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RESEARCH ARTICLE

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Framework, model and algorithm for the global control of urban automated driving traffic

Abstract Automated driving has recently attracted significant attention. While considerable research has been conducted on the technologies and societal acceptance of autonomous vehicles, investigations into the control and scheduling of urban automated driving traffic are still nascent. As automated driving gains traction, urban traffic control logic is poised for substantial transformation. Presently, both manual and automated driving predominantly operate under a local decision-making traffic mode, where driving decisions are based on the vehicle's status and immediate environment. This mode, however, does not fully exploit the potential benefits of automated driving, particularly in optimizing road network resources and traffic efficiency. In response to the increasing adoption of automated driving, it is essential for traffic bureaus to initiate proactive dialogs regarding urban traffic control from a global perspective. This paper introduces a novel global control mode for urban automated driving traffic. Its core concept involves the central scheduling of all autonomous vehicles within the road network through vehicle-infrastructure cooperation, thereby optimizing traffic flow. This paper elucidates the mechanism and process of the global control mode. Given the operational complexity of expansive road networks, the paper suggests segmenting these networks into multiple manageable regions. This mode is conceptualized as an autonomous vehicle global scheduling problem, for which a mathematical model is formulated and a modified A-star algorithm is developed. The experimental findings reveal that (i) the algorithm consistently delivers high-quality solutions promptly and (ii) the global scheduling mode significantly reduces traffic congestion and equitably distributes resources. In conclusion, this paper presents a viable and efficacious new control mode that could substantially enhance urban automated traffic efficiency.

Keywords automated driving, urban traffic control, global scheduling mode, autonomous vehicle route planning, A-star algorithm

1 Introduction

As one of the most innovative and pioneering technologies in the 21st century (Paden et al., 2016; Sener et al., 2019; Golbabaei et al., 2020; Narayanan et al., 2020), automated driving stands poised to reshape the automotive industry and revolutionize traffic and urban infrastructure (Fagnant and Kockelman, 2015). Since the onset of the century, automated driving has attracted significant attention due to its substantial potential benefits (Milakis et al., 2017; Morando et al., 2018; Fafoutellis and Mantouka, 2019). Numerous traditional automobile manufacturers, first-tier suppliers, internet giants, and research institutions have invested in the development of related technologies (Greenblatt and Shaheen, 2015; Xu et al., 2018a). Prominent technology companies such as Google, Baidu, Huawei, and Tesla have propelled the rapid advancement of advanced technologies such as 5G communications, the Internet of Things, and high-precision mapping. Low-level autonomous vehicles are increasingly entering markets, while high-level autonomous vehicles are gradually progressing to the testing stage (Tesla, 2016; Google, 2020). Fully autonomous vehicles are anticipated to become a reality in the coming decades (Piao et al., 2016; Cascetta et al., 2022). Automated driving will significantly affect urban transportation systems, prompting government administrators, transportation experts, and scholars to explore new approaches to advance the management of automated transport systems (Lipson and Kurman, 2016).

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However, the current literature predominantly centers on technological development and public intentions, with limited exploration of the management of urban automated driving traffic. Consequently, this paper aims to address the following two pivotal questions that are absent from the literature:

(i) What changes will occur in the future management mode of urban traffic as automated driving becomes more prevalent?

(ii) Within the new control mode, are there any innovative methods for optimizing traffic, and what benefits can be realized for urban traffic?

Urban transport control modes can be broadly categorized into two types: local scheduling modes and global scheduling modes. Presently, even though some low-level autonomous vehicles are integrated into the road network, urban traffic predominantly adheres to manual driving under the local scheduling mode. This mode includes route and trajectory planning (including lane changes) for a vehicle to minimize costs based on its origin, destination, and real-time perception of the immediate environment. The existing vehicle-infrastructure cooperation (VIC) approach also falls within the purview of the local scheduling mode. Nevertheless, this approach tends to engender unequal allocation of road resources, thereby constituting a primary cause of traffic congestion. Conversely, the global scheduling mode regulates and schedules all vehicles within a region equitably, relying on their information and real-time traffic conditions. This mode can optimally harness the potential benefits of automated driving on urban traffic by centralizing vehicle control authority within the traffic department. Consequently, the allocation of road network resources transitions from a passive model based on driver decisions to an active model dictated by system decisions, eventually evolving into a collaborative framework governed by the interactions between vehicles and the road network.

Automated driving serves as the technical foundation for the global scheduling mode, as it transforms unpredictable and uncontrollable human behavior into predictable and controllable system decisions (Mordue et al., 2020). Although no literature specifically addresses the global scheduling mode within the context of urban automated driving, analogous concepts and issues have been successfully implemented in other scenarios. A notable example is the automated guided vehicle (AGV) scheduling system employed in intelligent warehouses, such as Amazon's KIVA system. In this entirely closed and automated transport setting, the intelligent warehouse functions analogously to a road network, with AGVs assuming the role of autonomous vehicles. All the AGV routes and driving information are collected and determined by the warehouse scheduling system. Warehouse managers are primarily responsible for introducing, arranging, and maintaining systems and facilities, as well as refining scheduling algorithms. Compared to traditional manual operation warehouses, this automatic global scheduling system enhances operational efficiency by a factor of 2-4 (Wulfraat, 2012).

Numerous studies have investigated the adoption of the global scheduling mode in specific contexts, such as city road intersections. For instance, in closed and autonomous material handling scenarios such as ports and smart workshops, the global scheduling mode is commonly employed. Concerning urban traffic challenges, Chouhan and Banda (2018) proposed the introduction of a central controller capable of assigning a consistent speed to each autonomous vehicle within an intersection area. They also devised a heuristic algorithm to assess the performance of this centralized control mode. The findings underscore the substantial enhancement of traffic efficiency and congestion alleviation through the implementation of global control at intersections. Similarly, Liu et al. (2020) and Pan et al. (2023) conducted studies on the scheduling problem of autonomous vehicles at intersections under centralized control. Moreover, the literature, such as that of Leclercq et al. (2021), has emphasized the importance of balancing traffic flow from macro- and global perspectives to mitigate congestion. These studies provide theoretical underpinnings for the adoption of the global scheduling mode in urban traffic with automated driving.

In the context of urban automated driving traffic, the vehicle scheduling problem within the global scheduling mode can be summarized as follows: leveraging a traffic control platform to devise a collision-free driving plan for multiple autonomous vehicles. This approach aims to optimize the overall operation of the road network while considering the current state of the road network. Notably, the autonomous vehicle global scheduling problem (AVGSP) differs from that in previous literature in two key aspects. First, it necessitates the establishment of new transportation operation logic, identification of participating entities, and clarification of their respective responsibilities. Second, explicit and rational traffic control rules must be implemented to address unique situations, such as multi-vehicle conflicts. In terms of infrastructure, driving rules, control methods, policies, and regulations, the global scheduling mode deviates significantly from the current local scheduling mode. Therefore, a comprehensive discussion of the traffic operation framework, process, and control rules of this mode is crucial.

Anticipating modernized urban transport systems in the coming decades, innovative transit modes and vehicles are expected to play a defining role (Gao et al., 2023). Many countries are prioritizing the development of intelligent transport systems (ITSs) integrated with automated driving as a strategic direction for urban traffic. The primary contributions of this paper are as follows:

(i) Proposing a novel global scheduling mode for urban automated driving traffic based on VIC, elucidating its operational mechanism and rules.

(ii) Introducing a “road network zoning-global scheduling of vehicles within the subregion” strategy and defining the AVGSP within this framework.

(iii) Formulating the new problem as a mixed-integer linear programming problem (MILP). To increase the amount of MILP solution needed, valuable cuts are introduced. The experimental results demonstrate that these inequalities reduce solution times by an average of 61%.

(iv) Considering the problem as a variant of the shortest path problem, a modified A-star algorithm (MASA) is developed and evaluated for its effectiveness through comparisons with MILP and the traditional A-star algorithm. The results indicate that the proposed algorithm efficiently obtains optimal or near-optimal solutions in a short time. Importantly, experiments with different penetration rates of autonomous vehicles highlight that the global scheduling mode significantly enhances traffic efficiency and resource allocation balance.

The paper is structured into seven sections. Section 2 reviews pertinent related research. Section 3 outlines the operational mechanisms and rules governing the global scheduling mode in urban automated driving traffic. Section 4 formulates the AVGSP as a MILP model. Section 5 presents the development of an enhanced A-star algorithm. Section 6 discusses the computational experiments and their analysis. Finally, Section 7 provides a summary of the conclusions and suggests potential directions for future research.

2 Literature review

Automated driving has become a prominent global phenomenon in the 21st century (Czech, 2018). Extensive academic research has been dedicated to this subject. In this study, we systematically reviewed approximately 1000 highly pertinent papers published between January 2012 and December 2022 extracted from the Web of Science database. Our search criteria included keywords such as “autonomous vehicle,” “automated vehicle,” “driverless,” “autonomous driving,” and “automated driving.”

