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Research on Vehicle-Road Intelligent Capacity Redistribution and Cost Sharing in the Context of Collaborative Intelligence

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Abstract: The vehicle-road collaborative intelligence approach has become an industry consensus. It can efficiently tackle the technical hurdles and reduce the performance requirements and costs of on-board perception and computing devices. There is a need for in-depth quantitative studies to optimize the allocation of vehicle-road intelligent capabilities for collaborative intelligence. However, current research tends to focus more on qualitative analysis, and there is little research on the redistribution of vehicle and roadside intelligent capabilities. In this paper, we present a model for distributing perception and computing capabilities between vehicle-side and roadside, ensuring to meet the needs of various autonomous driving levels. Meanwhile, the collaborative intelligence approach will also introduce the costs of intelligent infrastructure deployment, energy, and maintenance. Different roads have varying scene characteristics and usage intensities. It is necessary to conduct a cost-effectiveness analysis of the intelligent deployment of different road types. A vehicle-road cost allocation model is developed based on the lifecycle traveled distance of vehicles and the lifecycle traffic flow of various roads to evaluate the function-cost effectiveness. Our study presents several vehicle-road intelligent schemes that meet the needs of various autonomous driving levels and selects Beijing for case analysis. The results indicate that primary intelligent infrastructure can reduce the lifecycle cost of the vehicle-side intelligent scheme for intermediate autonomous driving from ¥65,301 to ¥37,703, and advanced intelligent infrastructure can reduce the lifecycle cost for advanced autonomous driving from ¥126,938 to ¥42,180. Considering the distributed cost of vehicle-side and roadside, urban roads in Beijing have higher function-cost effectiveness compared to highways, especially urban expressways, which are expected to generate 43.3 times the vehicle-function-cost benefits after the advanced intelligent upgrades. The corresponding research findings can serve as a reference for city managers to make decisions on intelligent road deployment.

Keywords: collaborative intelligence; intelligent vehicle; intelligent infrastructure; intelligent capacity distribution; function-cost effectiveness

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1. Introduction

Intelligent vehicles represent the strategic high ground in the future form and key technologies of automotive products. Autonomous driving, as a key feature of intelligent vehicles, has become an important factor in determining the future of the automobile industry. Intelligent vehicles can either support or fully take over the driving process, offering a more comfortable and convenient experience for drivers. They also enhance traffic efficiency [1–4], contribute to environmental sustainability by cutting down on energy use and carbon emissions [5–7], and improve traffic safety [8,9]. The development of autonomous driving technology, though in its infancy, is progressing rapidly. The combined driving assistance function, which represents primary autonomous driving, is gradually becoming a standard configuration for new car models released by car manufacturers [10].

Intermediate and advanced autonomous driving are still mainly in the testing and regional demonstration stages. Although the commercialization process in simple scenarios such as closed parks and trunk logistics is accelerating, there are still many bottlenecks. Addressing the technical hurdles inherent to a higher level of autonomous driving as well as the economics associated with large-scale application, intelligent connected vehicles (ICVs) are globally acknowledged as the pivotal path for future development, which is powered by the latest generation of information and communication technology [11,12]. More and more countries and companies are gradually turning to the vehicle-road collaborative intelligent route [13].

Under a collaborative intelligent technical route, ICVs interact with roadside intelligent infrastructure to enhance their environmental perception and make optimized decisions and driving behaviors. Therefore, the intelligent infrastructure should match the functions and technical requirements of ICVs and complete the intelligent upgrade [14]. Intelligent infrastructure can provide vehicles with a wider range of perception data, expand the vehicle's perception range and capabilities, improve safety, and solve a series of "perception long-tail" problems such as perception occlusion and extreme weather [15]. Intelligent infrastructure can also reduce the performance requirements for on-board sensing equipment, thereby reducing the on-board computing requirements related to perception. By providing global route planning and decision optimization for ICVs, collaborative intelligence can meet the challenges of multi-vehicle autonomous driving decision-making games in mixed traffic scenarios, improving traffic efficiency while reducing the computing power related to planning and decision. Meanwhile, the collaborative intelligence route means adding the cost of roadside intelligent infrastructure deployment, energy, and maintenance while significantly reducing the relevant cost on the vehicle side. How to combine roadside intelligent infrastructure with vehicle-side intelligent configurations to meet the needs of different levels of autonomous driving and how to deploy roadside intelligent infrastructure cost-effectively at different stages of technological development are issues that warrant the attention of governments and related enterprises. This study is based on this background.

Some related studies and literature are listed in Table 1. Currently, most related research focuses on the analysis and optimization of the specific functions and technologies involved in the collaborative intelligence system [16–20]. Chang conducted a detailed study on the functional distribution from the perspective of intelligent connected cloud control systems and verified it through a real vehicle test platform [16]. Wang et al. outlined the application scenario requirements for high-level autonomous driving vehicles, clarifying the overall architecture, system functions, and performance requirements of the vehicle-road collaborative system [17]. Sánchez et al. proposed an intelligent transportation plan using a collaborative driving strategy where each vehicle infers traffic conditions based on its own status and information shared by surrounding vehicles and makes decisions based on real-time inferred traffic levels using fuzzy logic methods [18]. Zheng et al. established a two-stage optimization model for optimizing vehicle trajectories and signal timing at intersections under mixed traffic conditions to reduce vehicle delays and fleet carbon emissions [19]. Other scholars have conducted research on the layout of certain hardware facilities involved in the upgrade of transportation infrastructure, such as sensors [16,21–24], roadside units [25–28], communication infrastructure [14,29,30], and edge computing platforms [31,32]. These studies generally establish mathematical optimization models for the layout of certain hardware facilities, aiming to find the most cost-effective, energy-efficient, or optimal performance layout plan. However, its combination with the functional requirements of ICVs is not strong. The China Highway Society has proposed a classification for vehicle-road collaborative autonomous driving systems, believing that the same level of collaborative systems can be achieved through different levels of ICVs and intelligent roads [33], but it is more limited to qualitative analysis. Liu et al. designed the deployment methods and upgrade routes of intelligent infrastructures by sorting out the demands of ICVs [14]. In summary, there is little research on the redistribution of vehicle and roadside intelligent capabilities corresponding to satisfying different levels of autonomous driving under the background of collaborative intelligence. In actual industrial practice, there is still a lack of theoretical basis for the prerequisite of function-cost effectiveness for the intelligent transformation of road infrastructure.

Table 1. Comparison of related studies and literature.

Classification	Literature and Contribution	Limitation
Micro-level: research on functions and technologies	Chang conducted a study on the functional distribution and optimization from the perspective of intelligent connected cloud control systems [16].	Constrained to analysis and optimization of specific functions and technologies involved in collaborative intelligence.
	Wang et al. outlined the application scenario requirements and key technology for high-level autonomous driving vehicles in the vehicle-road collaborative system [17].	
	Sánchez et al. proposed an intelligent transportation plan using collaborative driving strategy [18].	
	Zheng et al. established a optimization model for optimizing vehicle trajectories and signal timing at intersections under mixed traffic conditions [19].	
Micro-level: research on the layout of certain roadside devices	Sensors [16,21–24].	Weak correlation with the functional requirements of ICVs, especially with autonomous driving.
	Roadside units [25–28].	
	Communication infrastructure [14,29,30].	
	Edge computing platforms [31,32].	
Macro-level: research on collaborative intelligent system	The China Highway Society proposed a classification for vehicle-road collaborative autonomous driving systems [33].	Limited to qualitative analysis.
	Liu et al. designed the deployment methods and upgrade routes of intelligent transportation infrastructures by sorting out the demands of ICVs [14].	Lack of discussion on the perception and computing capabilities required to achieve advanced autonomous driving. Lack of functional-cost effectiveness analysis for deploying intelligent infrastructure.
	Zhu et al. designed the cost evaluation model for the cooperative intelligent system and corresponding comprehensive costs to realize advanced autonomous driving are evaluated [34].	
	Innovations and Contributions: This paper optimized the allocation of vehicle-road intelligent capabilities to realize different levels of autonomous driving. By constructing the vehicle-road intelligent cost-sharing model, this study guaranteed the deployment planning of intelligent infrastructure on different road types satisfying function-cost effectiveness. The findings can provide a reference for city managers.	

The purpose of this study is to clarify the substitution logic of intelligent infrastructure for on-board intelligent configuration, re-coordinate the distribution of vehicle-road intelligent capabilities, and analyze the combination and distribution of vehicle-road intelligent configurations for different levels of autonomous driving. The intelligent-related costs of the vehicle side and the roadside under different schemes are also quantitatively analyzed. Different road types have different scene characteristics and require different intelligent infrastructure schemes, combined with the various usage intensities. This study constructs a vehicle-road intelligent cost-sharing model to guarantee the deployment planning of intelligent infrastructure to be carried out under the premise of meeting function-cost effectiveness, avoiding the waste of road intelligent infrastructure as a social public resource, and achieving a higher level of autonomous driving with the lowest total cost. Beijing has 7.128 million motor vehicles [35], ranking first among Chinese cities. Urban transportation's safety, congestion, environmental, and energy issues are prominent [36], and the demand for the intelligent transformation of transportation infrastructure is urgent. This study selects Beijing for case analysis, and the findings provide a reference for city managers when making decisions about deploying intelligent infrastructure.

This study is organized as follows: Firstly, it combs typical vehicle-side and roadside perception schemes. Thereafter, the quantification sub-model for perception capabilities and the matching sub-model for computing power are designed to identify combinations of vehicle-side schemes and roadside schemes that enable different levels of autonomous driving functions. Next, the cost-sharing model for vehicle-road intelligence is designed to calculate the per-mile cost corresponding to different vehicle intelligent schemes over the vehicle's lifecycle as well as the annual average cost of intelligent infrastructure for different roadside schemes over their lifecycle. Subsequently, by integrating the average traffic flow data of different road types in Beijing, the study determines the function-cost effectiveness reflected at the vehicle-side after different levels of roadside intelligent transformation at various stages. Finally, implications for governments and related enterprises in developing vehicle-road collaborative intelligent systems are drawn.

2. Vehicle-Road Intelligent Capability Allocation Model

2.1. Architecture of Vehicle-Road Collaborative Intelligent System

Leveraging C-V2X and 5G communication technologies, collaborative intelligence builds upon vehicle intelligence and fully harnesses the advantages of roadside perception, edge computing, cloud servers, and networking. Through vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N), and vehicle-to-pedestrian (V2P) collaboration, it is possible to achieve complex environmental perception, decision optimization, and collaborative control, ultimately leading to higher levels of autonomous driving. Cloud platforms, roadside infrastructure, ICVs, communication networks, and resource platforms are the core components of the collaborative intelligence system. The specific connection architecture and the roles played by each component within the system have been introduced and analyzed in detail in my previous studies [34], and this paper will not repeat them. The vehicle-road collaborative intelligence system architecture will also serve as the foundation for subsequent research on the distribution of vehicle-road intelligent capabilities.

2.2. Model Framework

This section establishes the logical architecture for the allocation of vehicle-road collaborative intelligent capabilities, as shown in Figure 1. Initially, the key elements of vehicle intelligence and roadside intelligence are deconstructed and taken as the research subjects of this study. The intelligent elements on the vehicle side include perception, computation, communication, and actuation, while the roadside intelligent elements encompass perception, computation, and communication. In this context, high-performance communication equipment on the vehicle and roadside communication devices are considered as added support facilities for collaborative intelligence. Intelligent vehicle actuation devices are matched with the level of autonomous driving achieved. By constructing a quantification model for perception capabilities, the perception capabilities of different levels of vehicle-side perception schemes and those combined with different levels of roadside perception schemes are quantified. A vehicle-roadside computational capability matching model is developed, considering factors such as software complexity and perceptual configuration schemes, to quantify the computational capability requirements on both the vehicle and roadside for different vehicle-road collaborative intelligent schemes. Based on this, combinations of vehicle-road intelligent schemes that meet different levels of autonomous driving can be obtained, scientifically resolving the issue of intelligent capability allocation under the vehicle-road collaborative technical route. Finally, taking Beijing as an example and integrating statistical data on the usage intensity of different types of roads, forecast data on the sales volume and stock of ICVs with different levels of intelligence, and data on the cost and energy consumption of intelligent hardware configurations, a vehicle-road intelligent cost allocation model is constructed. This model explores the deployment plan of roadside intelligent infrastructure with the highest function-cost effectiveness in different road scenarios under different ICV penetration rates.

