maps at a reduced cost. Concurrently, communication carriers and HD map service providers will actively engage in the operation of roadside intelligent infrastructure, including 5G base stations and cloud servers. They will share the responsibilities of maintaining and covering the energy consumption costs of roadside equipment in use.

3.4. Sensitivity Analysis. As evident from the results depicted in Figure 7, both the acquisition cost of fleet intellectualization and the deployment cost of intelligent infrastructure constitute a significant portion of the cumulative cost. Consequently, we proceed to analyze the sensitivity of costs associated with various vehicle-side and roadside facilities.

Figure 9 illustrates the effects of ± 20% changes in the costs of various facilities, compared to reference values, on the cumulative costs in Beijing from 2023 to 2050 under the vehicle intelligence scenario. A 20% change in the cost of various vehicle-side facilities would result in impacts ranging from 0.02% to 1.27% on the cumulative cost. Among these facilities, Lidar, high-precision localization, and the central computation platform have the most significant impacts on the overall result. This is primarily because advanced autonomous driving in the vehicle intelligence scenario necessitates vehicle-side Lidar, localization, and computation with higher performance, leading to higher acquisition and maintenance costs.

Figure 10 illustrates the effects of ± 20% changes in the costs of various facilities, compared to reference values, on the cumulative costs in Beijing from 2023 to 2050 under the collaborative intelligence scenario. A 20% change in the cost of various vehicle-side facilities would result in impacts

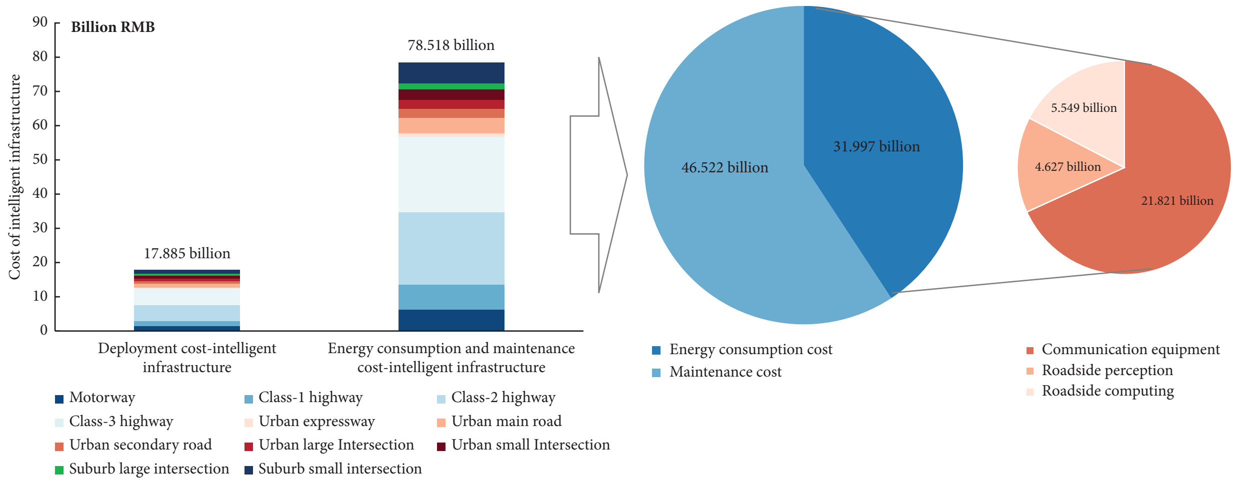

FIGURE 8: Deployment and operational costs of intelligent transportation infrastructure.