To analyze this corpus of literature, we harnessed the VOS Viewer, a powerful tool. This approach facilitated the creation of a network map that considered keywords with a minimum occurrence of five and set a threshold of 38. Of the 3979 keywords, we selected the 300 most frequently recurring ones. As depicted in Fig. 1, the existing body of literature can be categorized into three principal subsections:

(i) Research on automated driving technologies constitutes a substantial portion of the literature. It includes various facets, such as autonomous vehicle positioning (Zheng et al., 2019); collision avoidance strategies (Guo

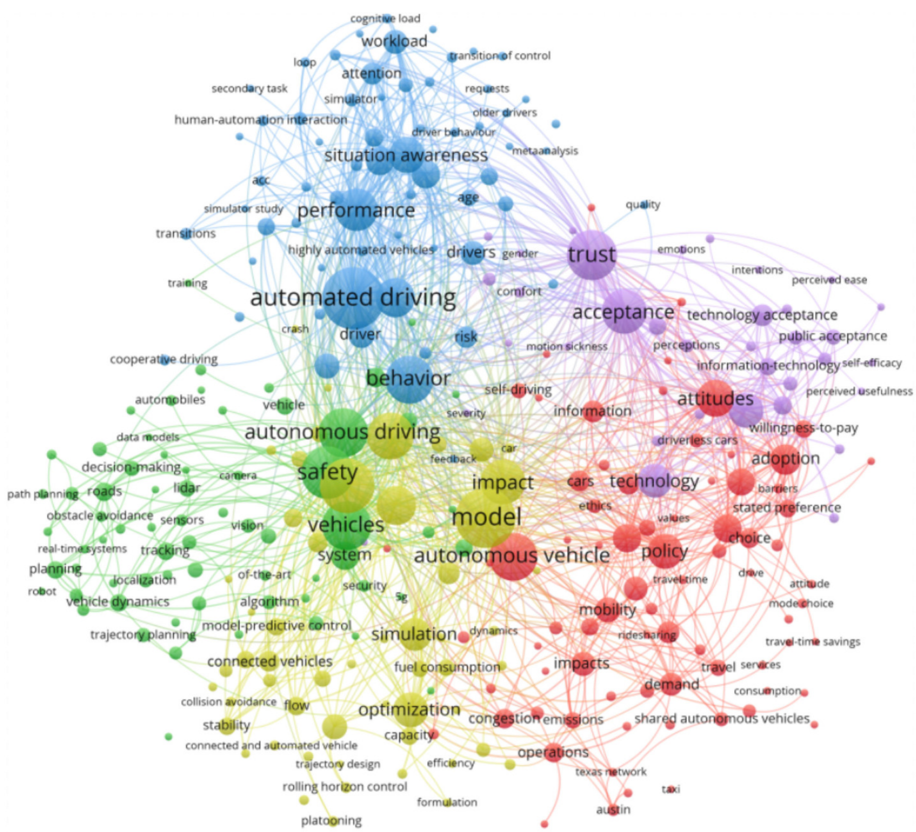

Fig. 1 Network visualization of the 300 most frequently occurring keywords in automated driving.

et al., 2019); control of driving behaviors, including lane changes, shifting, and turning (Khattak et al., 2020); and intersection scheduling and local path planning (Lam et al., 2016). Additionally, research in this domain addresses the construction of test scenarios (Shao et al., 2019) and the design of both hardware and software components (Fayazi et al., 2019).

(ii) Research related to policies, public acceptability, and acceptance (Panagiotopoulos and Dimitrakopoulos, 2018; Rosell and Allen, 2020; Pigeon et al., 2021) constitutes another significant body of work. Studies in this category predominantly focus on the current stage of autonomous vehicle acceptance (Gkartzonikas and Gkritza, 2019), pivotal factors influencing public acceptance (Kyriakidis et al., 2015; Zhang et al., 2019; Golbabaei et al., 2020; Rezaei and Caulfield, 2020; Janatabadi and Ermagun, 2022), and associated themes.

(iii) Research about the implementation methods of automated driving includes both individual automated driving (IVD) and VIC (Bansal and Kockelman, 2017; Ma, 2020). Additionally, scholars have conducted surveys to evaluate the effects of automated driving on traffic efficiency, traffic regulations, urban development, and other pertinent aspects (Fagnant and Kockelman, 2015; Duarte and Ratti, 2018).

However, to the best of our knowledge, the control mode of urban automated driving traffic has not been extensively studied thus far.

2.1 Automated driving technology

Since the mid-20th century, automated technologies have undergone continuous refinement and enhancement (Alawadhi et al., 2020). The present progress in high-level automatic driving systems is largely attributable to the emergence of innovative technologies (Ma et al., 2020). Prominent global entities, including Google, Baidu, Uber, Huawei, and Tesla, have achieved notable milestones in the domain of urban unmanned buses and robot taxis. Notably, in China, Baidu's Apollo 2.0 driverless platform system enabled automated driving on urban roads as early as 2017 (National Bureau of Statistics, 2018). In October 2020, a 5G unmanned bus operating at Level 4 automation was introduced through a collaboration between China Mobile and Light Boat Smart, and it has since been in regular operation in the Suzhou High-speed Railway New City. On April 28, 2022, China marked a significant milestone with the launch of Baidu's fully automated travel service in Beijing (Baidu Apollo, 2022), establishing the world's first unmanned travel service in a megacity. Furthermore, a survey conducted by McKinsey Company involving 75 executives from automotive, transportation, and software companies engaged in global autonomous driving endeavors revealed that large-scale deployments of self-driving taxi services are anticipated by 2026 or beyond, with China and the US leading this transformative market (Heineke et al., 2021). In summary, China's automated driving technologies have exhibited remarkable maturity, as evidenced by groundbreaking projects and successful corporate initiatives.

Moreover, while automated driving has yet to attain full implementation in specific urban traffic scenarios, the AGV scheduling system within smart warehouses serves as a compelling proof of concept. In this context, a warehouse essentially mirrors a conventional road network, where AGVs assume the role of autonomous vehicles, physical facilities represent obstacles, and order parallel travel requirements. Consequently, the internal logistics processes of smart warehouses can be likened to automated traffic operations within controlled, enclosed road networks. Presently, numerous e-commerce enterprises have seamlessly integrated unmanned robotic systems, such as Amazon's KIVA system, Jingdong's unmanned warehouse system, and Cainiao Tmall's supermarket fast warehouse system. The operational paradigms and regulations employed within these smart warehouses yield invaluable insights into the domain of urban automated driving traffic. Additionally, as urban local logistics scenarios, including unmanned ports and unmanned distribution, continue to advance, urban management authorities have the opportunity to accumulate practical experience and explore more refined development models.

2.2 Individual automated driving and vehicle-infrastructure cooperation

Automated driving unfolds along two principal development trajectories: the IVD and VIC. Historically, research has focused primarily on IVD, involving the reliance of vehicles on a suite of sensors, including vision, millimeter-wave radar, and lidar devices, as well as computing units and wired control systems. These components collectively enable environmental perception, computational decision-making, and control execution. However, the IVD has noteworthy limitations:

(i) Safety concerns persist (Koopman and Wagner, 2017). Despite substantial advancements in enhancing safety, IVDs have managed to mitigate risks by up to 99%; however, the remaining 1% of risk remains unresolved and poses a challenge that is unlikely to be fully surmounted for the foreseeable future. Ensuring the reliability and capability of Level 5 autonomous vehicles to navigate complex traffic scenarios solely through single-vehicle intelligence remains a formidable challenge.

(ii) Economic impediments have surfaced. The integration of additional onboard sensors and systems in autonomous vehicles significantly inflates costs, presenting a bottleneck in the widespread adoption of these vehicles.

(iii) The challenges associated with road environment recognition persist. Urban traffic scenarios introduce variables such as unpredictable human behavior, extreme weather conditions, and unforeseen accidents, creating a milieu of uncertainties external to the vehicle. These complexities render it difficult for single-vehicle intelligence to accurately discern the road environment and effectively navigate complex situations.

In response to the limitations of IVD, VIC has emerged as a viable alternative. VIC pivots toward enhancing intelligent infrastructure built upon the foundation of IVDs. This approach mandates equipping automated vehicles with vehicle-to-everything devices, enabling seamless connectivity across the human-vehicle-road-cloud nexus through advanced wireless communications and next-generation internet technologies. In contrast to the IVD, the VIC compensates for deficiencies in vehicle perception, thereby bolstering safety and efficiency in driving. Furthermore, the cost paradigm shifts from individual vehicles to infrastructure, distributing the economic burden over time and across the infrastructure itself. VIC holds the promise of alleviating economic constraints for residents, rendering autonomous vehicles more accessible for widespread commercialization. Given these advantages, policymakers, industry experts, and researchers are increasingly gravitating toward VIC or connected autonomous vehicles (Bansal and Kockelman, 2017). The prevailing consensus is that VIC represents a more auspicious approach to achieving global optimization of the overall efficiency of a transportation system (Ma, 2020).

It is noteworthy that the current VIC implementations primarily operate within a local scheduling mode. The fundamental distinction between VIC and IVD resides in how vehicles interact with their surroundings and the degree to which environmental information is harnessed. Under the IVD framework, vehicles amass local environmental data through their sensor systems and devise optimal paths to minimize driving costs. Conversely, the VIC mode emphasizes the aggregation of all information via Internet technologies before disseminating distilled data to each vehicle. Ideally, the VIC framework should facilitate global control with the overarching goal of optimizing overall traffic operations. Nevertheless, in practice, current VIC implementations predominantly focus on optimizing individual vehicle performance rather than achieving comprehensive global optimization.

2.3 National policies and social acceptance

Policy support constitutes a pivotal driving force for the advancement of automated driving. In 2013, the National Highway Traffic Safety Administration of China (NHTSA) issued the "*Preliminary Statement of Policy Concerning Automated Vehicles*," a seminal document that initially defined levels of driving automation. Subsequently, in 2016, the Vienna Convention for Road Traffic (Geneva) officially embraced automated driving. Concurrently, the Society of Automotive Engineers of China introduced a more detailed classification system comprising six levels for autonomous vehicles (SAE, 2016). Recently, countries have been actively formulating policies to regulate, guide, and promote the development of autonomous transportation. In 2019, the European Union unveiled the "*Guidelines for the EU Autonomous Vehicle License Exemption Process*." In 2020, the United States promulgated "*Ensuring American Leadership in Automated Vehicle Technologies: Automated Vehicles 4.0*." Notably, in May 2021, the German Bundestag ratified a draft of "*Autonomous Driving Legislation*," rendering Germany the world's first country to permit driverless vehicles to operate in daily traffic.