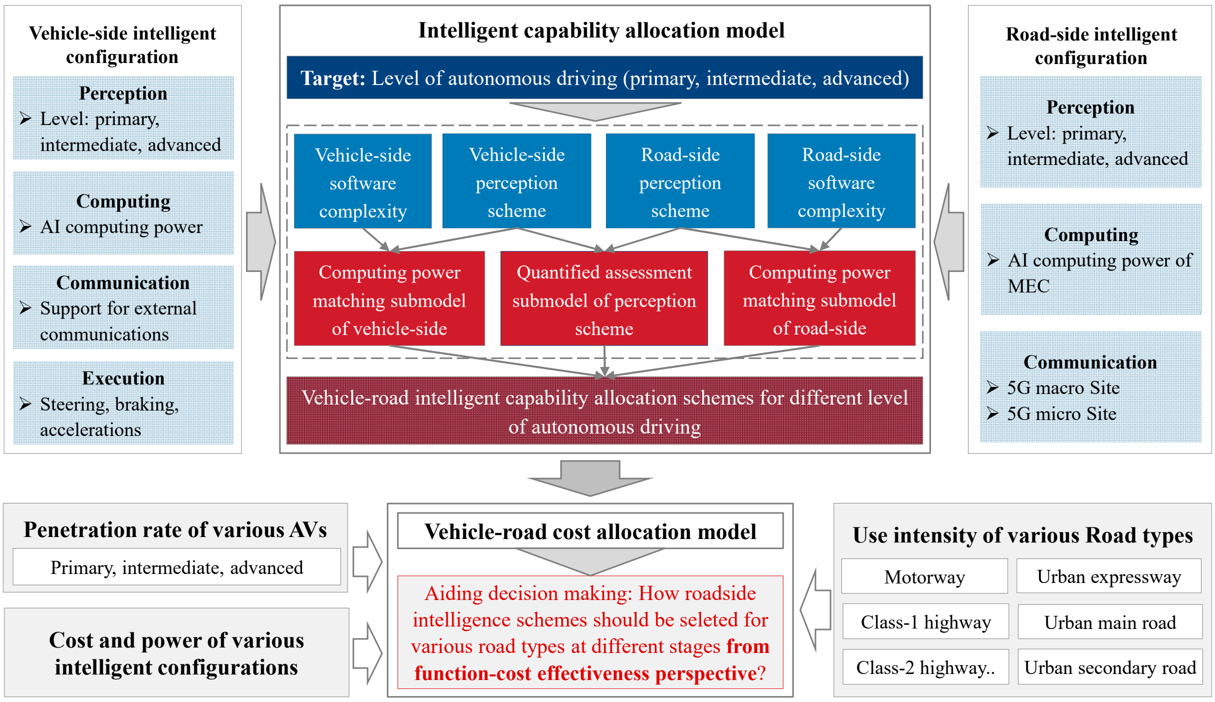

Figure 1. Intelligent capability allocation model of vehicle-road collaborative intelligent system.

For the reader's understanding, an explanation of the classification of autonomous driving levels in this study is provided. Referring to the SAE's (Society of Automotive Engineers) categorization [37], autonomous driving is divided into six distinct levels based on the relationship between humans and vehicles as well as environmental conditions: no automation (L0), driver assistance (L1), partial automation (L2), conditional automation (L3), high automation (L4), and full automation (L5). In this study, the primary intelligent vehicles referred to have L1-L2 autonomous driving capabilities, where the system can perform one or more operations such as steering and acceleration/deceleration, with the remaining driving operations completed by humans. Intermediate intelligent vehicles have L3 autonomous driving capabilities where the system can complete all driving operations under specific conditions and the driver provides appropriate intervention based on the system's request. Advanced intelligent vehicles have L4-L5 autonomous driving capabilities, where the system completes all driving operations, and the driver may not respond to system requests or may not need to intervene.

2.2.1. Quantified Assessment Sub-Model of Perception Scheme

Typical Vehicle-Side and Roadside Perception Scheme

As the level of autonomous driving increases, intelligent vehicles based on the vehicle intelligence technical route need to significantly increase the quantity and variety of sensors to enhance perceptual reliability in different scenarios. Currently, the integration of multi-sensor perception based on deep learning video streams, LiDAR point clouds, and millimeter-wave data has become the mainstream technology in the perceptual systems of intelligent vehicles [38]. This paper organizes the perceptual hardware configuration schemes for primary (mass production phase), intermediate (mass production phase), and advanced (testing phase) autonomous driving that are commonly adopted in the industry, as shown in Figure 2. The primary perception scheme mainly adopts 5V3R, the intermediate perception scheme mainly adopts 5V5R2L, and the advanced perception scheme mainly adopts 8V8R6L [39].

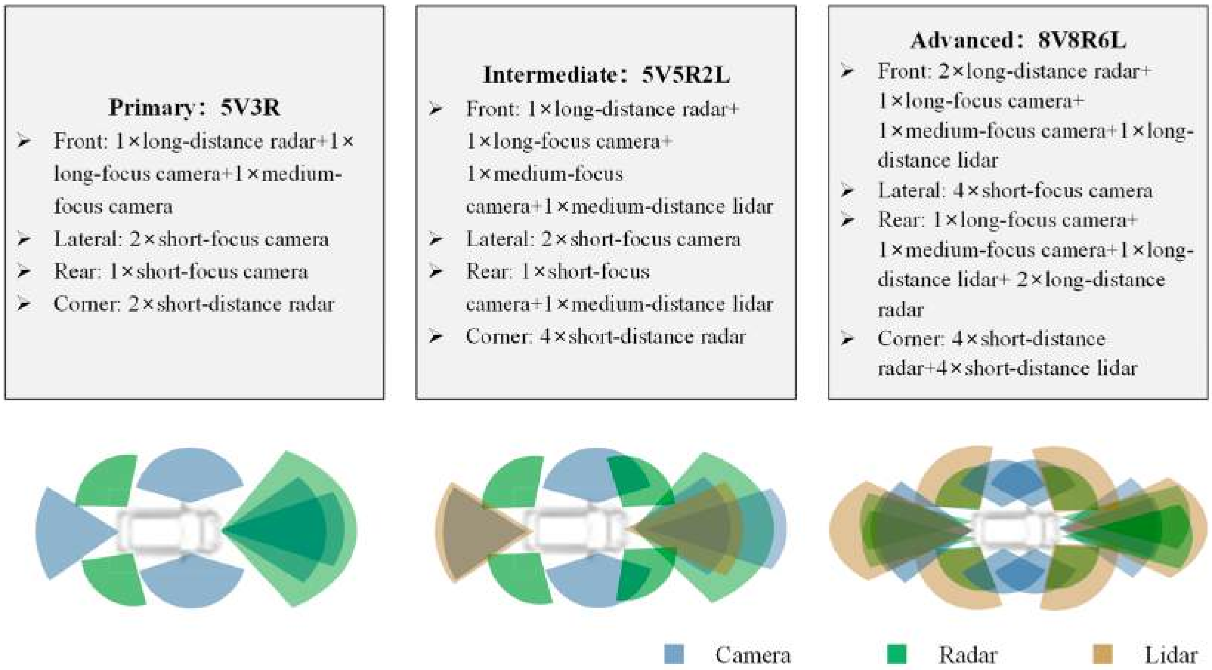

Figure 2. Typical perception schemes of ICVs.

Under the vehicle-road collaborative intelligent technology approach, both the vehicle and roadside possess perception capabilities, serving as sources of perceptual information for the vehicle. Vehicles can share perceptual information with surrounding vehicles through V2V communication, and roadside perceptual devices can share perceptual information with vehicles through V2I communication. Referring to the industry group's classification of roadside perception [40], the schemes include primary perception with pure visual coverage, intermediate perception with coverage of both visual and millimeter-wave data, and advanced perception with simultaneous coverage of visual, millimeter-wave, and LiDAR point cloud data, as shown in Figure 3. The specific deployment plan for roadside perceptual devices is related to the road scenario and can refer to previous research on the deployment schemes of intelligent infrastructure for different types of roads [34].

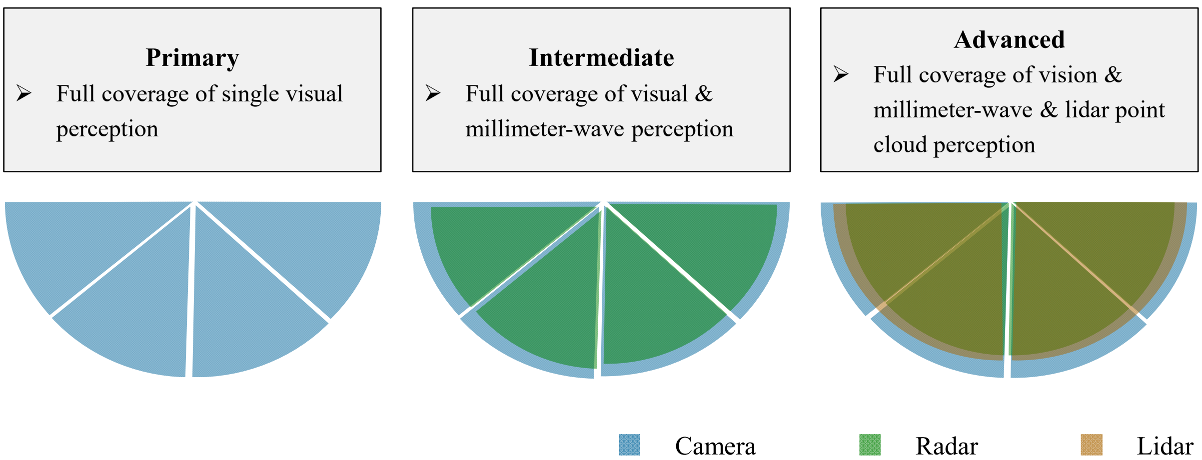

Figure 3. Perception schemes of roadside.

Performance of Various Perception Devices

Different perception devices have varying perception ranges. Table 2 organizes the average perception distance and field of version (FOV) for various sensors. Cameras mainly include long-focus, medium-focus, and wide-angle cameras. Long-focus and medium-focus cameras are primarily used for the forward and rearward perception of vehicles, while wide-angle cameras are mainly applied to the lateral perception. Millimeter-wave radars are primarily divided into long-range and short-range radars, with long-range millimeter-wave radars mainly used for the forward and rearward perception and short-range millimeter-wave radars primarily serving as corner radars installed near the four corners of the vehicle to reduce perceptual blind spots. LiDAR is also categorized into short-range, medium-range, and long-range types, with medium-range and long-range LiDARs mainly used for the forward and rearward perception. Similar to short-range millimeter-wave radars, short-range LiDARs are primarily installed as corner radars near the vehicle's four corners.

Table 2. Perception range of various sensors.

Classification	Facility	Perception Distance (m)	Field of Version (FOV) (°)
Camera	short-focus (lateral)	50	150
	medium-focus (front/rear)	120	60
	long-focus (front/rear)	250	30
Millimeter-wave radar	long-distance (front/rear)	200	90
	short-distance (corner)	50	120
LiDAR	short-distance (corner)	100	120
	medium-distance (front/rear)	150	120
	long-distance (front/rear)	250	120

Additionally, cameras, millimeter-wave radars, and LiDARs each have their own strengths and weaknesses across various dimensions such as detection distance, detail resolution, adverse weather conditions, night mode, and pedestrian recognition. Cameras excel in detail resolution and pedestrian recognition but are greatly affected by dark environments and poor weather. Millimeter-wave radars have the best adaptability in the dark and under adverse weather conditions but fall short in terms of detail resolution and the accuracy of target identification. LiDARs offer the best perceptual stability in complex scenarios but are more significantly impacted by extreme weather conditions. Referring to the current industry's performance evaluation of different sensors across various dimensions [39], the evaluation scores are shown in Table 3.

Table 3. Performance evaluation of various sensors.

Classification	Detail Resolution	Dark Mode	Pedestrian Recognition	Bad Weather	Stability
Camera	5	0.5	5	1.8	2.5
Millimeter-wave radar	0.5	5	1	5	1
LiDAR	3	5	4	2.5	4

The implementation of autonomous driving functions primarily relies on environmental perception around the vehicle to carry out path planning, decision-making, and execution. Integrating other relevant studies and mainstream installation methods of on-board sensors [38,41,42], this research defines the effective perception area of a vehicle as an ellipse with a major axis of 200 m and a minor axis of 50 m, centered around the vehicle. This area is evenly divided into six sectors at equal angles: forward (Sub-region A), rearward (Sub-region B), left front (Sub-region C), right front (Sub-region D), left rear (Sub-region E), and right rear (Sub-region F), as shown in Figure 4. It is considered that the effective perception area encompasses all the information required for intelligent vehicles to conduct planning and decision-making.

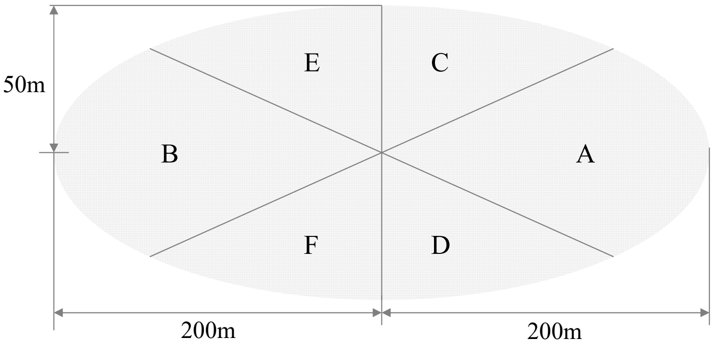

Figure 4. The effective perception area of vehicle.