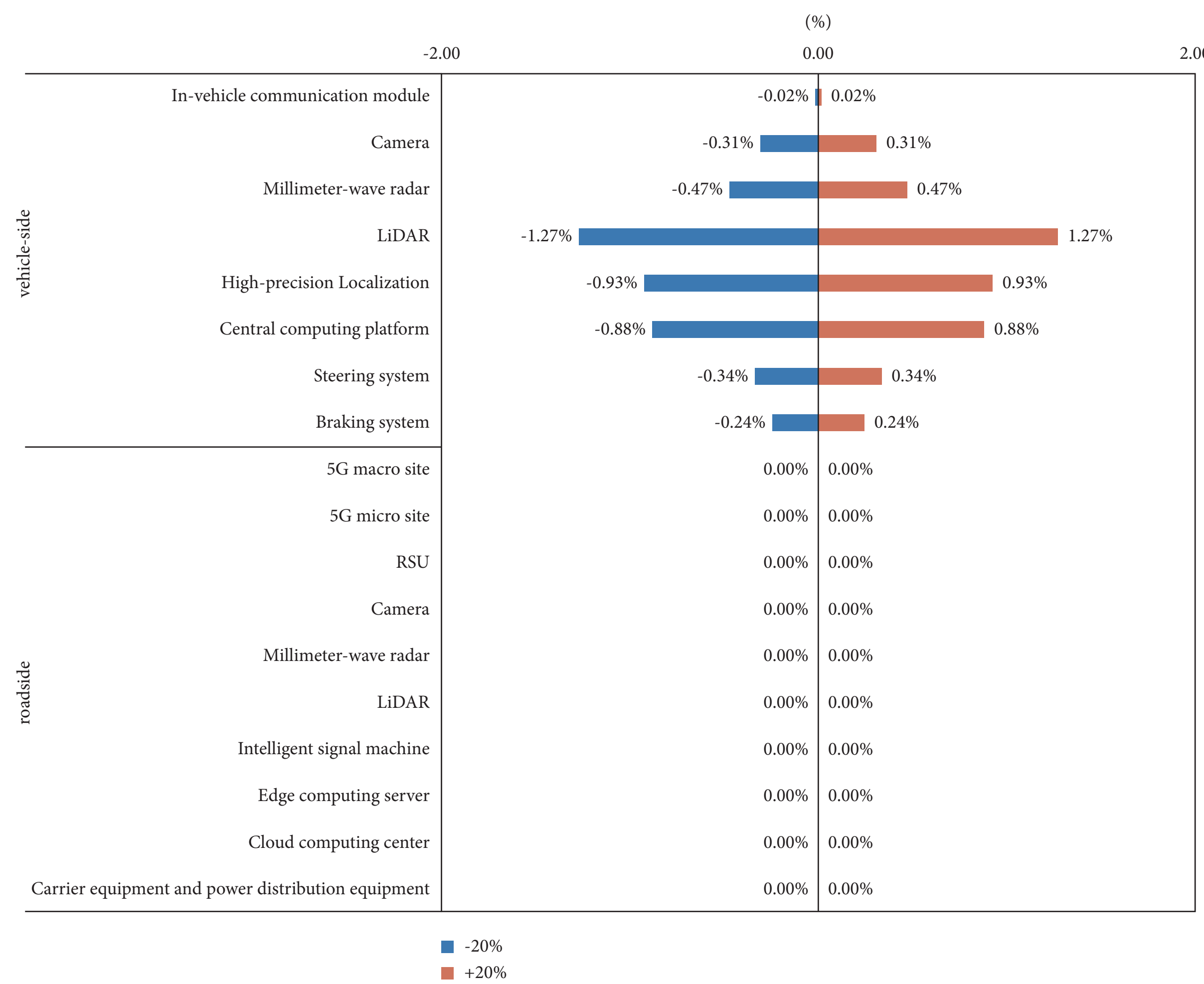

FIGURE 9: Uncertainty analysis for $\pm$ 20% changes from reference values for cost of various facilities on cumulative cost from 2023 to 2050 under vehicle intelligence scenario.

ranging from 0.01% to 0.84% on the cumulative cost. Notably, the central computation platform and in-vehicle communication module have the most significant impact on the overall result. Similarly, a 20% change in the cost of various roadside facilities would result in impacts ranging from 0.0017% to 0.89% on the cumulative cost. Here, the 5G macro site and RSU have the most substantial impact on the overall result.