In recent years, China has notably bolstered its policy guidance and support for automated driving. In 2018, the National Development and Reform Commission of China identified the intelligent automobile industry as a "strategic and pillar industry." In February 2020, the "*Intelligent Vehicle Innovation Development Strategy*" further refined the top-level blueprint for China's intelligent vehicle industry development. This study articulated the objective of achieving large-scale production of intelligent vehicles with conditional automated driving and promoting the market adoption of highly autonomous vehicles in specific environments. As of June 2023, a cumulative total of more than 100 policies pertaining to the autonomous driving industry have been collectively issued by national-level entities and 18 provincial-level entities in China. Importantly, the Chinese government has accorded significant attention to VIC and has actively devised strategic plans and standards. The VIC is consistently emphasized as the preferred developmental route, aligned with big data information platforms, for constructing an integrated transport system and advancing intelligent transportation. Notably, in 2021, with the commencement of China's "14th Five-Year Plan," intelligent transportation has emerged as a critical factor in enhancing national transportation infrastructure. The integration and harmonization of "human, vehicle, road, and cloud" technologies have become significant, and the deployment and utilization of VIC and the Internet of Vehicles technologies have experienced notable acceleration. Consequently, the trajectory of urban automated driving will be predominantly guided by VIC as the principal approach.

Public willingness and acceptance hold significant importance in expediting the development of automated traffic (Xu et al., 2018b; Liu et al., 2019). Empirical studies employing randomized methods have collected data from international organizations or specific national regions. These findings consistently underscore widespread public support for automated driving and the anticipation of its broader integration into future traffic (Kyriakidis et al., 2015; Schneble and Shaw, 2021). Furthermore, there has been a consistent upward trend in public acceptance of autonomous vehicles over the years (Zmud et al., 2016;

Sener et al., 2019). Additionally, ample literature reveals that public acceptance is influenced by various factors, including age (Zou et al., 2022), technological literacy (Ho et al., 2020), educational attainment (Haboucha et al., 2017), income levels (Howard and Dai, 2014), and pricing considerations (Rezaei and Caulfield, 2020). Trust in autonomous technologies emerges as a pivotal determinant of people's willingness to utilize autonomous vehicles (Piao et al., 2016; Kaur and Rampersad, 2018; Rezaei and Caulfield, 2020). In 2021, research data from the E-Car Research Institute indicated that 32.28% of Chinese users were willing to pay for self-driving cars, with only 15.65% expressing reluctance. Notably, 52.07% adopted a wait-and-see stance, suggesting a high likelihood of conversion to willing users. Collectively, this body of literature underscores that as self-driving vehicles accumulate greater testing mileage, expand their range of test scenarios, and demonstrate enhanced safety, public trust in the associated technologies will substantially increase. This heightened trust is poised to drive the rapid expansion of the autonomous vehicle market, particularly in China, and catalyze the advancement of automated traffic systems.

2.4 Centralized and decentralized decision modes

Moreover, research into urban traffic control modes and methodologies can be divided into two primary paradigms: centralized control and decentralized decision-making. In a centralized system, all traffic data are transmitted to a central controller, which assumes responsibility for executing all control actions (Chow and Sha, 2016). In contrast, within a decentralized system, each vehicle autonomously determines its actions based on information acquired through sensors or received from other vehicles and roadside units, aiming to maximize its performance (Yao and Li, 2020). A substantial body of literature has explored the efficacy of centralized and decentralized decision modes in the context of urban traffic. However, it is noteworthy that almost all of the literature addressing centralized or decentralized decision modes, without considering the traffic environment, predominantly concentrates on optimizing traffic signal timings, as evident in Table 1. These studies prioritize the minimization of traffic delays within the road network by regulating the timing plan of all traffic signals across the network. Notably, these endeavors are not oriented toward controlling individual vehicles or influencing vehicle trajectories. Given their vehicle-agnostic nature, these studies fail to distinguish between human-operated and automated driving environments.

Conversely, within the domain of automated driving environments, research has predominantly explored the concept of centralized decision-making within localized scenarios, particularly at intersections. These investigations often treat the intersection as the focal point,

Table 1 An overview of the relevant literature

Literature	Traffic environment a)	**C/D** b)	Problems	Methods
Chow and Sha (2016)	U	C&D	Traffic signal control	A cell transmission model
Chow et al. (2020)	U	C&D	Traffic signal control	A model-based approach
Fei et al. (2023)	U	D	Traffic signal control	Stochastic mixed-integer programming and benders decomposition
Liang et al. (2023)	M	D	Traffic signal control	A decentralized arterial signal control algorithm
Yu et al. (2023)	M	D	Traffic signal control	A deep reinforcement learning approach
Li and Zhou (2017)	A	C	Traffic signal control	Branch-and-bound algorithms
Xu et al. (2019)	M/A	C	Trajectory optimization of a single vehicle in multiple intersections	A double-layer speed optimization method
Wei et al. (2017)	M	C	Jointly optimizing multi-vehicle trajectories in a platoon	A 0–1 integer linear programming model and dynamic programming
Yao and Li (2020)	M	D	Minimize each automated vehicle own travel time, fuel consumption and safety risks at an isolated signalized intersection	A decentralized connected automated vehicle trajectory optimization model
Mansourianfar et al. (2021)	M	C	Simulation-based dynamic traffic assignment	Mixed equilibrium simulation-based dynamic traffic assignment algorithm.
Bifulco et al. (2024)	M	D	The safe crossing problem of an unsignalized intersection	Model and simulation
Chen et al. (2020)	A	C	Cooperative control of multiple vehicles in non-signalized intersection networks	Establish a microscopic traffic model with the conflict-free geometry topology, the communication topology, and the control algorithm
Bian et al. (2020)	A	D	Distributed cooperative driving at unsignalized intersections beyond IVD and VIC	Distributed observation, optimization, and control algorithms
Hao et al. (2023)	A	C	Vehicle trajectories at an isolated "signal-free" intersection without lane allocation	A mixed-integer linear programming (MILP) model
This paper	A	C	Autonomous vehicle global route planning	A MILP model and heuristic algorithm

Notes: a) A–Automated driving traffic, M–Mixed traffic, U–unlimited; b): C–centralized, D–decentralized.

delineating a control radius and establishing a centralized decision zone. Within this zone, the system dictates parameters such as vehicle speed, priority (governed by collision avoidance rules), and other pertinent factors (Chen et al., 2020). Furthermore, some studies have investigated the domain of distributed cooperative driving at unsignalized intersections, extending beyond the domains of the IVD and VIC (Bian et al., 2020). Nonetheless, these studies chiefly concentrate on controlling specific driving decisions within the local road network with the aim of enhancing traffic efficiency. They do not involve the planning of vehicle paths, nor do they endeavor to balance the utilization of road network resources or regulate traffic density within individual road segments. This observation aligns with the findings of a recent review conducted by Li et al. (2023), which included research on automated transportation.

Additionally, a subset of studies centers on the planning of vehicle paths or trajectories within mixed-traffic environments, including both human-driven and automated vehicles. For instance, Xu et al. (2019) investigated trajectory optimization for a single vehicle navigating multiple intersections, with a focus on enhancing fuel efficiency and trip efficiency. Nevertheless, the paths or trajectories of partially human-driven vehicles inherently exhibit unpredictability and resistance to centralized control. Consequently, comprehensive planning of vehicle paths from origin to destination using a singular system remains a formidable challenge.

2.5 Analysis

Certainly, automated driving confronts an array of formidable challenges, including limitations in test mileage accumulation; elevated production costs; and substantial regulatory, legal, and ethical hurdles (Sparrow and Howard, 2017). However, the potential advantages stemming from automation, including both direct economic and environmental benefits, in addition to the prospect of enhancing residents' overall quality of life, are indeed profound (Howard and Dai, 2014). As technology continues to advance and regulatory frameworks evolve, automated driving traffic is likely to emerge as the predominant mode of transportation on a global scale within the span of a few decades. Nevertheless, current research patterns reveal a noteworthy disparity, with more than 80% of the scholarly literature predominantly concentrating on autonomous technology disciplines, such as engineering, computer science, and automation control systems. In stark contrast, a mere 0.3% of the literature is dedicated to addressing scientific aspects, with a mere 0.03% focusing on urban-centric issues. This distribution underscores that scholarly endeavors have predominantly centered on technological facets, with a limited cohort of researchers engaging in comprehensive analyses concerning the effect of autonomous vehicles on future traffic dynamics and the requisite adaptations of traffic systems to accommodate this transformative shift.

In light of these considerations, the primary objective of this paper is to investigate the urban traffic scheduling mode within the context of an automated driving environment. This exploration will investigate the operational conditions, underlying mechanisms, and prospective advantages inherent to this emergent scheduling paradigm. Through this endeavor, the paper seeks to furnish a better understanding of the future landscape of autonomous vehicles within urban traffic systems.

3 Global scheduling mode of urban automated driving traffic

The overarching objective of automated driving development is the attainment of complete driving automation (Panagiotopoulos and Dimitrakopoulos, 2018). Nevertheless, the pace of implementation and the strategies for managing automated driving initiatives exhibit considerable disparities among nations. These disparities stem from marked distinctions in technical standards, policies, regulations, and road attributes. This paper, in particular, concentrates on the context of China by rigorously scrutinizing the pivotal facets of fully automated driving. This examination will include the developmental trajectory and the associated traffic scheduling paradigm.