Quantified Assessment of Perception Schemes

To scientifically evaluate the perceptual capabilities of different vehicle-based perception schemes and vehicle-road collaborative perception schemes, scope, reliability, and stability are adopted as the three key indicators of assessment. The perceptual scope refers to the area covered by the vehicle's actual perception within the effective perception range. Perceptual reliability primarily represents the difference in overall reliability brought about by the coverage of the same perceptual area by different types of perception devices. Additionally, there are differences in the perception dimensions between vehicle-based perception and collaborative perception. Collaborative perception effectively addresses the occlusion blind spot issues inherent in vehicle-based perception. Therefore, perception stability is used to characterize the differences between vehicle-based perception and vehicle-road collaborative perception in this regard.

In terms of perception range, based on the perception distances and FOVs of different perception devices outlined in Table 1, the coverage area of various vehicle perception schemes within the respective sub-regions of the effective perception area can be determined. It is assumed that all three roadside perception schemes can achieve full coverage of the vehicle's effective perception area, with differences lying solely in the types of perception devices used.

In terms of perception reliability, based on the performance differences of various perception devices across different dimensions as presented in Table 2, the comprehensive perception reliability of different device combinations of the vehicle-side and roadside within each sub-region i of the effective perception area is calculated, as shown in Equation (1). By integrating the perception reliability of the vehicle scheme with that of the roadside scheme, the perception reliability of vehicle-road collaborative perception within each sub-region of the effective perception area can be obtained, as illustrated in Equation (2).

$$\begin{aligned} Reliability = \; & reliability_{camera} + sign(m-1) \times (1 - reliability_{camera}) \times reliability_{radar} \\ & + sign(m-2) \times [reliability_{camera} + (1 - reliability_{camera}) \times reliability_{radar}] \\ & \times reliability_{lidar} \end{aligned} \tag{1}$$

$$Reliability_{vr} = Reliability_{v} + (1 - Reliability_{v}) \times Reliability_{r} \tag{2}$$

$reliability_{camera}$, $reliability_{radar}$, $reliability_{lidar}$ represent the reliability of a single sensor for the camera, millimeter-wave radar, and LiDAR, respectively. Their values are obtained by normalizing the average of the performance evaluations across five dimensions for the three types of sensors. $reliability_{v}$, $reliability_{r}$ represent the perceived reliability of the vehicle scheme and the roadside scheme, respectively. $reliability_{vr}$ is the comprehensive reliability of vehicle-road collaborative perception.

$$Integrated\_Reliability_{v} = \left(\sum_{i=1}^{6} (Range_{v,i} \times Reliability_{v,i})\right) / Range_{effective} \tag{3}$$

$$Integrated_{Reliability_{vr}} = (\sum_{i=1}^{6} (Range_{vr,i} \times Reliability_{vr,i}) + (Range_{r,i} \times Reliability_{r,i}))/Range_{effective} \tag{4}$$

$Range_{v,i}$ represents the effective coverage area of vehicle perception scheme v in sub-region i; $Reliability_{v,i}$ denotes the reliability of vehicle perception scheme v in sub-region i; $Range_{vr,i}$ indicates the joint coverage area in sub-region i where both are covered by vehicle perception and roadside perception; $Reliability_{vr,i}$ is the perception reliability within the joint coverage area; $Range_{r,i}$ is the coverage area of the standalone roadside perception within sub-region i; $Reliability_{r,i}$ is the perception reliability of the roadside perception scheme r in its coverage area within sub-region i; $Range_{effective}$ is the area of the effective perception region.

In terms of perception stability, vehicles often face obstructions from surrounding vehicles for most of the travel time, which results in the actual perception range being significantly lower than the vehicle's perception capability. By conducting a statistical analysis of the time probability density of the different range intervals of the actual perception area of vehicles traveling in Beijing at various times, the perception stability coefficient for single-vehicle intelligence is obtained as 0.13. Due to the high-dimensional perspective of roadside perception, the issue of occlusion blind spots inherent in vehicle-based perception will become nonexistent through collaborative intelligence. Therefore, the perception stability coefficient for vehicle-road collaborative intelligence is set to 1.

Taking into account the three key indicators of perception range, perception reliability, and perception stability, the capabilities of vehicle-based perception and vehicle-road collaborative perception can be calculated using Equations (5) and (6), respectively.

$$Performance_{v,perception} = (\sum_{i=1}^{6} Range_{v,i} \times Reliability_{v,i}) \times Stability_{v} \tag{5}$$

$$Performance_{vr,perception} = (\sum_{i=1}^{6} (Range_{vr,i} \times Reliability_{vr,i}) + (Range_{r,i} \times Reliability_{r,i})) \times stability_{vr} \tag{6}$$

$Stability_{v}$ represents the stability coefficient for vehicle-based perception; $Stability_{vr}$ is the stability coefficient for vehicle-road collaborative perception.

Performance Comparison of Various Perception Schemes

A comparative analysis of the perception capabilities of 12 schemes across two technical routes—vehicle intelligence and collaborative intelligence—is presented, as depicted in Figure 5. The vehicle intelligence encompasses 3 vehicle-based perception schemes (AVP, AVI, and AVA), while the collaborative intelligence includes 3 vehicle perception schemes (ICVP, ICVI, and ICVA) and 3 roadside perception schemes (IRP, IRI, and IRA), with each pair combining in various ways, resulting in a total of 9 distinct schemes.

Under the vehicle intelligence technical route, higher-level intelligent vehicles expand their perception range and enhance perception reliability by adding redundant perception devices around the vehicle. However, vehicle-based perception is prone to obstruction by surrounding vehicles and other obstacles, resulting in significant blind spots and poor perception stability. Consequently, the method of enhancing vehicle perception performance by adding redundant sensors to the vehicle has limited effectiveness. This is precisely the reason why it is challenging to achieve higher levels of autonomous driving within the vehicle intelligence technical route.

Under the collaborative intelligence technical route, the deployment of roadside perception devices can achieve vehicle-road collaborative perception, significantly enhancing perception performance. This is especially true for the reliability and stability requirements of advanced autonomous driving, where the advantages of vehicle-road collaborative perception are particularly pronounced. It is noteworthy that, with the completion of advanced perception deployment on the roadside, the improvement of vehicle perception configurations has a minimal impact on the final comprehensive perception performance and reliability. The perception performance and reliability of the ICVA-IRA scheme, which combines primary vehicle perception with advanced roadside perception, are far superior to the AVA perception schemes of vehicles.

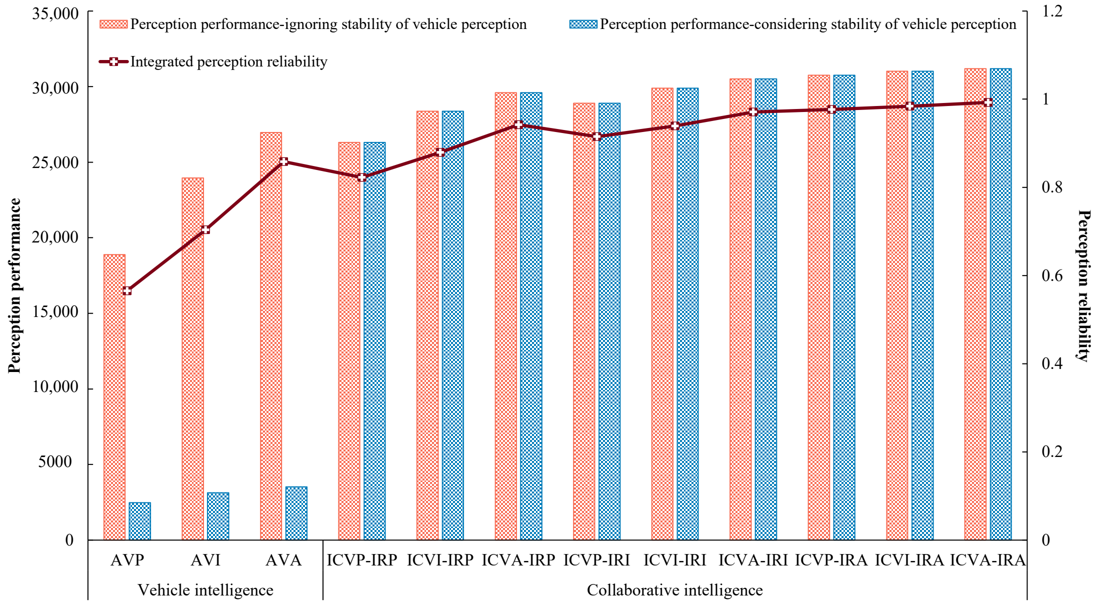

Figure 5. Comparison of perception capabilities of various schemes.

2.2.2. Computing Power Matching Sub-Model

The computing chips of intelligent vehicles mainly consist of CPUs, MCUs, and AI processing chips, including NPUs and GPUs. The CPU is primarily responsible for the logical calculations involved in path planning and controls the decision-making of intelligent vehicle; the MCU is in charge of functional safety and vehicle control; and AI processing chips mainly undertake the substantial computational demands of environmental perception and deep learning. As the perception capabilities of intelligent vehicles increase and the complexity of data-driven neural network algorithms soars, AI computing power has become a key factor in determining whether the vehicle's intelligent capabilities can be enhanced. At the same time, the computational requirements and costs of CPUs and MCUs are significantly lower than those of AI processing chips. This paper only discusses the AI computing power required for intelligent vehicles and intelligent infrastructure.

"Cloud-edge-device" is the current mainstream layout for computing infrastructure, with roadside computing facilities divided into three tiers: the central cloud, the edge cloud, and the mobile edge computers (MEC). The central cloud's applications in the fields of transportation and automotive include traffic model training, full-domain monitoring and overall system status monitoring, city-level route planning and scheduling, and storage and updating of high-precision maps. The edge cloud's applications include information services such as traffic intersection signal information and functional services like planning, decision-making, and precise distribution. The application of MEC includes real-time roadside perception data fusion and dynamic map updating and distribution, where real-time roadside perception data fusion mainly involves the disassembly and integration of video data, LiDAR scanning data, and microwave perception data to form structured data such as traffic flow, vehicle speed, and queue length. Since the cloud platform's services are not limited to the fields of intelligent transportation and autonomous driving but also include government services, city management, etc., its computing power matching is not discussed in this paper. MECs will serve intelligent driving more, and subsequent modeling and analysis of their computing power matching will be conducted.

In terms of vehicle autonomous driving software, the end-to-end AI model has become an industry consensus. It uses sensor data (images, point clouds, radar) as input and outputs control commands (accelerating, braking, steering) for the vehicle. The intermediate process is completed through neural network models (perception network + planning and control network). This paper assumes that automotive companies and related technology companies will develop autonomous driving software according to the end-to-end AI solution. With the improvement of vehicle intelligence, more complex neural network software schemes and larger amounts of data are needed to train the model to handle the needs of multi-source fusion perception and complex decision-making. The number of convolutional neural network layers required for primary, intermediate, and advanced autonomous driving is 10, 20, and 80, respectively [43]. Based on current industry practice, the perception network, as a large network, occupies about 80% of the network layers because of the characteristics of perceptual information and the technical characteristics of the perception network, and the planning and control network, as a small network, accounts for about 20% of the network layers. The specific parameters of the end-to-end AI model are shown in Table 4.

Table 4. Parameters of AI model for autonomous driving.

Level of Autonomous Driving	Total Layer of AI Model	Perception Layer	Planning-Control Layer	Volume of Training Data
Primary	10 × CNN	8 × CNN	2 × CNN	1 PB
Intermediate	20 × CNN	16 × CNN	4 × CNN	50–100 PB
Advanced	80 × CNN	64 × CNN	16 × CNN	2 EB

In terms of roadside MEC software, since roadside perception at different levels achieves full coverage of the road area, the difference lies only in the types of perception devices. Therefore, the scope of the feature maps for roadside perception at all levels is the same. The number of perceptual neural network layers is mainly directly related to the scope of the feature maps collected by the perception scheme and has a smaller correlation with the types of perception devices. Hence, the perceptual convolutional neural network layers corresponding to the roadside perception schemes at different levels are all set to 60.

Cameras, millimeter-wave radars, and LiDARs, due to their distinct perceptual principles, result in different amounts of data generated per unit of time. The number of pixels or lines in the sensing devices approximately proportionally affects the amount of data produced per unit time. Table 5 illustrates the data volume generated per unit time by different sensors and the application of these sensors at various levels of autonomous driving vehicle perception schemes, as depicted in Figure 2 [44].

Table 5. The data volume generated by various sensors.