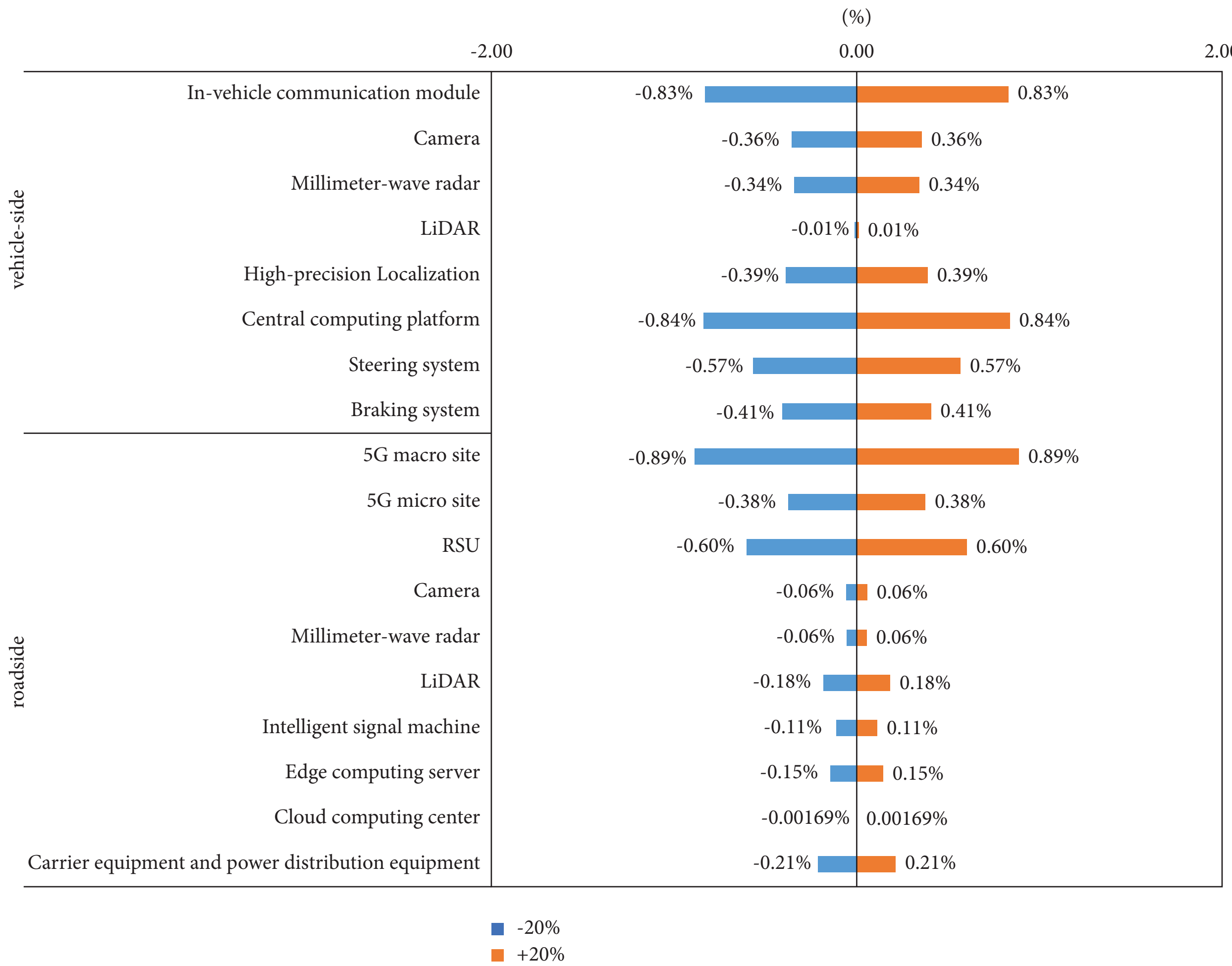

Figure 10: Uncertainty analysis for ± 20% changes from reference values for cost of various facilities on cumulative cost from 2023 to 2050 under collaborative intelligence scenario.

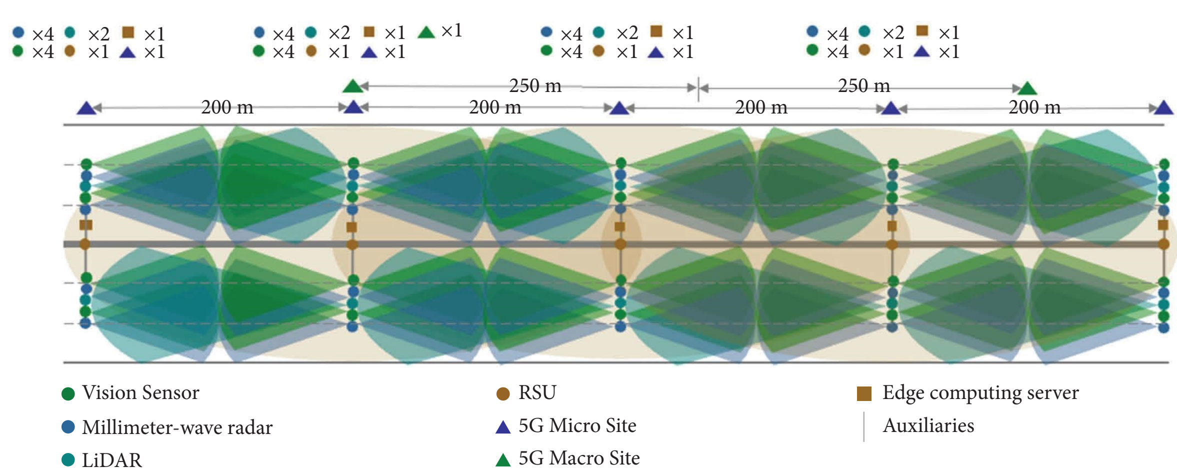

Figure 11: The roadside intelligence schemes of motorway.