3.1 Concept of the global scheduling mode

This paper introduces an innovative global scheduling mode tailored for urban automated driving traffic. Drawing inspiration from the concept of VIC, this mode positions the urban traffic department as the central hub, harnessing the capabilities of the ITS and incorporating data from vehicle onboard systems within its jurisdiction to orchestrate comprehensive and uniform vehicle scheduling across the entire road network. The mode accentuates two overarching global dimensions:

(i) Network-wide vehicle scheduling, which entails the universal scheduling of all vehicles within a specific road network.

(ii) Comprehensive vehicle path planning, which involves the rigorous generation of detailed and complete driving paths for each vehicle, spanning from its point of origin to its intended destination.

In the conventional traffic paradigm, key components include traffic regulations, driver proficiency, and traffic signalization. However, as autonomous vehicles progressively integrate into urban traffic, a transition toward mixed traffic configurations becomes apparent. During this transitional phase, some autonomous vehicles autonomously determine their local paths based on real-time road conditions within their immediate vicinity. Nevertheless, the presence of human-driven vehicles necessitates continued reliance on traffic regulations, human driving skills, and traffic signals. In a future scenario where only autonomous vehicles populate urban traffic, the necessity for traffic signals may diminish (Duarte and Ratti, 2018). Traffic regulations can be seamlessly integrated into scheduling algorithms, thereby obviating the need for the general public to acquire traditional driving skills. Information sourced from infrastructure and vehicles on the road could be interconnected and consolidated within an urban ITS framework. This overarching system assumes responsibility for the holistic scheduling of all vehicles, ultimately facilitating the development of a highly efficient urban road network.

Fully automated driving traffic underpinned by centralized control and global scheduling offers an array of compelling advantages:

(i) Augmented urban road network capacity: Autonomous vehicles are inherently designed to operate at elevated speeds while maintaining minimal yet safe separation from other vehicles. This characteristic serves to mitigate traffic congestion and enhance traffic efficiency. Concurrently, global scheduling ensures that each vehicle can identify the optimal or near-optimal path aligned with the current conditions of the road network, further amplifying overall traffic efficiency.

(ii) Enhanced risk management and emergency response: Global scheduling empowers traffic management authorities to monitor the real-time operational status of the entire road network, enabling swift responses to unforeseen traffic incidents. Specialized vehicles such as police cars, ambulances, and fire trucks can be scheduled with increased flexibility, ensuring expedited passage when exigent circumstances arise.

(iii) Elevated traffic safety: Global scheduling amalgams vehicle data and accurately anticipates the driving trajectories of each vehicle. This approach mitigates issues such as delayed responses and imprecise identification often encountered in localized decision-making, resulting in a safer and more dependable driving experience.

In summary, global scheduling maximizes the inherent benefits of automated driving and fosters the sustainable evolution of urban traffic, characterized by efficiency, orderliness, safety, convenience, and environmental sustainability. As automated driving has gained widespread adoption and the VIC paradigm has matured, seamless real-time information exchange among vehicles, road infrastructure, pedestrians, and cloud-based platforms has become the norm. Capitalizing on dynamic traffic data across both spatial and temporal dimensions, global scheduling is primed to emerge as a pivotal trend shaping the future of transportation.

3.2 The mechanism of the global scheduling mode

While global scheduling has a multitude of advantages, as elucidated in Section 3.1, it also imposes more demanding prerequisites on hardware and software configurations. The ideal global scheduling mode depends on a centralized cloud control platform capable of affecting the comprehensive management of all autonomous vehicles. However, within the context of the urban traffic landscape, characterized by openness, high complexity, nonlinearity, and a plethora of participants, this ideal mode poses considerable challenges to the administrative capabilities and computational capacities of traffic department equipment.

To confront the intricacies of control and surmount computing limitations, the incorporation of existing urban traffic control concepts has given rise to the concept of large-scale road network partition control (Walinchus, 1971; Dantsuji, 2020). This approach entails the division of the road network into multiple homogeneous and manageable traffic subregions, predicated on specific criteria, followed by the implementation of interregional coordination-zoning control (Leclercq et al., 2021). The global scheduling of autonomous vehicles is executed within each subregion. Notably, the control mechanism for each subregion mirrors that of an unzoned urban area, differing primarily in response time due to computational capabilities.

The urban road network partition and global scheduling mechanism within each traffic control subregion are visually shown in Fig. 2. Each subregion includes a standardized and unified ITS, with seamless data integration among systems. The ITS comprises multiple functional modules responsible for data collection, traffic information processing, and vehicle scheduling. The scheduling module assumes two pivotal functions:

(i) Monitoring and real-time updating of global road network information within the subregion, including high-precision map data, road conditions (e.g., vehicle density and intersection flow), and environmental factors such as weather.

(ii) Scheduling of autonomous vehicles within the subregion. Ideally, the ITS would make real-time scheduling decisions for every autonomous vehicle entering the road network. However, practical challenges arise concerning computational power when managing real-time scheduling for a continuously growing influx of vehicles. To address this, we propose scheduling decision-making based on fixed cycles, during which the driving requests of autonomous vehicles poised to enter the road network are collected. When the next scheduling cycle commences, the ITS uniformly schedules them.

The scheduling process can be succinctly summarized as follows: At predetermined intervals P (in seconds or minutes), the ITS uniformly schedules newly entering autonomous vehicles. When an autonomous vehicle transmits a driving request, its onboard system instantaneously uploads pertinent information (e.g., vehicle location, destination) to the ITS. If the request moment does not coincide with the initiation of a specific cycle, the

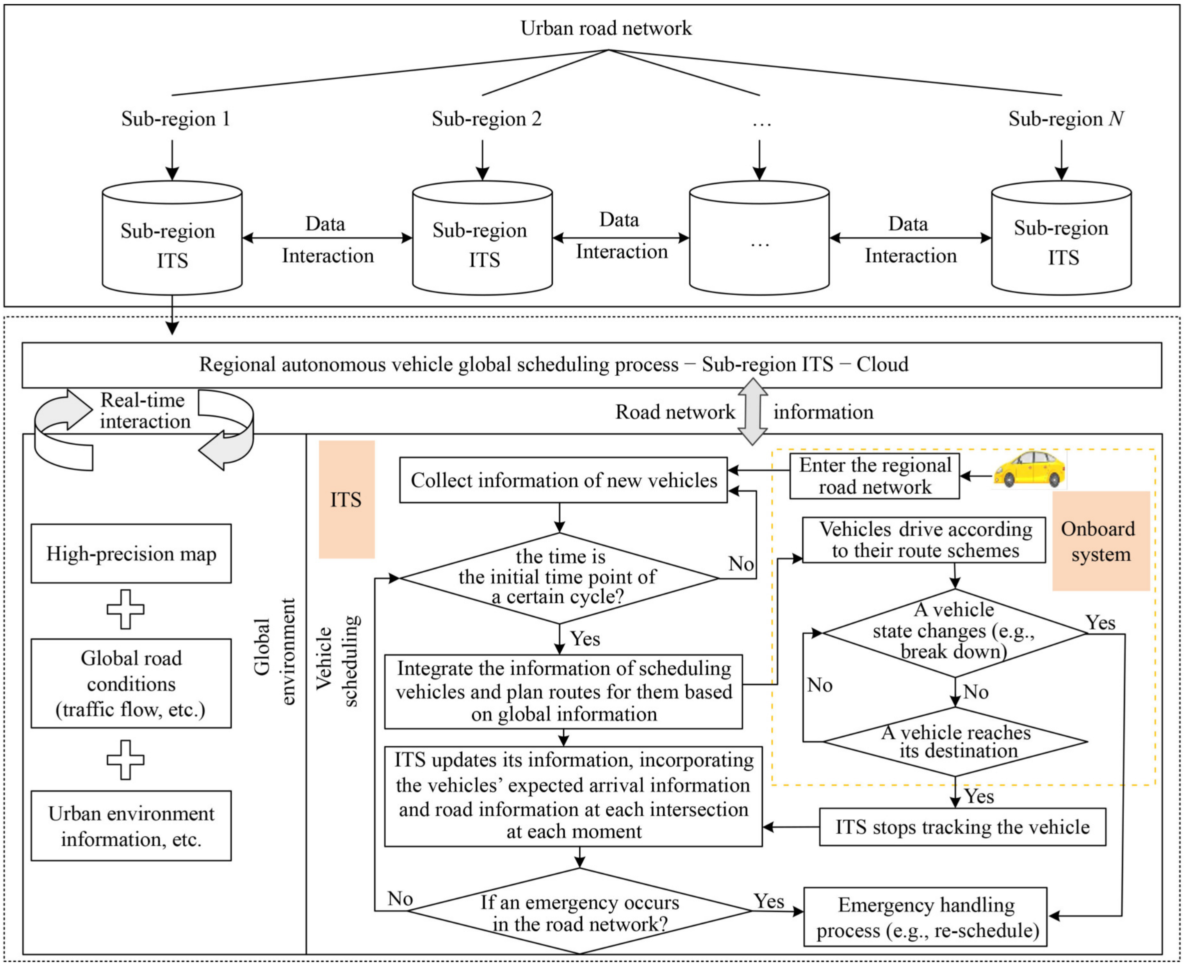

Fig. 2 Mechanism and process of the global scheduling mode.

vehicle maintains its current state. The ITS continues to accumulate requests from incoming vehicles. Upon reaching the inception of the scheduling cycle, the ITS assimilates information about the batch of vehicles scheduled, incorporating prevailing road conditions, driving regulations, and vehicle requisites. Subsequently, the scheduling algorithm is applied to generate comprehensive driving plans for each vehicle. These plans include designated intersections to traverse, arrival times, waiting times at each intersection, and other relevant details. To optimize traffic flow, it is impractical for autonomous vehicles entering the current subregion from neighboring subregions to halt and await scheduling at regional boundaries. We advocate for the simultaneous scheduling of these vehicles across all interconnected subregions, facilitating seamless transitions between subregions while minimizing disruptions to traffic continuity. When these vehicles initially enter the network, their locations and anticipated times of crossing subregion boundaries are estimated, enabling the formulation of driving plans that include all pertinent subregions. Following the determination of routes, the status of the scheduled vehicles is updated accordingly. The ITS continuously monitors road conditions, while vehicle onboard systems oversee real-time vehicle states. In the event of emergencies, such as traffic accidents, an emergency protocol is enacted. For instance, if a vehicle experiences a sudden breakdown, its information is promptly transmitted to the ITS, instigating an emergency response that includes temporary traffic restrictions within the affected region and the rescheduling of affected vehicles.