<table>
<tr><th>Classification</th><th>Facility</th><th>Amount of Data Generated (Mb/s)</th><th>Application</th></tr>
<tr><td rowspan="3">Camera</td><td>2MP</td><td>500</td><td>➢ Panoramic/short-focus</td></tr>
<tr><td>8MP</td><td>2000</td><td>➢ Front/medium-focus of primary and intermediate perception
➢ Front and Rear/medium-focus of advanced perception</td></tr>
<tr><td>12MP</td><td>3000</td><td>➢ Front/long-focus of intermediate and advanced perception</td></tr>
</table>

Table 5. *Cont.*

Classification	Facility	Amount of Data Generated (Mb/s)	Application
Millimeter-wave radar	long-distance	10	➢ Front/Rear
	short-distance	5	➢ Corner
LiDAR	64-line	50	➢ Front and Rear of intermediate perception ➢ Corner of advanced perception
	128-line	100	➢ Front and Rear of advanced perception

The AI computing power required for autonomous driving primarily depends on two factors: the perception scheme and the complexity of the software. The perception schemes of vehicles and the roadside directly affect the amount of data generated per unit of time. Equations (7) and (8) calculate the data volume produced per unit time for vehicle and roadside perception schemes, respectively. Furthermore, a computational power matching model is established to quantify the AI computing power needed for vehicles and roadside MEC, as shown in Equation (9).

$$Data\_volume_v = \sum_{s=1}^{7} data\_volume_s \times amount_s \tag{7}$$

$$Data\_volume_r = \sum_{s=1}^{7} data\_volume_s \times deploy\_density_s \tag{8}$$

$$Computing\_Power = Data\_volume \times Layer\_AImodel \times Conversion\_Ratio \tag{9}$$

$s = 1, 2, \ldots, 7$ represents 2 MP camera, 8 MP camera, 12 MP camera, long-distance millimeter-wave radar, short-distance millimeter-wave radar, 64-line LiDAR, and 128-line LiDAR, respectively. $Data\_volume_v$ is the amount of data generated per second by the vehicle's perception scheme v. $data\_volume_s$ is the amount of data generated per second by the sensing device s. $amount_s$ is the number of sensing devices s equipped with the vehicle. $Data\_volume_r$ is the amount of data generated per second by the roadside perception scheme r. $deploy\_density_s$ is the deployment density of roadside sensing devices s. $Layer\_AImodel$ is the number of neural network layers in the vehicle or roadside MEC. $Conversion\_Ratio$ is the conversion factor. By conducting a regression analysis based on the perception schemes and convolutional neural network layers of current mainstream vehicle models, a value of 0.001TOPs/(CNN*Mbit/s) is adopted for the conversion factor.

Subsequently, by integrating the scene characteristics of different road types, such as urban expressways, highways, and main urban roads, deployment schemes for corresponding perception coverage are designed (refer to Appendix A). Based on the computational power matching model of this section, the demand for MEC-AI computing power per mile of intelligent road under different road types and perception schemes can be obtained.

2.2.3. Vehicle-Road Intelligent Capability Allocation Scheme

The differences among vehicles with different levels of autonomous driving are primarily reflected in the variations in perception, planning, and control capabilities, with the level of vehicle intelligence equated to the representation of integrated perceptual, planning, and control capabilities. Intelligent vehicles of different levels have perceptual hardware configurations with different scopes of perceptual feature maps, which require integration with perceptual neural networks of corresponding layers to leverage the performance of the vehicle's perceptual configuration. Roadside perceptual devices, combined with MEC, can achieve real-time fusion of roadside perceptual data. The roadside perceptual information, obtained through real-time communication between the roadside unit RSU and the onboard unit OBU, can greatly enhance the vehicle's perceptual capabilities, reducing the demand for vehicle perceptual configuration and the complexity of the corresponding perceptual neural networks. The deployment of roadside RSUs is matched with roadside perceptual and computing devices, meaning one set of roadside perceptual devices is paired with an RSU responsible for the transmission and reception of information.

Based on the quantification sub-model for perception capability in Section 2.2.1, the perception capabilities of different vehicle-based perception schemes and vehicle-road collaborative perception schemes can be obtained. In the absence of cloud computing support, since the roadside MEC generally does not participate in the vehicle's planning and control, the onboard central computing platform must independently carry out vehicle planning and control. By matching the corresponding planning and control neural networks on the basis of meeting the perceptual capabilities of the corresponding level of intelligence, the corresponding level of autonomous driving can be achieved. The deployment of cloud platforms can leverage the advantages of abundant computing power and easy scheduling at the roadside and in the cloud, achieving applications such as multi-vehicle collaborative planning and decision-making, as well as road network-level route planning and scheduling. Based on expert interviews, the deployment and application of cloud platforms are expected to reduce the complexity of vehicle planning and control neural networks by 25%, thereby reducing the computing power requirements related to planning and decision-making. Based on the computing power matching sub-model in Section 2.2.2, the MEC required computing power for different roadside perception schemes, as well as the onboard required computing power for achieving a certain level of intelligence under different vehicle-road collaborative intelligence schemes, can be obtained. The overall architecture diagram representing the vehicle-road collaborative intelligence level is shown in Figure 6.

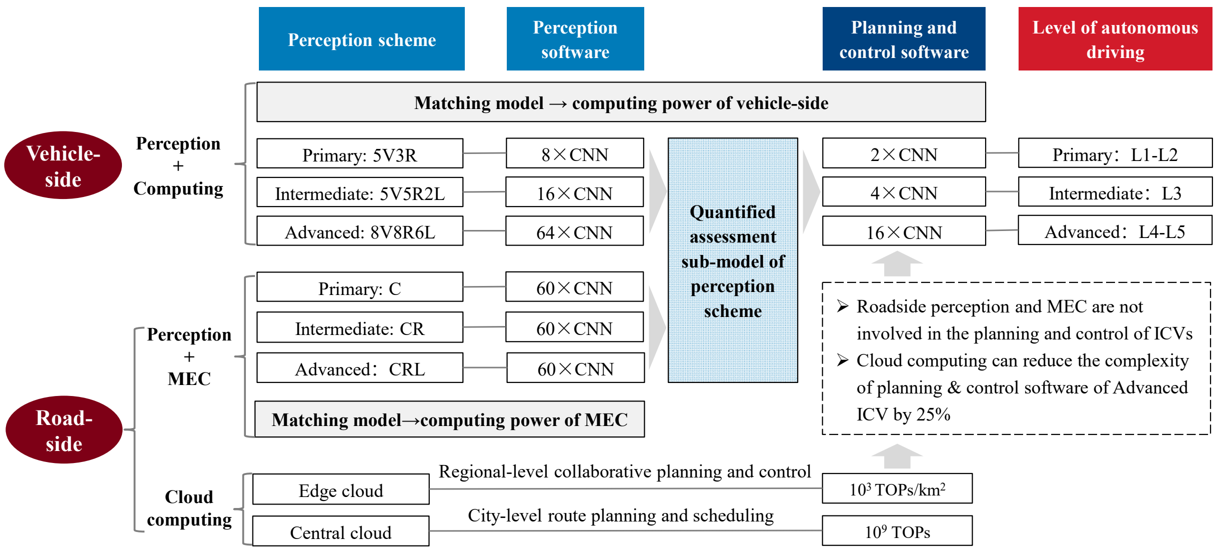

Figure 6. Overall structure of vehicle-road intelligence level representation.

Based on the logical architecture and related sub-models of vehicle-road collaborative intelligent capacity distribution, combinations of vehicle-road intelligent capacity allocation schemes for achieving different levels of autonomous driving are obtained, as shown in Figure 7. Among them, there are 2 schemes for primary autonomous driving, 7 vehicle-road intelligent capacity distribution schemes for intermediate autonomous driving, and 13 schemes for advanced autonomous driving. This study assumes that under any distribution scheme, intelligent vehicles retain basic perception and computing capabilities to ensure the normal use of safety-related assisted driving functions such as Automatic Emergency Braking (AEB) and Lane Keeping Assist (LKA) in the absence of intelligent infrastructure coverage.

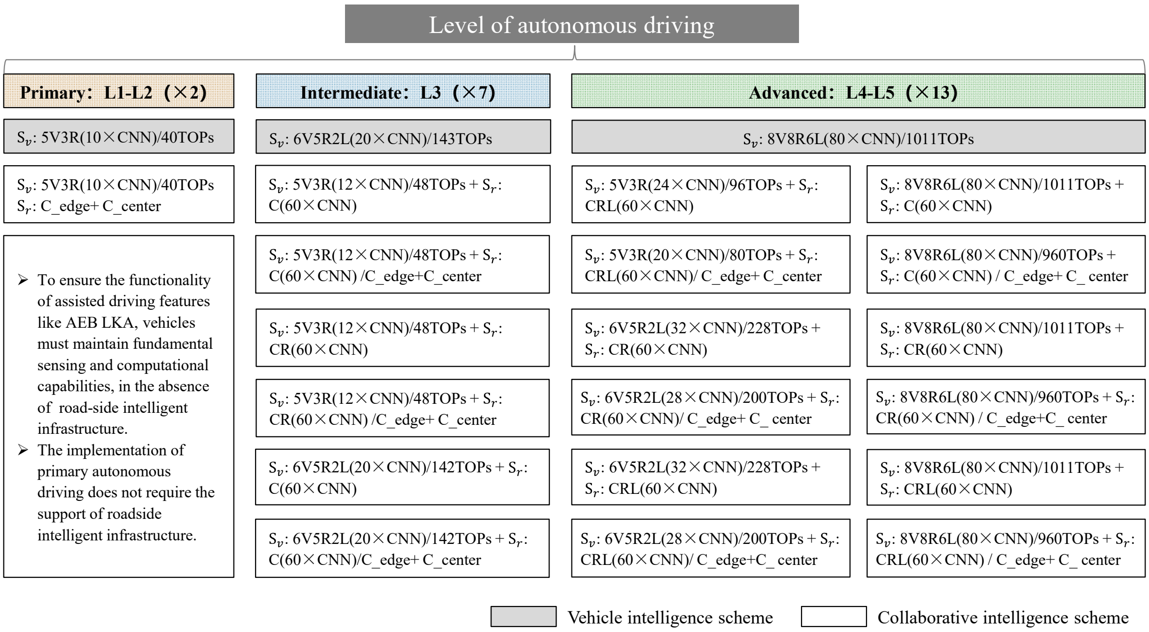

Figure 7. Vehicle-Road intelligent capability allocation scheme.

Different vehicle-road intelligent capacity distribution schemes, combined with the cost and power consumption data of intelligent devices, allow for the determination of corresponding intelligent costs for both vehicles and roadsides. Subsequently, by integrating predictions of future intelligent vehicle penetration rates and the usage intensity of different types of roads in Beijing, matched deployment of intelligent infrastructure can be conducted. This ensures the function-cost effectiveness of roadside intelligent upgrades for the fleet's intelligent level, that is, to achieve the same or higher levels of autonomous driving functions for the fleet at the lowest comprehensive social cost.

2.3. Vehicle-Road Cost Allocation Model

Finally, a vehicle-road intelligent cost allocation model has been established, as shown in Figure 8. The model inputs are vehicle-road collaborative intelligent schemes that meet different levels of autonomous driving, based on a database of costs and power consumption of intelligent devices, combined with data on the average driving distance and duration of vehicles. This allows for the calculation of the per-mile shared cost of vehicle intelligent schemes over their lifecycle. Similarly, based on roadside intelligent schemes of different levels for different types of roads, their corresponding deployment costs and power consumption costs can be calculated. Combined with the service life of roadside intelligent infrastructure, the average annual cost of the roadside intelligent scheme over its lifecycle can be obtained. By integrating statistical data on the usage intensity of different types of roads in the city and forecast data on the penetration rate of intelligent vehicles, the effective service vehicle flow for different types of roads can be determined, which in turn allows for the calculation of the shared cost per kilometer per vehicle on the roadside. By combining the per-mile shared cost of vehicle intelligent schemes and the shared cost per kilometer per vehicle on the roadside, the rationality of deploying intelligent infrastructure under different road types and stages of intelligent vehicle penetration rates can be obtained from a comprehensive cost perspective.

The costs and power consumption associated with the intelligent devices for autonomous driving at both the vehicle-side and roadside are detailed in Table 6 [34]. The lifecycle of the vehicle-side intelligent device is aligned with the vehicle's lifecycle, which is set at 15 years [45]. Since roadside deployment is still in the early stages of pilot programs and lacks relevant standards and regulations, this study selects a service life of 7 years for roadside intelligent infrastructure, meaning that after the service life is reached, the roadside intelligent infrastructure needs to be updated and redeployed.