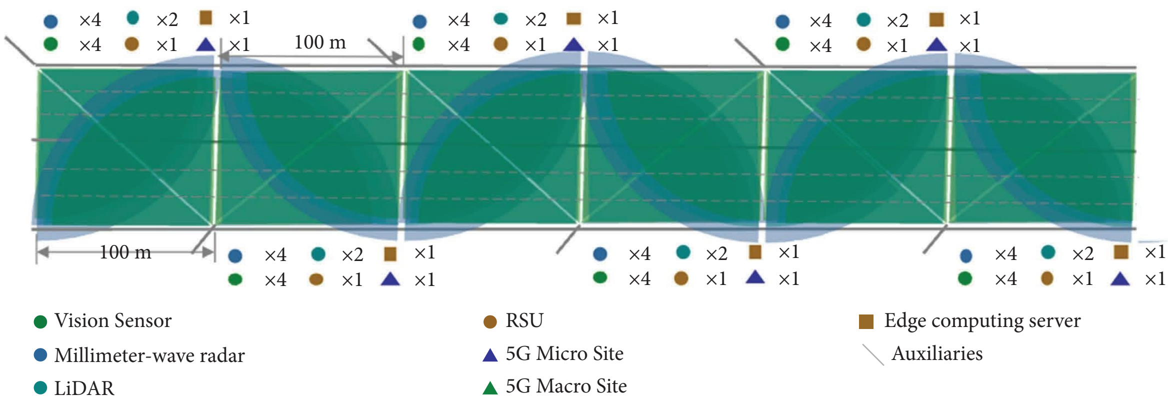

Figure 12: The roadside intelligence schemes of urban main road.

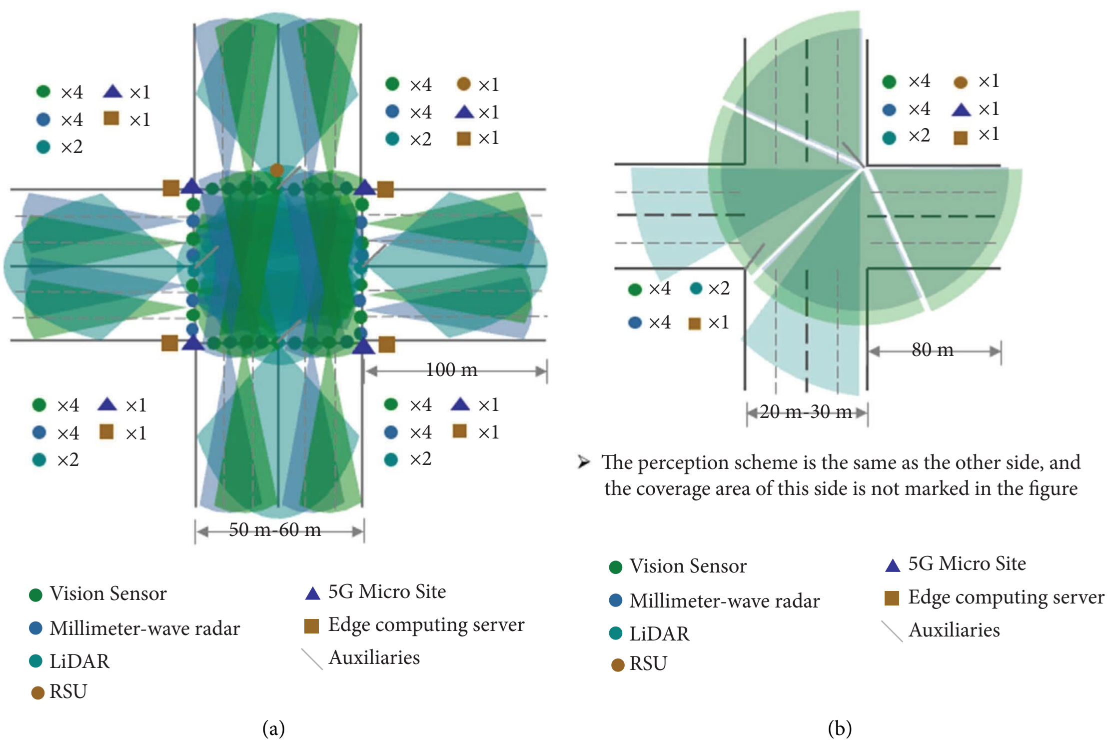

Figure 13: The roadside intelligence schemes of intersections. (a) Urban large intersection. (b) Urban small intersection.

4. Conclusions and Policy Suggestions

In this study, we constructed a cost evaluation model for the vehicle-road cooperative intelligent system based on its architecture and optimized scheme design to ensure technical feasibility. We chose Beijing as our case study to assess the upgrade cost of intelligent transportation infrastructure and to compare and analyze the costs of fleet intellectualization and the overall cost under two scenarios: collaborative intelligence and vehicle intelligence.