3.3 Collision avoidance strategy based on prioritization rules

Conventional traffic systems traditionally rely on the coordination of traffic lights and adherence to rules and regulations to avert collisions. Conversely, automated driving traffic systems necessitate the integration of traffic rules exclusively into the scheduling algorithm of the control platform. Given the varying levels of significance associated with different road segments and the necessary prioritization of certain vehicles, such as ambulances, fire engines, and police cars, this paper proposes a set of comprehensive priority rules that consider both road and vehicle hierarchies:

(i) Vehicle priority rules: Vehicles are categorized into two distinct classes. Class Ⅰ includes special vehicles, police vehicles, ambulances, fire engines, and similar entities. Class Ⅱ includes ordinary vehicles, which include all the other vehicle types. Class Ⅰ vehicles hold precedence over Class Ⅱ vehicles when traversing the traffic network.

(ii) Road priority rules: Road segments are classified into four distinct levels predicated on an array of factors, including capacity, overall traffic effect, and other pertinent indicators. The guiding principle entails that road segments interconnected by the same intersection correspond to differing priority levels. Vehicles traveling on higher-level road segments are afforded priority over those navigating lower-level road segments.

(iii) Mixed priority rules: Vehicle prioritization supersedes road prioritization in this hierarchical arrangement. In simpler terms, special vehicles traversing lower-level road segments are accorded priority over ordinary vehicles traversing higher-level road segments. This prioritization framework harmoniously integrates vehicle and road priorities, facilitating efficient and responsive traffic management.

3.4 Collision avoidance strategy based on scheduling rules

The traffic demand exhibits dynamic fluctuations characterized by the continuous entry and exit of autonomous vehicles into and from the road network. Consequently, when devising routes for vehicles designated for scheduling, hereafter referred to as "scheduling vehicles," collision avoidance among scheduling vehicles within the same batch and with scheduled vehicles already in transit is important. To address this complex challenge, this paper outlines the scheduling priority rules applicable at intersections for various batches of vehicles as follows: scheduled vehicles > scheduling vehicles of Class Ⅰ on high-level road segments > scheduling vehicles of Class Ⅰ on low-level segments > scheduling vehicles of Class Ⅱ on high-level road segments > scheduling vehicles of Class Ⅱ on low-level segments. This hierarchical framework signifies that vehicles entering the road network earlier are endowed with superior priority rights when encountering intersections, enhancing the overall efficiency and safety of traffic management.

4 Autonomous vehicle global scheduling problem

4.1 Problem description

This paper introduces a groundbreaking global scheduling mode for urban autonomous vehicles, marking the first instance of its proposal. To elucidate the intricacies of this global scheduling mechanism, we define the AVGSP. The AVGSP entails the utilization of a traffic control platform to formulate travel plans for all autonomous vehicles within a single cycle while considering the current state of the road network. The primary objective of AVGSP is to minimize the cumulative travel time for all scheduling vehicles in the batch, spanning from their points of origin to their respective destinations.

In this pioneering exploration of the global scheduling mode for autonomous vehicles, it is acknowledged that the majority of urban road networks adopt a crisscrossed pattern. To streamline our investigation, we simplify the urban traffic system into a structured road network comprising roads and autonomous vehicles exclusively. As depicted in Fig. 3(a), intersections are represented by the points where straight lines intersect, such as ① and ②, which are denoted by n_1 and n_2, respectively. The straight line segments between two intersections are road segments, where R_{ij} represents the road segment from n_i and n_j. Every road segment is presumed to comprise two

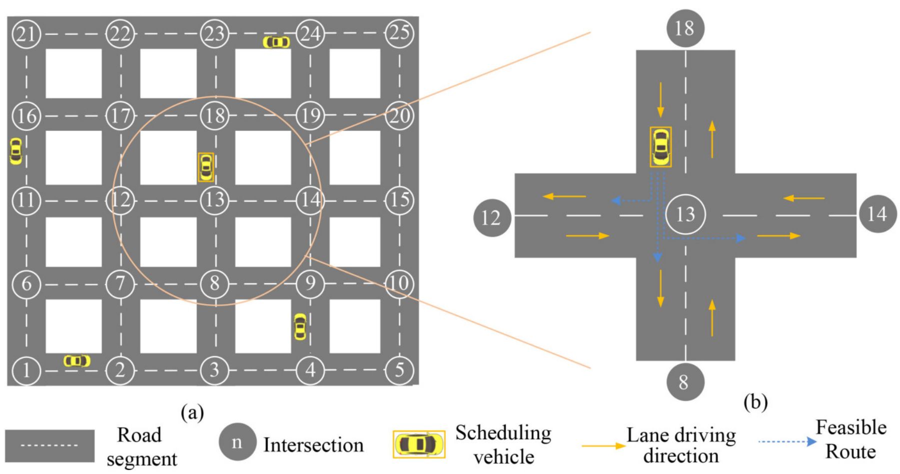

Fig. 3 Road network layout.

lanes, each designated for travel in opposite directions. At intersections, all vehicles have the option to turn or proceed straight, but they must adhere to the driving direction indicated by the lane. As shown in Fig. 3(b), a vehicle driving in $R_{18,13}$ can proceed straight into the downward lane $R_{13,8}$, turn right into the left lane $R_{13,12}$, or turn left into the right lane $R_{13,14}$.

In the domain of vehicle collisions, they can generally be classified into two distinct categories: mid-segment collisions and intersection collisions. Mid-segment collisions typically ensue from lane changes, deceleration, acceleration, or other vehicular maneuvers. In contrast, intersection collisions are predominantly attributed to the limited traffic capacity at intersections and the conflicting movements of vehicles. Within our simulated road network, the road segments include two unidirectional lanes, with vehicles maintaining a consistent speed throughout. Consequently, we concentrate on collisions transpiring at intersections, omitting considerations of mid-segment collisions. Various scenarios of intersection collisions are outlined in Fig. 4, illustrating the likelihood of a collision between vehicle 1, following the path denoted by the blue dashed line, and vehicle 2, progressing in the direction indicated by the red dashed line, when their trajectories intersect.

The AVGSP can be described mathematically in detail as follows. Let $G = (I, R)$ be a normal operating road network, where I is the set of intersections and R is the set of road segments. Autonomous vehicles, denoted as set K, are currently executing their assigned drive plans generated by the ITS. At a specific moment in time, denoted as t, a group of scheduling vehicles (referred to as set V) seeks entry into the traffic network and submits their requests to the ITS. The ITS promptly gathers pertinent information from all scheduling vehicles, including origin and destination data. Subsequently, an optimal solution comprising detailed drive plans is furnished for all scheduling vehicles, aimed at minimizing the collective travel time while ensuring the absence of traffic collisions. For the sake of facilitating mathematical modeling, the following assumptions are established:

(i) Vehicles maintain continuous movement along their routes, with the exception of necessary deviations for collision avoidance.

(ii) The acceleration and deceleration phases that typically accompany vehicle starts and stops are disregarded, and it is assumed that all vehicles maintain a constant speed.

(iii) This paper only considers ordinary vehicles.

(iv) Vehicles do not pose any impediment or obstructions to other vehicles within the road network before they enter or exit from this network.

The definitions of notations used are summarized in Table 2.

4.2 Mathematical model

The model of our AVGSP is formulated as follows:

$$\min \sum_{v\in V} (at_{vf_v} - at_{vs_v}), \tag{1}$$

$$\sum_{i\in I\setminus\{s_v\}} x_{vs_v i} = 1,\ \forall v \in V, \tag{2}$$

$$\sum_{i\in I} x_{vis_v} = 0,\ \forall v \in V, \tag{3}$$

$$\sum_{i\in I\setminus\{f_v\}} x_{vif_v} = 1,\ \forall v \in V, \tag{4}$$

$$\sum_{i\in I} x_{vf_v i} = 0,\ \forall v \in V, \tag{5}$$

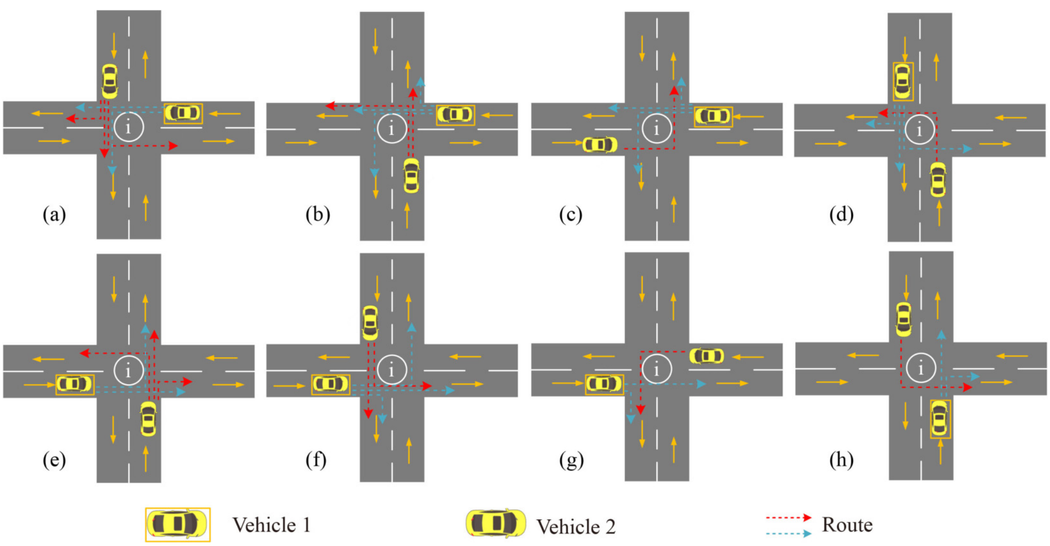

Fig. 4 Analysis of intersection collisions.