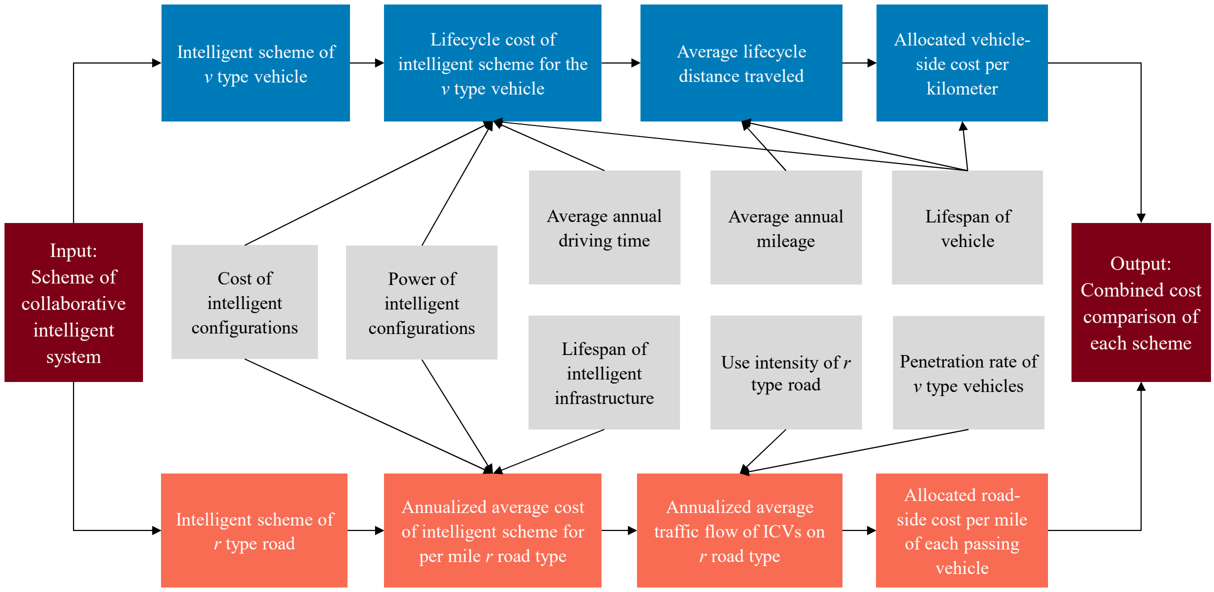

Figure 8. Vehicle-road cost allocation model.

Table 6. Cost and power of intelligent configurations.

	Facility	Classification	Cost (¥)	Power (W)
Communication	Vehicle communication	4G-LTE	140	10
		5G-V2X OBU	5250	20
	Roadside communication	RSU	5000	10
Perception	Camera	2-megapixel	220	10
		8-megapixel	625	15
		12-megapixel	990	20
	Millimeter-wave radar	Short-focus	510	5
		long-focus	940	12
	LiDAR	128-line	6250	40
		64-line	3750	35
Localization	High-precision localization	Submeter-class	2300	1
		Decimeter-class	7400	2
		Centimeter-class	13,500	4
Computing	Vehicle central computing platform	Low compute	50/TOPs	1/TOPs
		Middle compute	25/TOPs	1/TOPs
		High compute	10/TOPs	1/TOPs
	Roadside MEC	High compute	10/TOPs	1/TOPs
Actuator	Steering system	Electric-power-steering	1500	40
		Steering-by-wire	3500	70
	Braking system	Electric-power-braking	1200	50
		Braking-by-wire	2500	80

The characteristic data of the vehicle fleet in Beijing are shown in Table 7. To avoid the impact of the COVID-19 pandemic from 2020 to 2022 on the driving characteristics of the fleet, the average annual mileage per vehicle is taken from the average statistical data of the annual mileage in Beijing from 2010 to 2019. The annual driving duration per vehicle is taken from the statistical data of Beijing in 2019.

Table 7. The characteristic data of fleet in Beijing.

Classification	Value	Source
Vehicle lifespan (year)	15	[45]
Vehicle stock (million)	6.39	[35]
Average annual distance traveled (km/vehicle/year)	13,746.6	[46]
Average annual driving time (h/vehicle/year)	488.675	

Roads of various types exhibit unique usage intensity profiles. The average traffic volume and mileage data for various types of roads in Beijing are depicted in Figure 9, where the vertical axis represents the mileage for different types of roads, and the size of the circular areas corresponds to the average daily traffic volume (pcu/day/km). It is observable that the average daily traffic volume for different types of roads in Beijing, from highest to lowest, is as follows: urban expressway, urban main road, motorway, urban secondary road, class-1 highway, class-2 highway, and class-3 highway. The scale of mileage for different types of roads in Beijing, from largest to smallest, is as follow: class-3 highway, class-2 highway, class-1 highway, motorway, urban main road, urban secondary road, and urban expressway. It is particularly noteworthy that urban expressways have the shortest mileage (397 km) among all road types but the highest overall usage intensity at 32%. In contrast, although second-class and third-class roads have a large mileage scale, they have a smaller average traffic volume, accounting for only 6% and 2% of the total usage intensity, respectively.

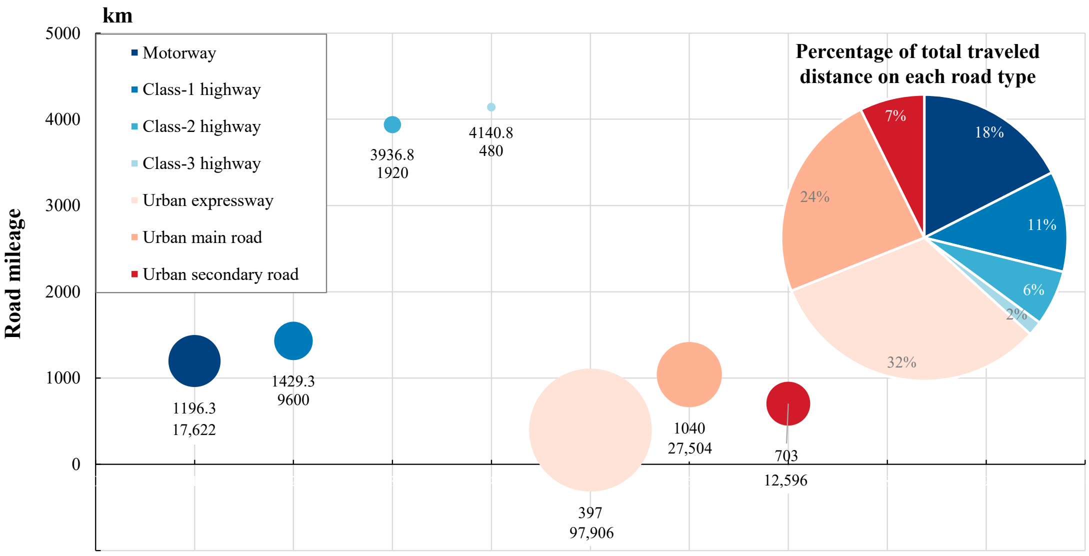

Figure 9. Use intensity and mileage of various road types in Beijing.

2.4. Function-Cost Effectiveness Analysis

This paper defines the ratio of the incremental benefits of fleet autonomous driving functionality brought by roadside intelligent transformation to the incremental cost of roadside infrastructure as "function-cost effectiveness". This metric is used to determine how to deploy intelligent infrastructure for different types of roads, as shown in Equations (10)–(12). The incremental benefit of fleet autonomous driving functionality primarily represents the difference between the cost of intelligent hardware required for the autonomous driving functions that users can obtain with collaborative intelligence and the actual cost paid. The cost of roadside intelligent infrastructure mainly consists of deployment costs and operational and maintenance costs, which include both power consumption costs and maintenance costs.

$$Ratio_{r,j} = \frac{Veh\_benefit_{r,j}}{Road\_cost_{r,j}} \tag{10}$$

$$Veh\_benefit_{r,j} = \sum_{i=1}^{i=3} (mile\_cost_{v,k} - mile_{cost\,v,i}) \times PR_{v,i} \times traffic\_volume_r \tag{11}$$

$$\begin{aligned} Road\_cost_{r,j} &= Deploy\_cost_{r,j}/lifespan_r + Operating\_cost_{r,j} \\ &= \sum_{e=1}^{e=6} Density_{r,j,e} \times cost_e + \sum_{e=1}^{e=6} Density_{r,j,e} \times (ecr_e + maintain_e) \end{aligned} \tag{12}$$

$Veh\_benefit_{r,j}$ represents the incremental autonomous driving functionality benefits to the fleet brought by the level j roadside intelligent infrastructure. $Road\_cost_{r,j}$ is the average annual cost of the level j roadside intelligent infrastructure. $mile\_cost_{v,i}$ is the per-kilometer cost for level i intelligent vehicles throughout the lifecycle. $mile\_cost_{v,k}$ is the per-kilometer cost for level i intelligent vehicles to achieve level k autonomous driving on level j intelligent road, under the vehicle intelligence technical route. $PR_{v,i}$ is the forecasted penetration rate of level i intelligent vehicles. $traffic\_volume_r$ is the average annual traffic volume per kilometer for r type road. $Deploy\_cost_{r,j}$ is the deployment cost for level j intelligent infrastructure on r type road. $Operating\_cost_{r,j}$ is the annual operational and maintenance cost for level j intelligent infrastructure on r type road. $lifespan_r$ is the lifecycle of roadside intelligent infrastructure. $Density_{r,j,e}$ represents the deployment density of intelligent equipment e on r type road. $cost_e$, ecr_e, and $maintain_e$ represent the hardware cost, energy consumption cost, and maintenance cost of roadside intelligent configuration e, respectively.

2.5. External Support Service-Communication

Vehicle-road collaborative intelligence requires high-speed, stable, and low-latency communication technology as support. The related hardware of the communication network mainly includes roadside 5G communication base stations and RSUs, as well as onboard OBUs for vehicles. Through C-V2X direct communication and 5G complementing each other and integrating into the network, it achieves all-round network connections such as V2V, V2I, V2P, and V2N. Multiple access methods meet different safety and informatization needs, as shown in Figure 10. Among them, the 5G base station communicates with the RSU and the onboard OBU through the Uu interface, mainly meeting the requirements of scenarios with high latency, such as high-precision map downloads, collaborative planning and scheduling, and OTA system upgrades. The RSU and the onboard OBU, and the onboard OBU with the onboard OBU, communicate directly through the PC5 interface, meeting the requirements of scenarios with low latency, such as vehicle-road collaborative perception and information sharing, green wave traffic for continuous signalized intersection, and cooperative lane changing.

The deployment of "macro base stations as the main body, with micro base stations as a supplement" is the main way to enhance future 5G network coverage [14]. A deployment plan for 5G macro and micro base stations is designed to meet the network communication requirements of ICVs for low latency, large bandwidth, and full coverage. Among them, the 5G macro base station solves the problem of large-scale communication coverage, which is less related to specific business scenarios, while the 5G micro base station fully considers the matching of road traffic business and is the main carrier of the access network. The performance, cost, and other parameters of the communication equipment are shown in

Table 8. In the actual use of communication equipment, the number of device access and bandwidth within the coverage of both macro and micro base stations are greater than the actual communication needs. The deployment plan diagrams for macro and micro base stations are shown in Figure 11, respectively.

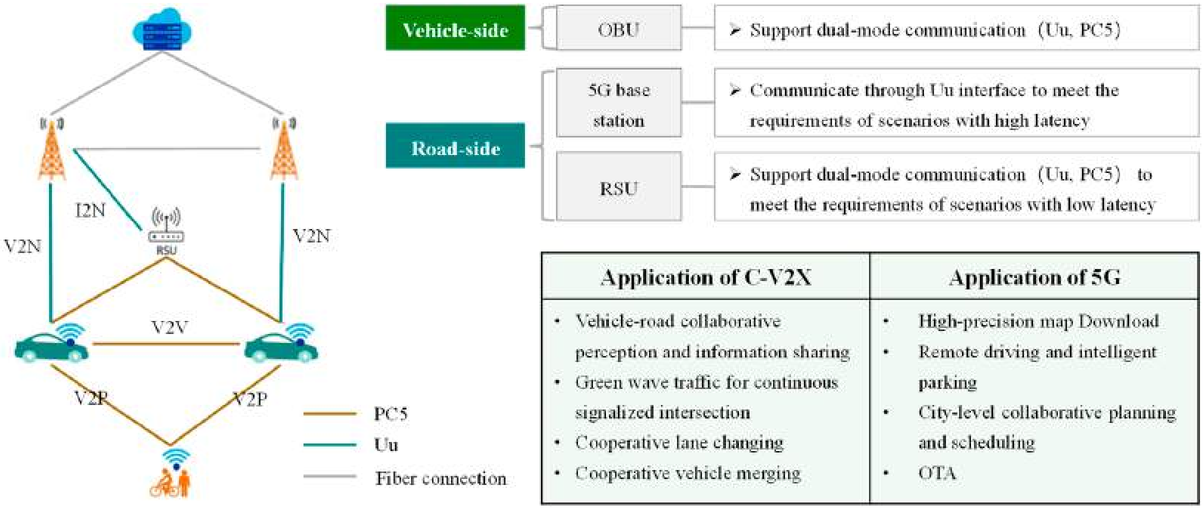

Figure 10. Communication equipment and function matching.

Table 8. Performance parameter and cost of communication equipment.