Our findings indicate that the deployment of intelligent transportation infrastructure in Beijing serves multiple purposes. It not only alleviates the current bottlenecks in the development of advanced autonomous driving technology but also significantly mitigates the increase in overall costs associated with the development of advanced intelligent vehicles. This, in turn, reduces the acquisition and usage costs for users. Lower costs for intelligent vehicles increase people's willingness to invest in them. Additionally, enhanced intelligent functions further boost people's purchase willingness. Ultimately, the willingness of individuals to acquire such vehicles determines the market penetration rate of intelligent vehicles. Furthermore, the collaborative intelligence solution, by transferring the intelligent configuration from the vehicle side to the roadside, achieves a greater reuse effect, benefiting a larger number of ICVs. This approach results in greater advantages in terms of total social expenses. The deployment cost of intelligent transportation infrastructure in Beijing, totaling ¥17.89 billion, accounts for approximately 3.8% of the cumulative cost from

2023 to 2050. However, it significantly reduces the comprehensive social cost by ¥243.18 billion, demonstrating a high degree of cost-effectiveness. To put this in perspective, the cost of deploying intelligent transportation infrastructure estimated in this study is only about 2.4% of the total investment in transportation infrastructure projects in Beijing for the period 2016–2020, which amounted to approximately ¥750.5 billion [46]. Furthermore, the operation of intelligent infrastructure can be shared by communication carriers, HD map service providers, and other industry participants, making it a realistic possibility.

The deployment of intelligent transportation infrastructure can not only support autonomous driving but also contribute to intelligent transportation, urban management, and other aspects of the development of smart cities. Greater benefits to society will be achieved in contrast to the vehicle intelligence scenario, in terms of traffic safety, efficiency, energy conservation, and environmental protection. As for road safety, vehicle intelligence can prevent 60% of traffic accidents, while V2X can cut traffic accidents by 81%, according to the U.S. Department of Transportation's review of 6 million vehicle accidents [47]. In term of traffic efficiency, telematics technology can increase road efficiency by 10%, lowering the costs associated with congestion, including time costs, carbon emission costs, and environmental management costs [48]. As a result, collaborative intelligence is a better solution from both the perspective of comprehensive social costs and public benefits.

The deployment of intelligent transportation infrastructure offers benefits that extend beyond supporting autonomous driving. It contributes significantly to various aspects of smart city development, including intelligent transportation and urban management. The collaborative intelligent system provides greater societal benefits in terms of traffic safety, efficiency, energy conservation, and environmental protection. In the context of road safety, vehicle intelligence can prevent 60% of traffic accidents, while V2X communication can reduce traffic accidents by 81%, as reported by the U.S. Department of Transportation's analysis of 6 million vehicle accidents [47]. In terms of traffic efficiency, telematics technology has the potential to increase road efficiency by 10%, thereby reducing the costs associated with congestion. These costs encompass various factors such as time costs, carbon emission costs, and environmental management costs [48]. Ultimately, collaborative intelligence emerges as the superior solution from both the perspective of comprehensive social costs and the broader public benefits it offers.

4.1. Government Initiatives. Aligning with national top-level planning, the government should prioritize the development of standardized systems, accelerate the deployment of C-V2X network environments, promote demonstrations of vehicle-road coordination applications, and prepare for the standardization and large-scale deployment of intelligent transportation infrastructure. Government funding for road intelligence construction should be a shared effort with enterprises, ultimately reducing the total cost of ownership for users. This support is critical for the industry to address technical challenges and facilitate commercialization.

4.2. Industry-Level Engagement. Industry participants should each leverage their strengths in the field of vehicle-road collaboration based on their core competencies. Internet technology companies, with their extensive experience in large data and collaborative software algorithms for autonomous driving, can play a vital role. Upstream intelligent component firms should drive product implementation through technological innovation, developing new sensing, location, and computing devices tailored to both vehicles and roadside infrastructure. Communication carriers should collaborate with the government to construct urban network environments with advanced networking technology, expanding the application scenarios and business models of 5G-V2X. Meanwhile, vehicle manufacturers should actively pursue multiparty cooperation to integrate technology, build vehicle networking systems, and offer the market ICVs with cost-effective solutions and superior functional performance.

In summary, it is imperative for all stakeholders to collaborate and share resources, leveraging their existing technical capabilities. Active participation in the construction of the industry ecosystem is essential, along with the acceleration of a comprehensive industrial system. Through these efforts, we can ultimately achieve advanced automation that delivers substantial social benefits while maintaining a lower overall cost to society.