Table 2 Parameters and variables

Parameters	Definitions
N	East west road set, $N = \{1, 2, ..., n\}$
M	North south road set, $M = \{1, 2, ..., m\}$
I	Intersection set, $I = \{1, 2, ..., nm\}$
R	Road segment set, $R = \{r_{12}, r_{1(1+m)}, r_{21}, r_{23}, r_{2(2+m)}, ..., r_{(nm)(nm-1)}\}$
F_{ij}	A binary parameter is 1 when intersection i is connected to intersection j. Otherwise, it is 0.
G	Road segment level set, $G = \{g_{12}, g_{i(i+1)}, g_{i(i-1)}, g_{i(i+m)}, g_{i(i-m)}, ..., g_{(nm)(nm-1)}\}$, $g_{ij} = g_{ji}$
L	Road segment length
W	Set of vehicles, $W = V \cup K$
V	Set of scheduling vehicles, $V = \{1, 2, ..., v\}$
K	Set of scheduled vehicles, $K = \{v+1, v+2, ..., v+k\}$
(s_v, f_v)	Origin and destination of vehicle v, $v \in V$
$\left(at^0_{ki}, dt^0_{ki}\right)$	Arrival time and departure time of scheduled vehicle k at intersection i, $k \in K, i \in I$
x^0_{kij}	A binary parameter is 1 when scheduled vehicle k passes through road segment r_{ij}. Otherwise, it is 0
$speed$	The speed of autonomous vehicles
wt	Waiting time for a vehicle to avoid another vehicle at an intersection
pt	The time for a vehicle to turn once
P	Planning cycle
st_p	The initial moment of cycle P
B	A sufficiently large constant
Decision variables	**Definitions**
x_{wij}	The 0–1 decision-variable which is 1 if vehicle w passes through the road segment r_{ij}, and 0 otherwise. $w \in W, r_{ij} \in R$
y_{viw}	The 0–1 decision-variable which is 1 if vehicle v needs to wait for vehicle w to pass through intersection i preferentially, and 0 otherwise. $v \in V, w \in W, i \in I$
z_{vij}	The 0–1 decision-variable which is 1 if vehicle v needs to turn from intersection i to intersection j. $v \in V, i \in I, j \in I$
at_{wi}	The integer decision-variable which is the time when vehicle w arrives at intersection i. $(at_{wi} = at^0_{wi}, \forall w \in K), w \in W, i \in I$
dt_{wi}	The integer decision-variable which is the time when vehicle w leaves intersection i. $(dt_{wi} = dt^0_{wi}, \forall w \in K), w \in W, i \in I$

$$x_{vij} \leqslant F_{ij},\ \forall v \in V,\ \{i,\ j\} \in I, \tag{6}$$

$$\sum_{p \in I} x_{vpi} = \sum_{j \in I} x_{vij},\ \forall v \in V,\ i \in I \backslash \{s_v, f_v\}, \tag{7}$$

$$\sum_{i \in I} x_{vij} \leqslant 1,\ \forall v \in V,\ j \in I, \tag{8}$$

$$at_{s_v} = st_p,\ \forall v \in V, \tag{9}$$

$$at_{vi} + wt \sum_{w \in W} y_{viw} = dt_{vi} \forall v \in V,\ i \in I \backslash \{f_v\}, \tag{10}$$

$$dt_i + L/speed + pt \cdot z_{vij} + B(1 - x_{vij}) \geqslant at_j,\ \forall v \in V,\ i, j \in I \tag{11}$$

$$dt_i + L/speed + pt \cdot z_{vij} - B(1 - x_{vij}) \leqslant at_j,\ \forall v \in V,\ i, j \in I \tag{12}$$

$$x_{vji} + x_{wji} - 1 \leqslant B(|at_{vi} - at_{wi}|),\ \forall \{i, j\} \in I,\ v \in V,\ w \in W \backslash \{v\} \tag{13}$$

$$(x_{v(i+1,i)} + x_{v(i,i-1)} + x_{v(i,i-m)} + x^0_{k(i+m,i)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),$$
$$\forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{14a}$$

$$(x^0_{k(i+1,i)} + x^0_{k(i,i-1)} + x^0_{k(i,i-m)} + x_{v(i+m,i)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),$$
$$\forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{14b}$$

$$(x_{v(i+1,i)} + x^0_{k(i-m,i)} + x^0_{k(i,i+m)} + x^0_{k(i,i-1)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),$$
$$\forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{15a}$$

$$(x^0_{k(i+1,i)} + x_{v(i-m,i)} + x_{v(i,i+m)} + x_{v(i,i-1)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),$$
$$\forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{15b}$$

$$(x_{v(i+1,i)} + x^0_{k(i-1,i)} + x^0_{k(i,i+m)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i+1, i+m\} \in \{I : i \neq f_v\} \tag{16a}$$

$$(x^0_{k(i+1,i)} + x_{v(i-1,i)} + x_{v(i,i+m)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i+1, i+m\} \in \{I : i \neq f_v\} \tag{16b}$$

$$(x_{v(i+m,i)} + x^0_{k(i-m,i)} + x^0_{k(i,i-1)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+m\} \in \{I : i \neq f_v\} \tag{17a}$$

$$(x^0_{k(i+m,i)} + x_{v(i-m,i)} + x_{v(i,i-1)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+m\} \in \{I : i \neq f_v\} \tag{17b}$$

$$(x_{v(i-1,i)} + x_{v(i,i+1)} + x_{v(i,i+m)} + x^0_{k(i-m,i)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{18a}$$

$$(x^0_{k(i-1,i)} + x^0_{k(i,i+1)} + x^0_{k(i,i+m)} + x_{v(i-m,i)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{18b}$$

$$(x_{v(i-1,i)} + x^0_{k(i+m,i)} + x^0_{k(i,i-m)} + x^0_{k(i,i+1)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{19a}$$

$$(x^0_{k(i-1,i)} + x_{v(i+m,i)} + x_{v(i,i-m)} + x_{v(i,i+1)} - 2) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{19b}$$

$$(x_{v(i-1,i)} + x_{v(i,i+1)} + x_{v(i,i-m)} + x^0_{k(i+1,i)} + x^0_{k(i,i-m)} - 3) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1\} \in \{I : i \neq f_v\} \tag{20a}$$

$$(x^0_{k(i-1,i)} + x^0_{k(i,i+1)} + x^0_{k(i,i-m)} + x_{v(i+1,i)} + x_{v(i,i-m)} - 3) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-1, i-m, i+1\} \in \{I : i \neq f_v\} \tag{20b}$$

$$(x_{v(i-m,i)} + x_{v(i,i+1)} + x_{v(i,i+m)} + x^0_{k(i+m,i)} + x^0_{k(i,i+1)} - 3) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{21a}$$

$$(x^0_{k(i-m,i)} + x^0_{k(i,i+m)} + x^0_{k(i,i+1)} + x_{v(i+m,i)} + x_{v(i,i+1)} - 3) \leqslant B(y_{vik} + |at_{vi} - at^0_{ki}|),\quad \forall v \in V,\ k \in K,\ \{i, i-m, i+1, i+m\} \in \{I : i \neq f_v\} \tag{21b}$$

$$(x_{v(i+1,i)} + x_{v(i,i-1)} + x_{v(i,i-m)} + x_{u(i+m,i)} - 2) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ \{i, i+1, i+m\} \in \{I : g_{i+m,i} > g_{i+1,i}\} \tag{22}$$

$$(x_{v(i+1,i)} + x_{v(i,i+m)} + x_{u(i-m,i)} + x_{u(i,i-1)} - 2) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ \{i, i-1, i-m, i+1, i+m\} \in \{I : g_{i-m,i} > g_{i+1,i}\} \tag{23}$$

$$(x_{v(i+1,i)} + x_{u(i-1,i)} + x_{u(i,i+m)} - 2) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ \{i, i-1, i+1, i+m\} \in \{I : g_{i-1,i} > g_{i+1,i}\} \tag{24}$$

$$(x_{v(i+m,i)} + x_{u(i-m,i)} + x_{u(i,i-1)} - 2) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ \{i, i-1, i-m, i+m\} \in \{I : g_{i-m,i} > g_{i+m,i}\} \tag{25}$$

$$(x_{v(i-1,i)} + x_{v(i,i+1)} + x_{v(i,i+m)} + x_{u(i-m,i)} - 2) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ \{i, i-1, i-m, i+1, i+m\} \in \{I : g_{i-m,i} > g_{i-1,i}\} \tag{26}$$

$$(x_{v(i-1,i)} + x_{u(i+m,i)} + x_{u(i,i-m)} + x_{u(i,i+1)} - 2) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ \{i, i-1, i-m, i+1, i+m\} \in \{I : g_{i+m,i} > g_{i-1,i}\} \tag{27}$$

$$(x_{v(i-1,i)} + x_{v(i,i+1)} + x_{v(i,i-m)} + x_{u(i+1,i)} + x_{u(i,i-m)} - 3) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ \{i, i-1, i-m, i+1\} \in \{I : g_{i+1,i} > g_{i-1,i}\} \tag{28}$$