Facility	Performance or Cost (Unit)	Value
5G macro site	Coverage radius (km)	0.25
	Quantity of Access Devices	>10,000
	Power (W)	3500
	Cost (¥)	450,000
	Service life (year)	7
5G micro site	Coverage radius (km)	0.1
	Quantity of Access Devices	512
	Power (W)	100
	Cost (¥)	30,000
	Service life (year)	7

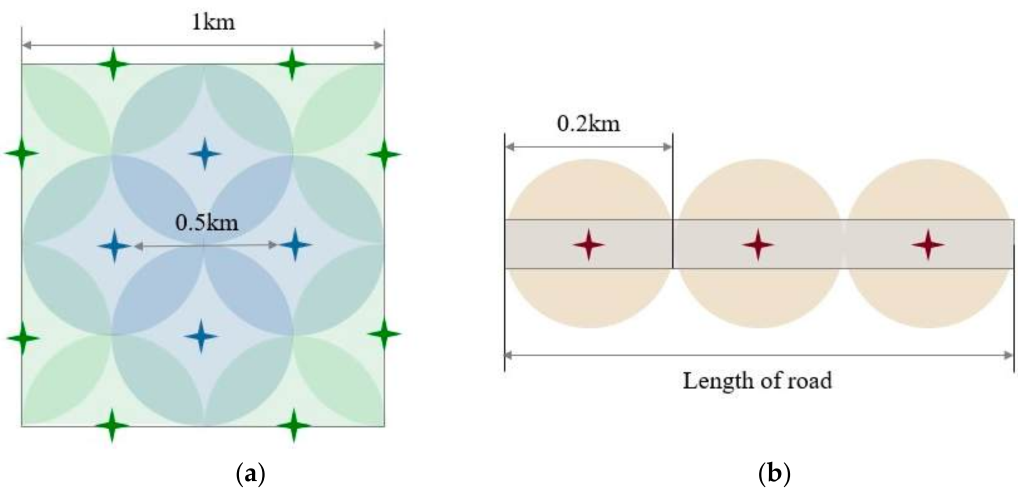

Figure 11. Deployment scheme of 5G base station. (**a**) 5G macro site. (**b**) 5G micro site.

Combining the base station deployment scheme with the urban coverage area and road mileage data, the deployment quantities of 5G macro base stations and 5G micro base stations can be obtained, as shown in Equations (13) and (14), respectively. Considering the service life of communication equipment, the annualized cost of communication infrastructure is shown in Equation (15), which includes the deployment cost, power consumption cost, operational cost, and maintenance cost of macro base stations and micro base stations.

$$Quantity_{macro\_site} = cover\_area \times Density_{macro\_site} \tag{13}$$

$$Quantity_{micro\_site} = road\_mileage \times Density_{micro\_site} \tag{14}$$

$$\begin{aligned} Cost_{communication} & \\ = & \left(cost_{macro\_site} \times Quantity_{macro\_site} \times 1/lifespan_{macro\_site} + maintain\_cost_{macro\_site}\right) \\ & + \left(cost_{micro\_site} \times Quantity_{micro\_site} \times 1/lifespan_{micro\_site} + maintain\_cost_{micro\_site}\right) \\ & + (Quantity_{macro_{site}} \times power_{macro_{site}} \\ & + Quantity_{micro_{site}} \times power_{micro_{site}}) \times running\_hour \times Electricity\_price \end{aligned} \tag{15}$$

3. Results and Discussions

3.1. Life Cycle Cost of Intelligent Scheme at Vehicle-Side

Based on the vehicle-road intelligent schemes for different levels of autonomous driving and combining the cost of intelligent devices and energy consumption with vehicle usage characteristic data, the lifecycle cost and per-kilometer allocation cost of the vehicle intelligence scheme can be calculated, as shown in Figure 12. In the "vehicle intelligence" scenario, the improvement of autonomous driving level means more sensors of various types and greater computing power, which significantly increases the cost on the vehicle side. At this time, the lifecycle cost of the intelligent scheme on the vehicle side for intermediate and advanced autonomous driving will reach ¥65,301 and ¥126,938, respectively. In the "collaborative perception" scenario, roadside primary perception can serve primary ICVs to achieve perception capabilities for intermediate autonomous driving. Combining vehicle-side intermediate-level planning and control neural networks matched with appropriate computational power, the primary ICVs can realize intermediate autonomous driving. At this time, the lifecycle cost of the intelligent scheme on the vehicle side to achieve intermediate autonomous driving will be reduced to ¥37,703. Roadside intermediate perception and advanced perception serve ICVs to achieve advanced autonomous driving and significantly reduce the cost of achieving advanced autonomous driving on the vehicle side. When the road side completes advanced perception coverage, primary ICVs can achieve perception capabilities for advanced autonomous driving. Combining vehicle-side advanced-level planning and control neural networks matched with appropriate computational power, the primary ICVs can realize advanced autonomous driving. The lifecycle cost of the vehicle side to achieve advanced autonomous driving will be reduced to ¥42,180. In the "collaborative perception and collaborative decision-making" scenario, through the collaborative planning and decision-making of the cloud control platform at the road network level, ICVs do not need to make complex decisions for multi-vehicle autonomous driving games, and the complexity of the vehicle-side planning and control neural network is also correspondingly reduced, thereby reducing the requirements for on-vehicle computing power and the purchase, maintenance, and power consumption costs related to computing power. In the "collaborative perception and collaborative decision-making" scenario, compared to the "collaborative perception" scenario, the per-kilometer allocation cost for advanced autonomous driving on the vehicle side will be reduced from ¥0.205/km to ¥0.197/km. For society, the reduction in per-kilometer allocation costs also means that the application of large-scale urban fleets can lead to lower overall energy consumption and carbon emissions.

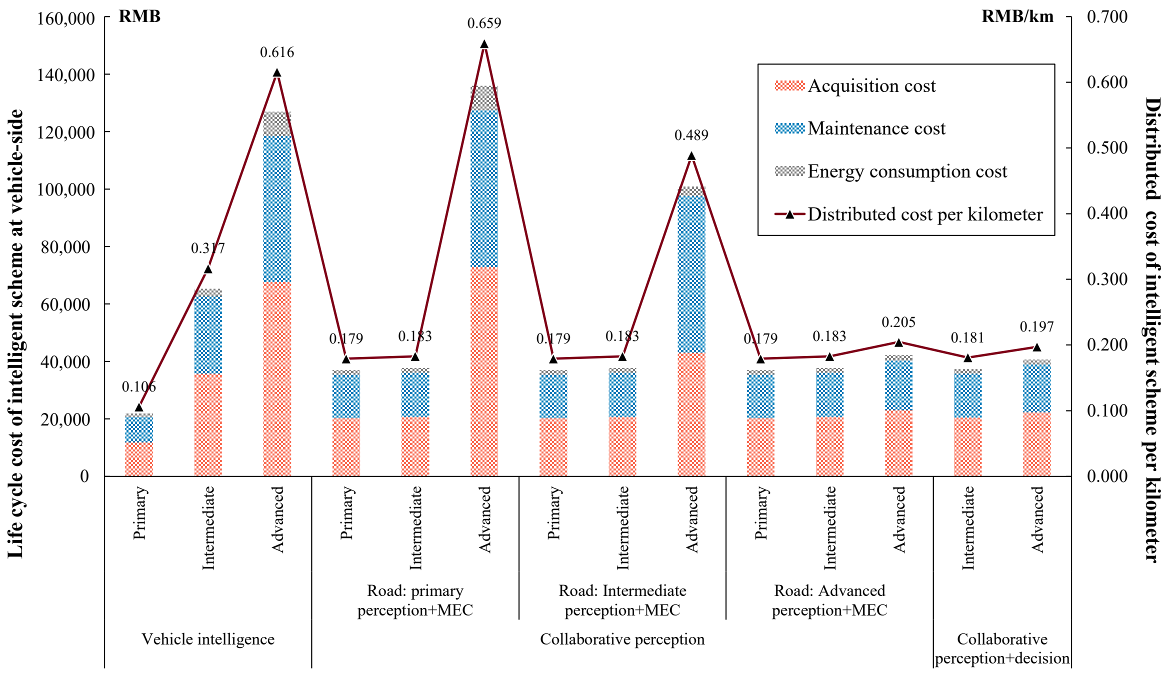

Figure 12. Life cycle cost of intelligent scheme at vehicle side.

3.2. Life Cycle Cost of Intelligent Scheme at Road Side

Based on the deployment scheme for intelligent infrastructure of different road types, combined with the cost and energy consumption data of intelligent equipment, the lifecycle cost of deploying intelligent infrastructure of different levels on different road types can be obtained. Combined with the service life of the roadside intelligent configuration, the corresponding annual cost can be derived, as shown in Figure 13. The annual costs for primary, intermediate, and advanced intelligent upgrades of urban expressway, class-1 highway, class-2 highway, and motorway are ¥87,370, ¥92,580, and ¥107,240, respectively. Urban main road and urban secondary road, as open roads with complex traffic scenarios, require denser perception equipment and greater computing power to address occlusion blind spots. The annual costs for primary, intermediate, and advanced intelligent upgrades are ¥174,740, ¥185,058, and ¥214,379 respectively. Since the roadside intelligent infrastructure needs to operate normally around the clock to support the functional realization of passing vehicles, its utilization rate and working time are much higher than the vehicle-side intelligent device, and it can be seen that the power consumption cost accounts for a larger proportion in the total cost.

Combining the usage intensity characteristics of different road types in Beijing and the costs related to intelligence, as well as the forecast data for the future ownership of intelligent vehicles in Beijing [34], the per-vehicle per-kilometer allocation cost for deploying intelligent infrastructure of different levels on highways and urban roads in different years can be obtained, as shown in Figure 14. Due to the higher usage intensity of urban roads, the allocation cost of roadside intelligent infrastructure is significantly lower than that of highways of all levels through cost-sharing due to the larger traffic flow. Especially for urban expressways, even if advanced intelligent infrastructures are deployed now, the allocation cost is only ¥0.0134/veh/km. In contrast, for class-3 highway, due to its lower usage intensity, even if the penetration rate of intelligent vehicles basically reaches 100% by 2050, the allocation cost for deploying primary intelligent infrastructures is still ¥0.2493/veh/km.

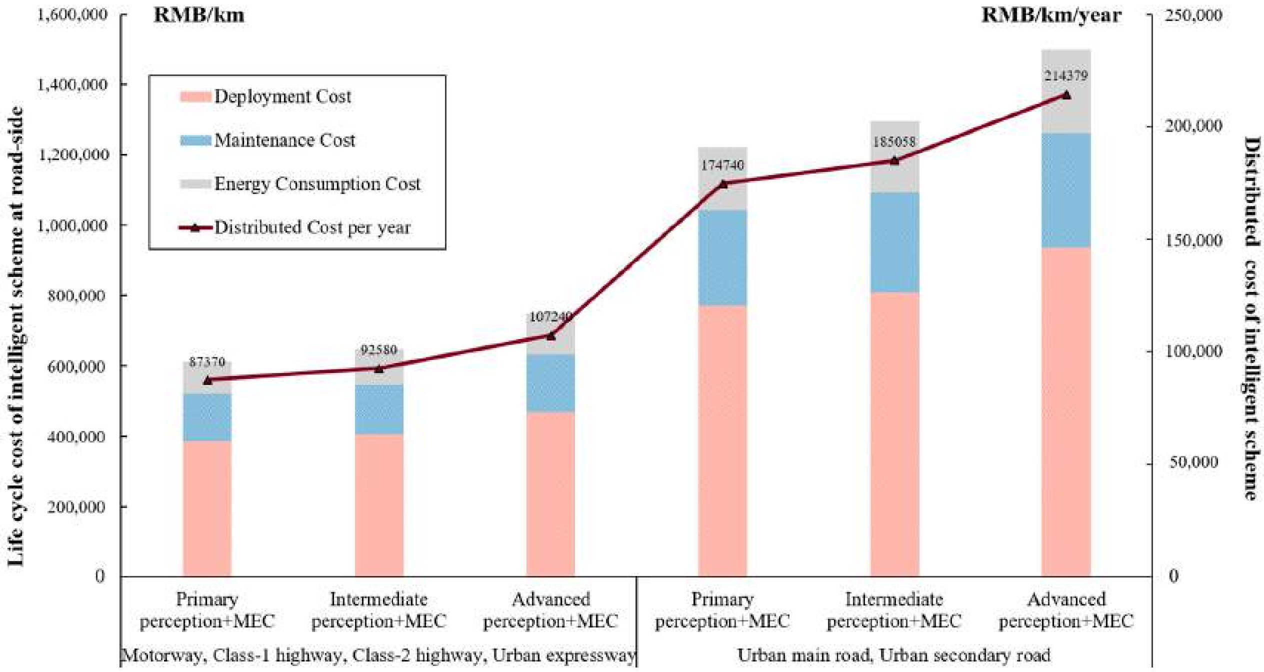

Figure 13. Life cycle cost of intelligent scheme at roadside.