This study has several limitations. While collaborative intelligence has emerged as the preferred option for advancing autonomous driving, it has also raised a set of intriguing questions that warrant further investigation. In our study, both the vehicle intelligence and collaborative intelligence scenarios were based on the forecasted penetration rates of autonomous vehicles outlined in the "Intelligent Connected Vehicle Technology Roadmap 2.0." However, we did not account for the potential increase in penetration rates under the collaborative intelligence scenario, attributed to the enhanced value of vehicles stemming from lower costs associated with high-level autonomous driving functions. It is crucial to recognize that people's willingness to purchase intelligent vehicles is influenced by a multitude of factors, including additional costs, socio-economic conditions, technological maturity, consumer perceptions of utility, and more. Ultimately, the market penetration rate of intelligent vehicles hinges on these considerations. Even without considering the variations in features and performance offered by intelligent vehicles, establishing clear and articulable correlations between the acquisition and usage costs of vehicle-side intelligent configurations and people's willingness to adopt them remains challenging. In future research, we intend to explore methods to quantify the correlation between vehicle intellectualization costs and the penetration rates of intelligent vehicles. Furthermore, this study exclusively delved into the comprehensive costs of implementing collaborative intelligence in Beijing to support advanced autonomous driving. However, as previously mentioned, collaborative intelligent solutions have the potential to generate substantial public benefits in areas such as safety, traffic management, and environmental impact. Quantifying these benefits will be a valuable aspect of our future research efforts.

Appendix

Based on the scene characteristics of different road types, considering the coverage requirements of high-level intelligent driving on roadside sensing, communication and computing, combining the capabilities, and performance of different intelligent devices, the corresponding intelligent infrastructure solutions are determined, which are explained in detail in this section. They are also verified through the related literature and industrial practice.

A. The Deployment Scheme of Intelligent Devices for Motorway

Motorway, as a typical closed road, generally consists of 6–8 lanes in both directions and the width will reach 40 meters or more considering two emergency lanes in both directions. The opposite lanes are often divided by a greenbelt as the separation zone. The design service capacity of motorway is relatively high. But the scene is relatively simple, with single traffic participant.

It is necessary to deploy the pole frame and other auxiliary equipment at the greenbelt, as well as the center of the highway, carrying two sets of intelligent devices for both directions to obtain the best observation view and the largest effective coverage area. This scheme for motorway can reduce the deployment cost and solve the problem of sensing blind areas caused by the greenbelt blockage, as shown in Figure 11.

The scene characteristics of urban expressway are similar to those of motorway. Combining the corresponding design service capacity and scene complexity factors, the deployment scheme and density of sensing, communication, and computing devices on urban expressway are determined accordingly.

B. The Deployment Scheme of Intelligent Devices for Urban Main Road

Urban main road, as a typical open road, generally consists of 6–10 lanes in both directions. The width will reach more than 40 meters, considering two nonmotorized vehicle lanes in both directions. The traffic scene is complex, including motor vehicles, nonmotorized vehicles, pedestrians, and other traffic participants. Meanwhile, the urban main road is with heavy traffic flow and serious obscuration between various traffic participants.

It is demanded to deploy intelligent devices alternately on both sides of the road, through multiview perception to solve blind areas problem caused by obscuration. More intensive edge computing server will be paired to better cope with the complex scenes of urban main road. Simultaneously, more roadside units and pole frame and other auxiliary equipment are also required in the roadside intelligence schemes of urban main road, as shown in Figure 12.

The scene characteristics of urban secondary road, class-1 highway, class-2 highway, and class-3 highway, are similar to those of urban main road. Combining the corresponding design service capacity and scene complexity factors, the deployment scheme and density of sensing, communication, and computing devices on urban secondary road, class-1 highway, class-2 highway, and class-3 highway are determined accordingly.

C. The Deployment Scheme of Intelligent Devices for Various Intersection Types

The roadside intelligent equipment at urban large intersections is arranged in each of the four corners and needs to be matched with larger scale sensing, communication, and computing equipment to achieve intersection coverage. On the basis of ensuring regional coverage, the equipment at urban small intersections is arranged diagonally to reduce the cost and difficulty of deployment, which is shown in Figure 13.

Data Availability

The data used in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was sponsored by the National Natural Science Foundation of China (52272371) and Natural Science Foundation of Beijing Municipality (9232011).

References

[1] B. van Arem, C. J. G. van Driel, and R. Visser, “The impact of cooperative adaptive cruise control on traffic-flow characteristics,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 4, pp. 429–436, 2006.

[2] C. Stogios, D. Kasraian, M. J. Roorda, and M. Hatzopoulou, “Simulating impacts of automated driving behavior and traffic conditions on vehicle emissions,” *Transportation Research Part D: Transport and Environment*, vol. 76, pp. 176–192, 2019.

[3] Y. Lu, X. Xu, C. Ding, and G. Lu, “A speed control method at successive signalized intersections under connected vehicles environment,” *IEEE Intelligent Transportation Systems Magazine*, vol. 11, no. 3, pp. 117–128, 2019.

[4] A. Olia, S. Razavi, B. Abdulhai, and H. Abdelgawad, “Traffic capacity implications of automated vehicles mixed with regular vehicles,” *Journal of Intelligent Transportation Systems*, vol. 22, no. 3, pp. 244–262, 2018.