$$(x_{v(i-m,i)} + x_{v(i,i+1)} + x_{v(i,i+m)} + x_{u(i+m,i)} + x_{u(i,i+1)} - 3) \leqslant B(y_{viu} + |at_{vi} - at_{ui}|),\quad \forall \{v, u \in V\},\ i \in \{I : g_{i+m,i} > g_{i-m,i}\} \tag{29}$$

$$B \sum_{i \in I} x_{vij} \geqslant at_{vj},\ \forall v \in V,\ j \in I \tag{30}$$

$$1 - (x_{vsi} + x_{vij}) + z_{vsj} \geqslant 0,\quad \forall v \in V,\ i \in I,\ \{s, j\} \in \{I\text{:}\ |s - j| = m+1\ \ or\ \ m-1\} \tag{31}$$

$$x_{wij} \in \{\ 0, 1\}\ ,\ \forall w \in W,\ \{i, j\} \in I \tag{32}$$

$$y_{viw} \in \{0,1\},\ \forall v \in V,\ i \in I,\ w \in W \tag{33}$$

$$z_{vij} \in \{0,1\},\ \forall v \in V,\ \{i,j\} \in I \tag{34}$$

$$at_{wi} \geqslant 0,\ \forall w \in W,\ i \in I \tag{35}$$

$$dt_{wi} \geqslant 0,\ \forall w \in W,\ i \in I \tag{36}$$

The objective function (1) minimizes the total time of all scheduling vehicles. Constraints (2) and (3) ensure that vehicle v starts from its origin intersection s_v. Constraints (4) and (5) guarantee that vehicle v ends at its destination f_v. Constraint (6) indicates that any vehicle cannot pass through r_{ij} when intersection i is not connected to intersection j. Constraint (7) ensures that vehicle v, which leaves the current road segment, must enter the next road segment from intersection i (i is not s_v or f_v). Constraint (8) stipulates that each vehicle is allowed to traverse a specific intersection at most once. Constraint (9) signifies that a vehicle's departure time from its origin coincides with the moment when the ITS commences planning its route. Constraint (10) dictates that the time at which vehicle v crosses intersection i equals its arrival time at that intersection plus the waiting time experienced there. Constraints (11) and (12) specify that the arrival time of vehicle v at the subsequent intersection is determined by the time of its departure from the preceding intersection, its travel time within the segment, and any needed turn time. Constraint (13) enforces single-lane restrictions. Constraints (14) to (21) ensure that if vehicle v and vehicle k approach intersection i simultaneously, potentially leading to a collision, vehicle v must yield to vehicle k. Constraints (14a) and (14b) cover the scenario depicted in Fig. 4(a), while constraints (15) to (21) address the situations from Fig. 4(b) to 4(h). Constraints (22) to (29) guarantee that if vehicle v and vehicle u simultaneously reach intersection i and might collide, vehicle v must yield to vehicle u if the latter is on a higher-level road segment. These constraints correspond to the scenarios presented in Fig. 4(a) to 4(h). Constraint (30) indicates that if a scheduling vehicle does not traverse an intersection, its actual arrival time at that intersection is set to 0. Constraint (31) determines whether a vehicle is executing a turn at an intersection. Constraints (32) to (36) establish proper bounds for the decision variables.

To narrow the solution space of the model, the following valid inequalities are introduced:

Constraints (37) and (38) describe the minimum number of road segments and indicate that vehicle v must navigate, respectively. Constraint (39) represents the shortest travel time for vehicle v. Given the focus on structured road networks, the Manhattan distance formula is employed to determine the minimum number of road segments needed to travel from s_v to f_v. Additionally, by comparing the horizontal and vertical coordinates of s_v and f_v, it determined whether the vehicle needs to turn. The shortest travel time takes into account both the time spent traversing road segments and the turn time.

$$\sum_{i\in I}\sum_{j\in I} x_{vij} \geqslant |\lceil s_v/m \rceil - \lceil f_v/m \rceil| + |(s_v - (\lceil s_v/m \rceil - 1)\cdot m) - (f_v - (\lceil f_v/m \rceil - 1)\cdot m)|,\ \forall v \in V \tag{37}$$

$$B \cdot \sum_{i\in I}\sum_{j\in I} z_{vij} \geqslant |\lceil s_v/m \rceil - \lceil f_v/m \rceil| \cdot |(s_v - (\lceil s_v/m \rceil - 1)\cdot m) - (f_v - (\lceil f_v/m \rceil - 1)\cdot m)|,\ \forall v \in V \tag{38}$$

$$at_{f_v} - at_{s_v} \geqslant \sum_{i\in I}\sum_{j\in I} x_{vij} \cdot L/speed + pt \cdot \sum_{i\in I}\sum_{j\in I} z_{vij},\ \forall v \in V \tag{39}$$

5 A modified A-star algorithm

The complexity of the AVGSP escalates significantly with the expansion of the scale of the traffic network. In practice, exact algorithms have become impractical for solving large-scale instances, which are prevalent. As a result, the development of more efficient heuristic algorithms is crucial.

The AVGSP, as proposed in this paper, may be regarded as a variant of the shortest path problem. Specifically, the urban traffic road network can be transformed into a directed graph with intersections serving as nodes and road segments serving as edges. Furthermore, the passage time of each road segment signifies the weight of its corresponding edge. In cases where the road network accommodates only one vehicle, the problem addressed in this paper involves identifying the shortest path from the vehicle's current node to the target node, closely resembling the classical shortest path problem. However, in scenarios involving multiple vehicles within the road network, the problem articulated in this paper necessitates the integration of collision avoidance constraints, thus imparting a greater degree of complexity to the shortest-path problem. The A-star algorithm stands out as one of the most well-established path planning algorithms for addressing the shortest-path problem and has been extensively applied in traffic navigation (Ju et al., 2020; He et al., 2022; Zhang et al., 2023). Consequently, we propose the utilization of a MASA to address this complex problem.

5.1 Data preprocessing: Decomposition of scheduled vehicles

In real-world scenarios, the traffic network often accommodates a multitude of scheduled vehicles in operation.

When applying the algorithm to ascertain collision avoidance strategies between scheduling vehicles and scheduled vehicles, significant computational challenges may arise if each scheduling vehicle is individually assessed for potential path conflicts with all scheduled vehicles. To address this issue, we propose the adoption of a multi-vehicle collision avoidance approach through the utilization of a time point vector at each intersection. For each autonomous vehicle, its initial route is established, which can be expressed in terms of the intersections it visits and the corresponding arrival times at these intersections. Furthermore, we can deconstruct a single vehicle's path into several individual segment-based vehicle paths. In the end, all vehicle paths are encapsulated within a map of intersections, wherein the intersections serve as keys and the associated values constitute a vector of arrival time points along with their respective vehicle IDs. Figure 5 provides a visual representation of this process using an illustrative example. The vehicle paths of v_1, v_2 and v_3 are $a(t_1) \to b(t_2) \to c(t_3)$, $d(t_1) \to e(t_2) \to c(t_3)$, and $c(t_1) \to f(t_2) \to g(t_3)$, where $v_1, v_2, v_3, \ldots$ denote different vehicles; $a, b, c, \ldots$ denote different intersections; and $t_1, t_2, t_3, \ldots$ denote arrival times at the intersections. Then, the path of v_1 arrives at intersection a at t_1, and so on. For intersection c, the vehicle set at time t_1 is $\{v_{31}\}$, and the vehicle set at time t_3 is $\{v_{13}, v_{23}\}$.

To apply the above decomposition strategy, several parameters and variables of the AVGSP model need to be adjusted, as shown in Table 3.

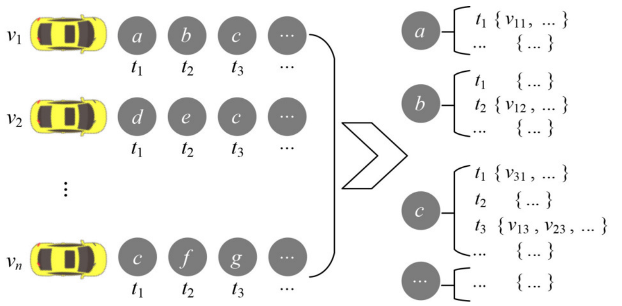

Fig. 5 Decomposition of scheduled vehicles from the intersection perspective.