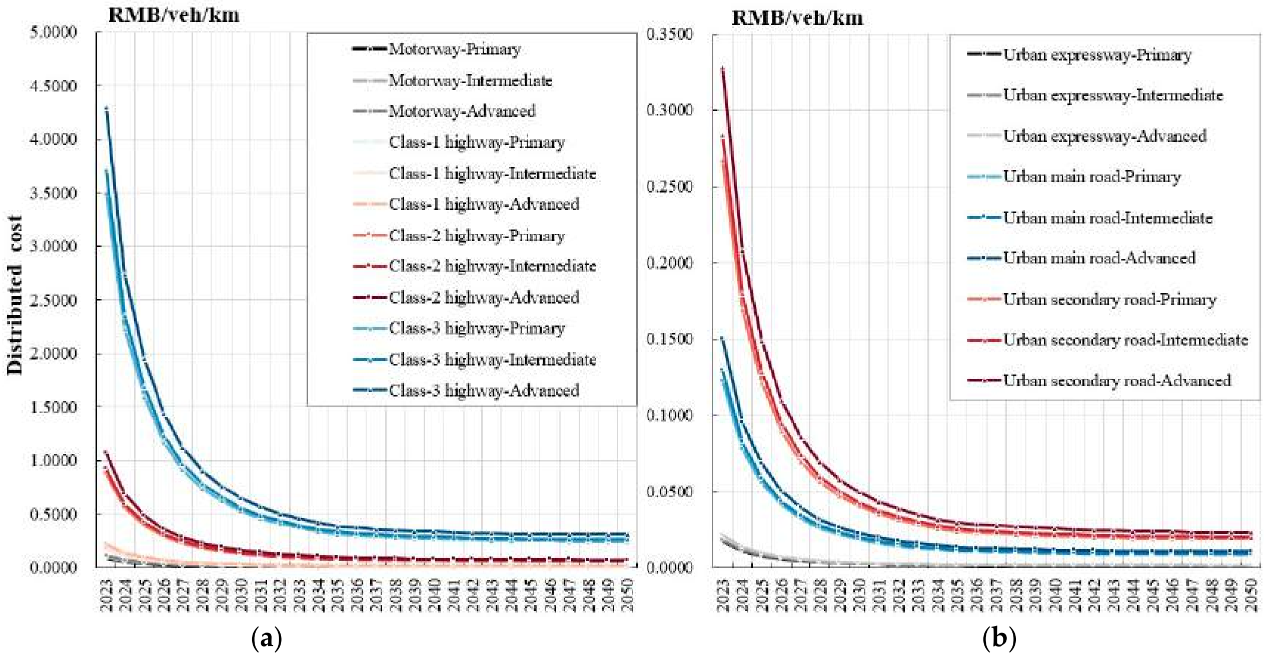

Figure 14. Distributed cost of intelligent scheme at roadside. (**a**) Highway. (**b**) Urban road.

3.3. Function-Cost Effectiveness Analysis of Collaborative Intelligent System

Based on the function-cost effectiveness analysis model discussed in Section 2.4, combined with the statistical data on average usage intensity of different types of roads in Beijing, the forecast data for the future ownership of intelligent vehicles in Beijing [34], the costs of roadside intelligent infrastructure at different levels, and the levels of autonomous driving functions that can be achieved by the vehicle-road collaborative intelligent scheme, the function-cost effectiveness brought by different levels of intelligent transformation of different levels of highways can be obtained, as shown in Figure 15. From the perspective of function-cost effectiveness, the order of intelligent upgrading of highways is as follows: motorway, class-1 highway, class-2 highway, and class-3 highway. It is worth noting that, regardless of the type of road, since the primary intelligent infrastructure can only serve primary and intermediate autonomous driving, with future technology and industry shifting towards the development of advanced autonomous driving, the function-cost effectiveness of the primary intelligent infrastructure will decrease year by year. The roadside intelligent capabilities will also need to be upgraded to higher levels to match the development needs of vehicle-side intelligence. Among them, as a closed road, expressways have a simple traffic scenario, lower technical difficulty, and possess the highest function-cost effectiveness, making expressways a priority for intelligent upgrading pilots. In contrast, by deploying primary/intermediate intelligent infrastructure on class-3 highways, the functional benefits reflected on the vehicle side, even by 2050, will not be able to recoup the costs of roadside intelligent infrastructure. It is expected that after 2035, directly deploying advanced intelligent infrastructure on class-3 highways will gradually become function-cost effective, and class-3 highways can be considered the last objects to be intelligently upgraded in the urban road network.

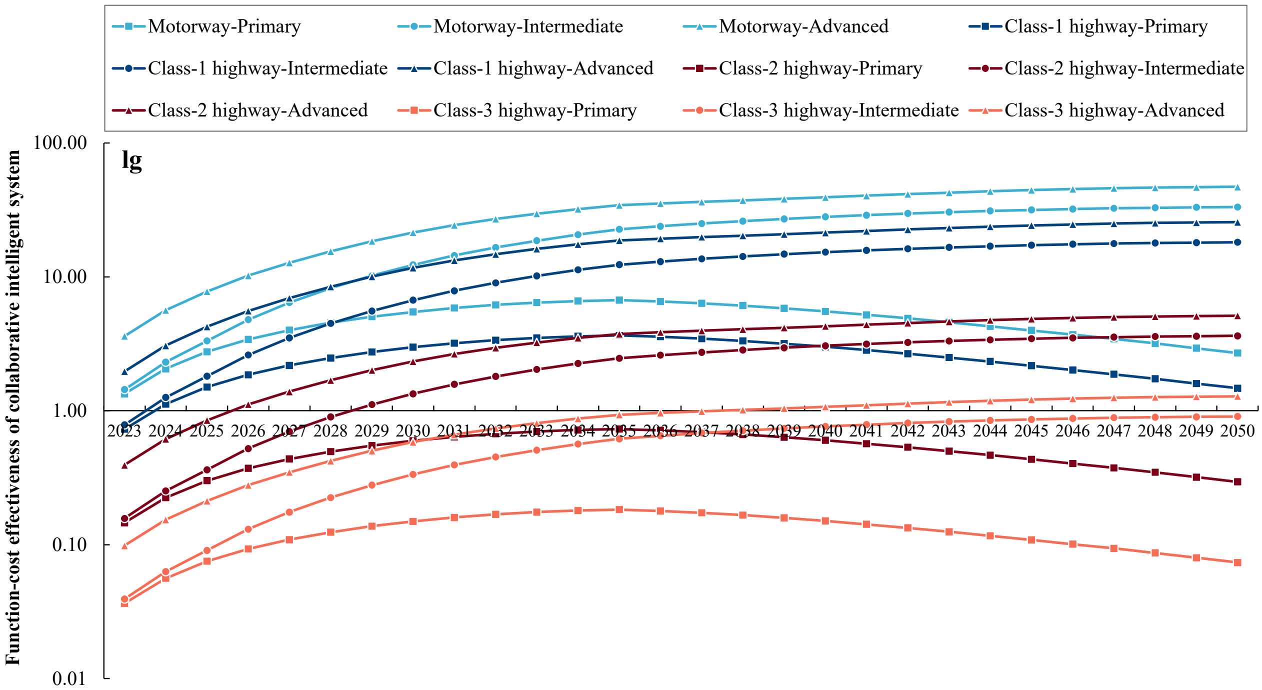

Figure 15. Function-cost effectiveness analysis of collaborative intelligent system (highway).

The results of the function-cost effectiveness brought by the intelligent transformation of different types of urban roads are shown in Figure 16. Overall, urban roads in Beijing have a higher function-cost effectiveness compared to highways. The order of intelligent upgrading of urban roads is as follows: urban expressways, urban main roads, and urban secondary roads. As semi-closed roads with relatively simple traffic scenarios, urban expressways have the smallest mileage scale and the highest function-cost effectiveness. They can be prioritized for intelligent upgrading on urban roads, and advanced intelligent schemes can be directly selected to support the demonstration and implementation of higher levels of autonomous driving, thereby achieving function-cost effectiveness. For main and secondary urban roads, the function-cost effectiveness of deploying primary or intermediate intelligent infrastructure is relatively low at the early stage of low penetration rates of ICVs. It is considered that with the improvement of the technical maturity of roadside intelligent schemes, the deployment of advanced intelligent roads on urban main and secondary roads can be completed after 2026 in sequence.

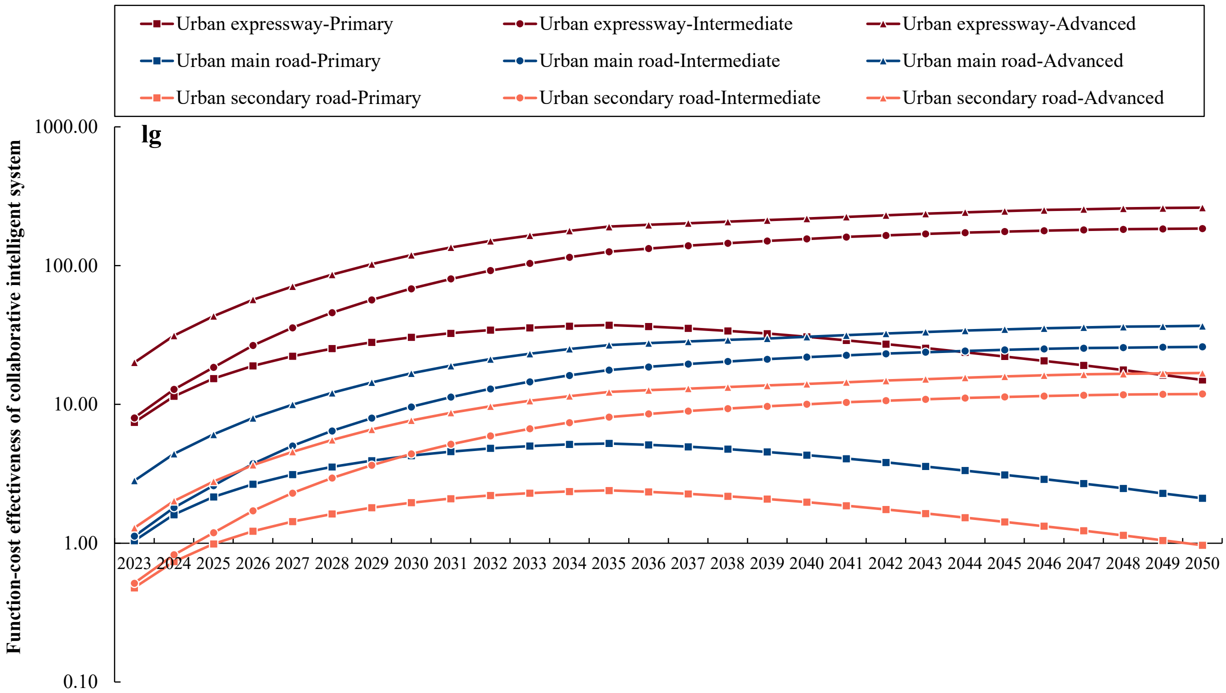

Figure 16. Function-cost effectiveness analysis of collaborative intelligent system (urban road).

3.4. Revenue and Cost Analysis of External Support Service

Revenue and Cost Analysis of Communication Carrier

Telecommunication operators, as key entities providing 5G communication services for ICVs, are assumed to deploy macro base stations and micro base stations along the roads of various types and bear the corresponding maintenance and power consumption costs. They aim to support the implementation of intermediate and advanced autonomous driving through 5G signal coverage for intelligent transportation. This paper considers three scenarios of user willingness to pay: the baseline scenario, the conservative scenario, and the optimistic scenario. In the baseline scenario, the vehicle communication service fee paid by users is the same as the 5G network service price of a mobile phone, which is ¥128/month. In the optimistic scenario, users fully recognize the role of high-performance communication networks in autonomous driving, and the vehicle communication service fee is ¥256/month. In the conservative scenario, users have a poor perception of the role of communication services and are willing to pay half the price of the mobile phone 5G network service for vehicle communication services. The paper calculates the relevant cost inputs of the 5G infrastructure for intelligent transportation by the telecommunication operators and the expected revenue under different scenarios, as shown in Figure 17.

Assuming the simultaneous deployment of macro base stations and micro base stations within the road network of Beijing, considering the deployment costs combined with their service life, maintenance costs, and power consumption costs, the comprehensive annualized cost for the telecommunication operators is ¥2.938 billion. By breaking down the annualized costs related to infrastructure, the costs associated with macro base stations account for nearly 95% of the total cost of communication infrastructure for the operators, with the power consumption cost of macro base stations accounting for 19% of the total cost. With the increase in demand for 5G communication networks due to the rise in the penetration rate of ICVs, under the baseline scenario, the total revenue obtained by the operators from users through communication service fees is expected to cover the related cost inputs in communication infrastructure by 2028. Under the optimistic scenario, the total revenue from communication service fees is expected to cover the related cost inputs in communication infrastructure by 2025. From the perspective of per-vehicle annualized cost allocation, with the increase in the penetration rate of intelligent connected vehicles, the per-vehicle annualized cost allocation for communication infrastructure has decreased from ¥6467/veh /year in 2023 to ¥314/veh/year by 2050. The actual revenue situation of communication operators in the future may vary due to factors such as industry competition, but it can be affirmed that intelligent transportation will become a key application scenario for 5G networks in the future, further expanding the market size of the communication industry. Considering that the actual deployment plan for macro base stations is often carried out according to regional scope, as shown in Figure 11a, and that Beijing has currently completed the deployment of 96,200 5G macro base stations in the main urban areas, the actual cost input of operators in communication infrastructure for intelligent transportation will be lower than the above calculation results.