[5] D. Milakis, B. van Arem, and B. van Wee, “Policy and society related implications of automated driving: a review of

literature and directions for future research," *Journal of Intelligent Transportation Systems*, vol. 21, no. 4, pp. 324–348, 2017.
[6] A. Olia, H. Abdelgawad, B. Abdulhai, and S. N. Razavi, "Assessing the potential impacts of connected vehicles: mobility, environmental, and safety perspectives," *Journal of Intelligent Transportation Systems*, vol. 20, no. 3, pp. 229–243, 2016.
[7] L. Qiu, L. Qian, Z. Abdollahi, Z. Kong, and P. Pisu, "Enginemap-based predictive fuel-efficient control strategies for a group of connected vehicles," *Automotive Innovation*, vol. 1, no. 4, pp. 311–319, 2018.
[8] T. Kuehbeck, G. Hakobyan, A. Sikora, C. C. Chibelushi, and M. Moniri, "Evaluation of performance enhancement for crash constellation prediction via car-to-car communication," in *Proceedings of the International Workshop on Communication Technologies for Vehicles*, pp. 57–68, Midtown Manhattan, NY, USA, May 2014.
[9] H. Tan, F. Zhao, H. Hao, and Z. Liu, "Estimate of safety impact of lane keeping assistant system on fatalities and injuries reduction for China: scenarios through 2030," *Traffic Injury Prevention*, vol. 21, no. 2, pp. 156–162, 2020.
[10] Y. Li, Z. Li, H. Wang, W. Wang, and L. Xing, "Evaluating the safety impact of adaptive cruise control in traffic oscillations on freeways," *Accident Analysis and Prevention*, vol. 104, pp. 137–145, 2017.
[11] Strategy&, "Digital auto report 2023," 2023, https://www.pwccn.com/zh/automotive/digital-automotive-report-2023-zh-1.pdf.
[12] China Industry Innovation Alliance for the Intelligent and Connected Vehicles, *China Intelligent and Connected Vehicles Market Analysis Report in 2022*, CAICV, Beijing, China, 2022.
[13] Z. W. Liu, *Zhao Fuquan's Insights on the Automotive Industry*, China Machine Press, Beijing, China, 2020.
[14] K. Li, *Annual Report on the Development of China's Intelligent Connected Vehicle Industry*, Social Sciences Academic Press, Beijing, China, 2019.
[15] K. Li, Y. Dai, and S. Li, "State-of-the-Art and technical trends of intelligent and connected vehicles," *Journal of Automotive Safety and Energy*, vol. 8, no. 1, pp. 1–14, 2017.
[16] Y. Wang and X. Yan, *Introduction to Intelligent Transportation Technology*, Tsinghua University Press, Beijing, China, 2020.
[17] X. Chang, "Intelligent and connected vehicles' cloud control system and its control technology," Doctor's thesis, Tsinghua University, Beijing, China, 2020.
[18] H. Wieker, J. Vogt, and M. Fuenfrocken, "Intelligent transportation system infrastructure and software challenges," in *Automotive Systems and Software Engineering*, pp. 295–319, Springer, Midtown Manhattan, NY, USA, 2019.
[19] J. Wan, D. Zhang, S. Zhao, L. Yang, and J. Lloret, "Context-aware vehicular cyber-physical systems with cloud support: architecture, challenges, and solutions," *IEEE Communications Magazine*, vol. 52, no. 8, pp. 106–113, 2014.
[20] J. Xu, L. Wu, L. Shi, Y. Shi, and W. Zhou, "Research on 5G Internet of vehicles facilities based on coherent beamforming," in *Proceedings of the International Conference on Wireless Algorithms, Systems, and Applications*, pp. 68–77, Midtown Manhattan, NY, USA, September 2020.
[21] W. Liu, F. Li, and Y. Zhang, "Research on technical scheme and application of eNB-type RSU," *Application of Electronic Technique*, vol. 46, no. 12, pp. 39–42, 2020.
[22] W. Zhang, "Research on layout optimization of hybrid VANET-sensor network for autonomous driving," Master's thesis, Dalian Maritime University, Dalian, China, 2019.
[23] H. Zhu, "Research of RSU deployment algorithms for VANET," Master's thesis, Dalian Maritime University, Dalian, China, 2016.
[24] Y. G. Fu, J. Zhou, and L. Deng, "Surveillance of a 2D plane area with 3D deployed cameras," *Sensors*, vol. 14, no. 2, pp. 1988–2011, 2014.
[25] F. Zhan, X. Wan, Y. Cheng, and B. Ran, "Methods for multitype sensor allocations along a freeway corridor," *IEEE Intelligent Transportation Systems Magazine*, vol. 10, no. 2, pp. 134–149, 2018.
[26] X. Xu, H. K. Lo, A. Chen, and E. Castillo, "Robust network sensor location for complete link flow observability under uncertainty," *Transportation Research Part B: Methodological*, vol. 88, pp. 1–20, 2016.
[27] Z. Liu, H. Song, H. Tan, H. Hao, and F. Zhao, "Evaluation of the cost of intelligent upgrades of transportation infrastructure for intelligent connected vehicles," *Journal of Advanced Transportation*, vol. 2022, Article ID 5841373, 15 pages, 2022.
[28] Beijing Municipal Government, "Beijing statistical bulletin of national economic and social development in 2021," 2021, http://www.beijing.gov.cn/gongkai/shuju/tjgb/202203/t20220301_2618806.html.
[29] G. Chen, "2022 annual commuting monitoring report for major cities in China," *Urban and Rural Development*, vol. 653, no. 2, pp. 56–65, 2023.
[30] H. Tan, "Research on the safety benefits and cost of autonomous vehicles based on multivariable coupling," Master's thesis, Tsinghua University, Beijing, China, 2023.
[31] Synced Review, "The Golden Age of HD Mapping for Autonomous Driving," 2018, https://medium.com/syncedreview/the-golden-age-of-hd-mapping-for-autonomous-driving-b2a2ec4c11d.
[32] MIT Technology Review, "There's no Google Maps for self-driving cars, so this startup is building it," 2018, https://www.technologyreview.com/s/612202/theres-no-google-maps-for-self-driving-cars-so-this-startup-is-building-it/.
[33] Future Car, "Lvl5 looks to crowdsourcing for help building hd maps for self driving cars," 2017, https://www.futurecar.com/1236/lvl5-Looks-to-Crowdsourcing-for-Help-Building-HD-Maps-for-Self-Driving-Cars.
[34] Institute for Ai Industry Research, *Key Technologies and Developing prospect of Vehicle Infrastructure Cooperated Driving (VICAD)2.0*, Tsinghua University, Beijing, China, 2022.
[35] Beijing Transport Institute of Beijing Jiao tong University, *Beijing Transport Development Annual Report*, Beijing Jiaotong University, Beijing, China, 2021.
[36] M. Cui, H. Huang, and Q. Xu, "Survey of intelligent and connected vehicle technologies: architectures, functions and applications," *Journal of Tsinghua University*, vol. 62, no. 03, pp. 493–508, 2022.
[37] Z. Wang, J. Chu, and H. Lin, "Analysis and exploration of sensory parameter priority for V2X system," *Mobile Communications*, vol. 46, no. 11, pp. 64–70, 2022.
[38] K. Li, J. Li, and X. Chang, "Principles and typical applications of cloud control system for intelligent and connected vehicles," *Journal of Automotive Safety and Energy*, vol. 11, no. 3, pp. 261–275, 2020.
[39] China Society of Automotive Engineers, *Vehicle-infrastructure Coordination Roadside Intelligent Decision-Making System*, CB Insights, Beijing, China, 2023.
[40] Z. Liu, W. Zhang, H. Tan, and F. Zhao, "Feature identification, solution disassembly and cost comparison of intelligent