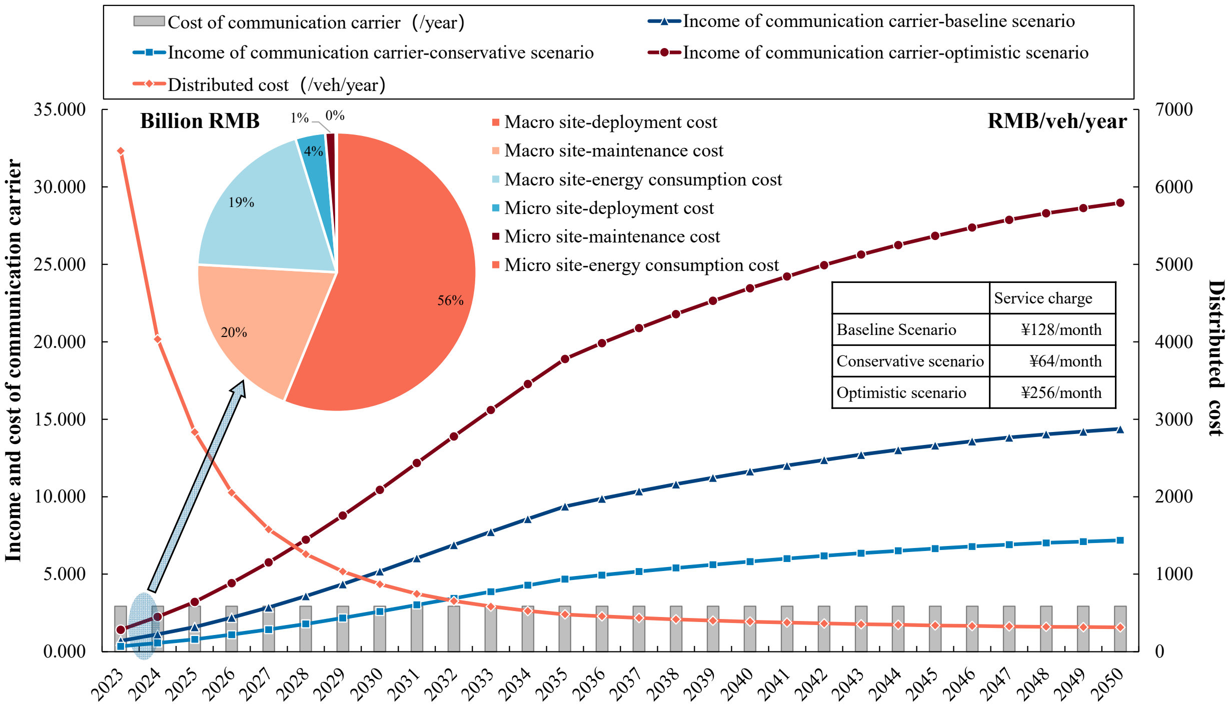

Figure 17. Revenue and cost analysis of communication carrier in Beijing.

4. Conclusions and Policy Suggestions

Contributions: This study, based on the architecture of the vehicle-road collaborative intelligent system, has constructed a model for the allocation of vehicle-road intelligent capabilities and a cost-sharing model. It has decomposed the intelligent capabilities of the vehicle side and roadside in terms of perception and computation, hardware and software, clarifying the mechanism by which vehicle-side intelligent capabilities are transferred to the roadside within the collaborative intelligent system. The study has built a quantification sub-model for perception capabilities and a matching sub-model for computing power, analyzing the allocation plans for vehicle-road intelligent capabilities to achieve different levels of autonomous driving functions. Different road types have different scenario characteristics. This study constructs a vehicle-road intelligent cost-sharing model and selects Beijing as a case study. Combining statistical data on the mileage scale and usage intensity of different highways and urban roads, as well as forecast data on vehicle ownership and the penetration rate of intelligent vehicles, it calculates the function-cost effectiveness of roadside intelligent schemes for different road types and analyzes the selection of roadside intelligent schemes and the corresponding deployment order for different road types in Beijing at different stages of development.

From the perspective of the allocation of vehicle-road intelligent capabilities, the research findings indicate that primary intelligent infrastructure primarily serves the intermediate autonomous driving of ICVs, while intermediate and advanced intelligent infrastructure can better cater to the advanced autonomous driving of ICVs, significantly reducing the cost of perception configurations and computing power on the vehicle side. In terms of the impact of roadside intelligent infrastructure deployment on the intelligent cost of vehicles, the primary intelligent infrastructure can reduce the lifecycle cost of the vehicle-side intelligent scheme for intermediate autonomous driving from ¥65,301 to ¥37,703. Advanced intelligent infrastructure can reduce the lifecycle cost of advanced autonomous driving from ¥126,938 to ¥42,180. In the future, with the deployment and utilization of urban cloud platforms, through collaborative planning and decision-making at the city road network level, the lifecycle cost for advanced autonomous driving on the vehicle side will further decrease to ¥40,687. The per-vehicle per-kilometer allocation cost will be reduced from ¥0.205/km to ¥0.197/km.

From the perspective of the function-cost effectiveness of intelligent infrastructure for the autonomous driving functions of ICVs, urban roads are generally superior to highways. The order of intelligent upgrading for urban roads is urban expressways, urban main roads, and urban secondary roads, while for highways, it is expressways, class-1 highways, class-2 highways, and class-3 highways. Among them, urban expressways, with the smallest mileage scale and the highest "function-cost effectiveness," can be prioritized for intelligent upgrading on urban roads, directly selecting advanced intelligent infrastructure schemes to support the demonstration and implementation of advanced autonomous driving. In contrast, class-3 highways will only gradually become function-cost effective after deploying advanced intelligent infrastructure after 2035 and can be considered the last objects for intelligent infrastructure upgrading in the urban road network.

From the perspective of the external support service, the urban communication operator is also the focus of this study in terms of costs and expected returns. By integrating the performance and costs of communication infrastructure with mainstream deployment schemes, this study calculates the deployment costs, power consumption costs, and maintenance costs associated with communication infrastructure. The annualized cost for communication operators to achieve 5G network coverage within the road network of Beijing is ¥2.938 billion. Under the baseline scenario, the 5G communication service fees obtained by communication operators from users will cover the annualized costs of the related infrastructure by 2028. The annualized allocation cost per vehicle for communication infrastructure will decrease from ¥6467 in 2023 to ¥314 by 2050. It can be said that as the support role of low-latency, high-bandwidth communication networks in intermediated and advanced autonomous driving functions of ICVs becomes increasingly evident, intelligent transportation will become an important application scenario for 5G networks in the future, driving further expansion of the market size of the communication industry.

Policy suggestions and industry participant recommendations: Based on national top-level planning, the government should improve the standard system construction, accelerate the deployment of the C-V2X network environment, and promote the demonstration of vehicle-road collaborative applications, preparing for the standardization and large-scale deployment of intelligent infrastructure. Financial support from the government for the construction of intelligent infrastructure will share the costs of vehicle intelligence with vehicle manufacturers, addressing the industry's profitability issues while reducing the costs of vehicle intelligence paid by users. To avoid the waste of intelligent infrastructure resources in the early stages, intelligent deployment and technological iterations can be prioritized on urban expressways and motorways. All industry participants in the collaborative intelligent system should leverage their existing business foundations to focus on the field of vehicle-road collaboration, build on their technological strengths, collaborate and divide tasks, actively participate in the construction of the intelligent connected vehicle industry ecosystem, and continuously accelerate the formation of a complete industrial system. This approach aims to implement higher-level autonomous driving solutions at a lower societal cost. Internet technology companies, with rich experience in big data and software algorithms, need to build perception networks, collaborative planning, and decision-making networks oriented towards the technological pathways of collaborative intelligence. Intelligent component enterprises should actively promote the landing of products with higher performance-cost ratios through technological innovation and actively develop roadside equipment adapted to different scenario characteristics, addressing the issue of low service life. With the support of intelligent road infrastructure, automotive companies should actively seek multi-party cooperation to achieve technological integration, accelerate the deployment of high-performance communication modules, and provide the terminal market with ICVs that are lower in cost and better in functional performance. Telecommunications companies, having accumulated rich experience in networking technology, should participate with the government in the construction of urban network environments, continuously expanding the application scenarios and business models of 5G-V2X.

This study has the following limitations. First, the "vehicle intelligence" scenario and the "collaborative intelligence" scenario are both based on the penetration rate forecasts of intelligent vehicles in the 'Intelligent Connected Vehicle Technology Roadmap 2.0.' without considering the potential increase in the penetration rate under the "collaborative intelligence" scenario. The deployment and use of intelligent infrastructure will reduce the cost of vehicle-side intelligence and significantly enhance the value of ICVs. However, the willingness of users to purchase intelligent vehicles is influenced by various factors, including the incremental costs of intelligence, the socio-economic situation, and the maturity of technology, which in turn affects the future market penetration rate. In our following research, we intend to quantify the correlation between the incremental costs associated with intelligence and the market penetration rate of intelligent vehicles. Second, in addition to achieving higher function-cost effectiveness in autonomous driving, collaborative intelligence schemes will also generate significant social and public benefits such as safety, efficiency, energy conservation, and emission reduction. Assessing and quantifying these benefits will represent a significant and valuable component of our forthcoming research endeavors.

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Appendix A

Combining the scene characteristics of different road types and the capabilities of various intelligent configurations, advanced schemes of intelligent infrastructure for different road types are designed, which has been published in our previous study [34]. Among them, the deployment scheme for urban expressways and highways is shown in Figure A1, and the deployment scheme for urban main roads and urban secondary roads is shown in Figure A2.

This study follows the previous advanced scheme of intelligent infrastructure. Since in this advanced scheme, different types of sensing devices all achieve full coverage of the road, the intermediate scheme, i.e., based on the advanced scheme, subtracts the deployment of LiDAR, retains the same number of cameras and millimeter-wave radars to achieve sensing coverage and matches the required computing and communication devices.

The primary roadside scheme retains the same number of cameras to achieve perceptual coverage and matches the required computing and communication equipment.

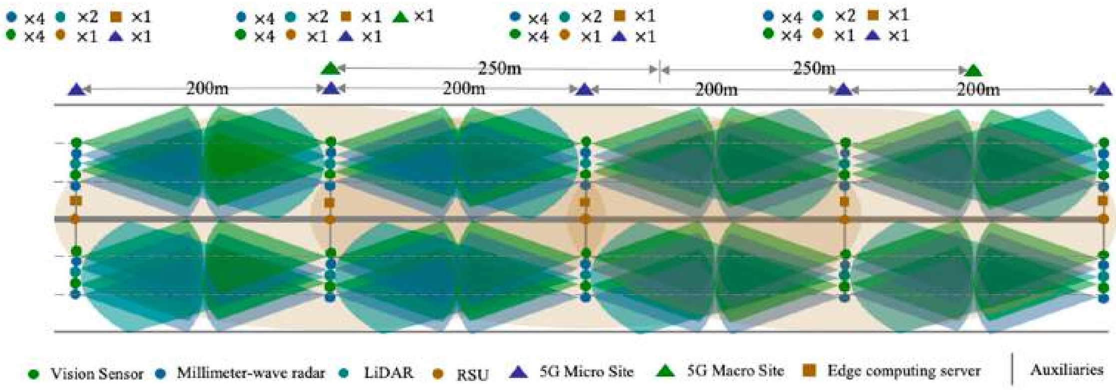

Figure A1. The roadside intelligence schemes of Motorway.

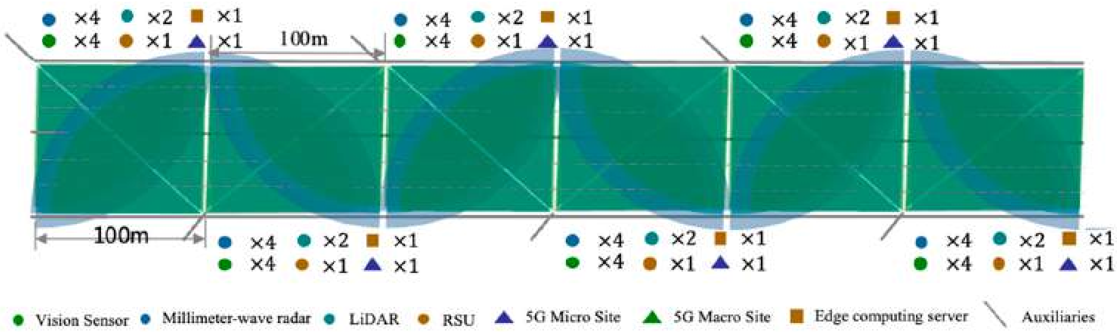

Figure A2. The roadside intelligence schemes of Urban road.

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