driving under different technical routes," *Applied Sciences*, vol. 13, no. 7, p. 4361, 2023.

[41] H. Tan, F. Zhao, Z. Liu, and H. Song, "Effects of nine typical technologies for primary autonomous vehicles on road safety in China," *Iscience*, vol. 26, no. 3, Article ID 106109, 2023.

[42] Z. Liu, H. Song, H. Hao, and F. Zhao, "Innovation and development strategies of China's new-generation smart vehicles based on 4S integration," *Chinese Journal of Engineering Science*, vol. 23, no. 3, pp. 153–162, 2021.

[43] Ministry of Commerce of the People's Republic of China, "The standard regulations of motor vehicle mandatory scrapping," 2013, http://www.mofcom.gov.cn/article/swfg/swfgbh/201303/20130300062947.shtml.

[44] The People's Government of Beijing Municipality, "2021 Beijing statistical bulletin of national economic and social development," 2022, http://www.beijing.gov.cn/gongkai/shuju/tjgb/202203/t20220301_2618806.html.

[45] Ministry of industry and information Technology of the People's Republic of China, *Intelligent Connected Vehicle Technology Roadmap 2.0*, Ministry of Industry and Information Technology, Beijing, China, 2020.

[46] The People's Government of Beijing Municipality, "Beijing thirteenth five-year period transportation construction and development plan," 2016, https://www.beijing.gov.cn/gongkai/guihua/wngh/sjzdzxgh/201907/t20190701_100237.html.

[47] China EV, "Analysis of the commercialization path of V2X," 2021, https://www.ev100plus.com/content/details1051_4515.html.

[48] K. Li, Y. Dai, and J. Li, "The development tendency and recommendation of intelligent connected vehicles," *Intelligent Connected Vehicles*, vol. 1, no. 1, pp. 12–19, 2018.