Constraint (40) is used instead of constraint (10). Constraints (41) and (42) are used instead of constraint (13). Constraints (43)–(50) are used instead of constraints (14)–(21).

$$at_{vi} + wt \cdot \left(\sum_{k \in K_{it}} y_{vik} + \sum_{u \in V} y_{viu}\right) \leqslant dt_{vi} + B \cdot |t - at_{vi}|, \quad \forall v \in V,\ i \in I \setminus \{f_v, s_v\},\ t \in T \tag{40}$$

$$x_{vji} + x_{uji} - 1 \leqslant B(|at_{vi} - at_{ui}|),\ \forall \{i, j\} \in I,\ \{v, u\} \in \{V : v \neq u\} \tag{41}$$

$$x_{vji} + \sum_{k \in K_{it}} d^1_{jikt} - 1 \leqslant B \cdot |t - at_{vi}|,\ \forall v \in V,\ \{i, j\} \in I,\ t \in T \tag{42}$$

$$x_{v(i+1,i)} + x_{v(i,i-1)} + x_{v(i,i-m)} + d^1_{(i+m,i)kt} - 2 \leqslant y_{vik} + B \cdot |at_{vi} - t|, \quad \forall v \in V,\ \{i, i-m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{43a}$$

$$d^1_{(i+1,i)kt} + d^1_{(i,i-1)kt} + d^1_{(i,i-m)kt} + x_{v(i+m,i)} - 2 \leqslant B(y_{vik} + |at_{vi} - t|), \quad \forall v \in V,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{43b}$$

$$x_{v(i+1,i)} + d^1_{(i-m,i)kt} + d^1_{(i,i+m)kt} + d^1_{(i,i-1)kt} - 2 \leqslant y_{vik} + B|at_{vi} - t|, \quad \forall v \in V,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it}, \tag{44a}$$

$$d^1_{(i+1,i)kt} + x_{v(i-m,i)} + x_{v(i,i+m)} + x_{v(i,i-1)} - 2 \leqslant B(y_{vik} + |at_{vi} - t|), \quad \forall v \in V,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{44b}$$

$$x_{v(i+1,i)} + d^1_{(i-1,i)kt} + d^1_{(i,i+m)kt} - 2 \leqslant y_{vik} + B|at_{vi} - t|, \quad \forall v \in V,\ \{i, i-1, i+1, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{45a}$$

Table 3 Newly introduced parameters

Parameters	Definitions
K_{it}	The set of scheduled vehicles passing through intersection i at time t. $K_{it} = \{1, 2, \ldots, k_{it}\}$
d^1_{jikt}	Scheduled vehicle k covers the road segment r_{ji} and arrives at intersection i at time t
T	The operating time of the road network
Decision variables	**Definitions**
x_{vij}	0–1 variable, it is 1 if and only if vehicle v passes r_{ij}. $\forall v \in V,\ (i, j) \in R$
y_{vio}	0–1 variable, it is 1 if and only if vehicle v needs to wait for vehicle o to pass through intersection i preferentially. $\forall v \in V,\ i \in I,\ o \in \bigcup_{t \in T} K_{it} \cup V$
at_{vi}	Integer variable, it represents the moment when vehicle v arrives at intersection i, $\forall v \in V,\ i \in I$
dt_{vi}	Integer variable, it represents the moment when vehicle v leaves intersection i, $\forall v \in V,\ i \in I$

$$d^1_{(i+1,i)kt} + x_{v(i-1,i)} + x_{v(i,i+m)} - 2 \leqslant y_{vik} + B|at_{vi} - t|,$$
$$\forall v \in V,\ \{i, i-1, i+1, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{45b}$$

$$x_{v(i+m,i)} + d^1_{(i-m,i)kt} + d^1_{(i,i-1)kt} - 2 \leqslant y_{vik} + B|at_{vi} - t|,$$
$$\forall v \in V,\ \{i, i-1, i-m, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{46a}$$

$$d^1_{(i+m,i)kt} + x_{v(i-m,i)} + x_{v(i,i-1)} - 2 \leqslant y_{vik} + B|at_{vi} - t|,$$
$$\forall v \in V,\ \{i, i-1, i-m, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{46b}$$

$$x_{v(i-1,i)} + x_{v(i,i+1)} + x_{v(i,i+m)} + d^1_{(i-m,i)kt} - 2 \leqslant y_{vik} + B|at_{vi} - t|,$$
$$\forall v \in V,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\},$$
$$t \in T,\ k \in K_{it} \tag{47a}$$

$$d^1_{(i-1,i)kt} + d^1_{(i,i+1)kt} + d^1_{(i,i+m)kt} + x_{v(i-m,i)} - 2 \leqslant y_{vik} + B|at_{vi} - t|,$$
$$\forall v \in V,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\},$$
$$t \in T,\ k \in K_{it} \tag{47b}$$

$$x_{v(i-1,i)} + d^1_{(i+m,i)kt} + d^1_{(i,i-m)kt} + d^1_{(i,i+1)kt} - 2 \leqslant y_{vik} + B|at_{vi} - t|,$$
$$\forall v \in V,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\},$$
$$t \in T,\ k \in K_{it} \tag{48a}$$

$$d^1_{(i-1,i)kt} + x_{v(i+m,i)} + x_{v(i,i-m)} + x_{v(i,i+1)} - 2 \leqslant y_{vik} + B|at_{vi} - t|,$$
$$\forall v \in V,\ \{i, i-1, i-m, i+1, i+m\} \in \{I : i \neq f_v\},$$
$$t \in T,\ k \in K_{it} \tag{48b}$$

$$x_{v(i-1,i)} + x_{v(i,i+1)} + x_{v(i,i-m)} + d^1_{(i+1,i)kt} + d^1_{(i,i-m)kt} - 3$$
$$\leqslant B(y_{vik} + |at_{vi} - t|),$$
$$\forall v \in V,\ \{i, i-1, i-m, i+1\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{49a}$$

$$d^1_{(i-1,i)kt} + d^1_{(i,i+1)kt} + d^1_{(i,i-m)kt} + x_{v(i+1,i)} + x_{v(i,i-m)} - 3$$
$$\leqslant B(y_{vik} + |at_{vi} - t|),$$
$$\forall v \in V,\ \{i, i-1, i-m, i+1\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{49b}$$

$$x_{v(i-m,i)} + x_{v(i,i+1)} + x_{v(i,i+m)} + d^1_{(i+m,i)kt} + d^1_{(i,i+1)kt} - 3$$
$$\leqslant B(y_{vik} + |at_{vi} - t|),$$
$$\forall v \in V,\ \{i, i-m, i+1, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{50a}$$

$$d^1_{(i-m,i)kt} + d^1_{(i,i+1)kt} + d^1_{(i,i+m)kt} + x_{v(i+m,i)} + x_{v(i,i+1)} - 3$$
$$\leqslant B(y_{vik} + |at_{vi} - t|),$$
$$\forall v \in V,\ \{i, i-m, i+1, i+m\} \in \{I : i \neq f_v\},\ t \in T,\ k \in K_{it} \tag{50b}$$

5.2 Improvement strategies

In the A-star algorithm, the calculation of the evaluation function plays a crucial role. The traditional A-star algorithm typically expresses the evaluation function as shown in Eq. (51). In this equation, $F(n)$ equals the summation of the estimated value from the current position to position n, $g(n)$, and the estimated value from position n to the destination, $h(n)$.

$$F(n) = g(n) + h(n) \tag{51}$$

While the AVGSP shares similarities with the shortest path problem, there are notable distinctions. This paper's objective shifts from merely identifying the shortest path to delivering a comprehensive solution that optimizes not only travel distance but also factors in the costs associated with conflicts among vehicles and the expenses related to turning at intersections. Consequently, we have tailored the traditional A-star algorithm to accommodate these additional considerations.

(i) Considering the waiting time and turning time

The overall time taken by a vehicle from its starting point to its destination includes not only the travel duration but also the waiting time and turning time, which are the results of collision avoidance strategies. Particularly in congested traffic segments, waiting time becomes a significant factor to consider. Therefore, when computing the estimated value from the current position to the subsequent position, we take into account travel time, expected waiting time (comprising waiting time for both scheduling and scheduled vehicles), and turning time. Eq. (52) represents the estimated value from intersection i to intersection j:

$$g_v(i \to j) = L/speed + wt \cdot (\sum_{k \in K_{it}} y_{vik} + \sum_{u \in V} y_{viu}) + pt \cdot z_{vij},$$
$$\forall v \in V,\ \{i, j\} \in I,\ t \in T. \tag{52}$$

(ii) Considering the direction factor

The determination of the direction from the origin to the destination occurs once these points are established. Conversely, traveling significantly increases both the global turning time and the driving time, which is undesirable. Hence, we incorporate incentives/penalties for the direction factor within the evaluation function, as represented by Eq. (53): $\min I_{if_v}$ is the number of segments passing at least from n to the destination. a is the direction penalty factor, forward driving is negative, and reverse driving is positive:

$$h_v(i \to j) = (1+a) \cdot [(\min I_{if_v} \cdot L)/speed], \ \forall v \in V, \ \{i, j\} \in I. \tag{53}$$

(iii) Considering the algorithm efficiency

In the case of "if a scheduling vehicle is being planned for a path, selects intersection j as its next intersection," it will conflict with vehicle $u(u \in V)$ in the current intersection. According to the road priority rules, vehicle v needs to wait for vehicle u to pass first." When vehicle v is determined to drive to intersection j, the system needs to replan the routes of vehicle u from the current intersection to its destination. This deteriorates the algorithm's efficiency. Therefore, we use $d_v(i \to j)$ to indicate the efficiency penalty of vehicle v from intersection i to intersection j, where u is a scheduling vehicle that needs to be rerouted.

$$d_v(i \to j) = \sum_{u \in V} y_{uiv} \cdot wt, \ \forall v \in V, \ \{i, j\} \in I. \tag{54}$$

In summary, the evaluation function of the MASA is as follows:

$$F_v(i \to j) = g_v(i \to j) + h_v(i \to j) + d_v(i \to j), \ \forall v \in V, \ \{i, j\} \in I. \tag{55}$$

5.3 The framework and process of the MASA

Our algorithm works as shown in Fig. 6.

Step 1: Initialization. Input the road network information and process the scheduled and scheduling vehicle information. TV represents the set of scheduling vehicles, PV is the set of scheduling vehicles that have initial paths, and RV is the set of scheduling vehicles that need rescheduled.

Step 2: Vehicle sorting. The minimum number of intersections that each scheduling vehicle needs to visit from its origin to destination is calculated, and the scheduling vehicles are sorted in descending order according to the results.

Step 3: Select a scheduling vehicle to plan a route: if $TV \neq \varnothing$, select vehicle v corresponding to the first element in TV; then, go to Step 4. If $TV = \varnothing$, go to Step 7.

Step 4: Plan the route for vehicle v. Set O includes intersections connected to intersection i where vehicle v is currently located (i.e., the next candidate intersection set). When $f_v \in O$, f_v will be the next intersection. Otherwise, calculate the evaluation function of all the elements in O, and select the intersection m with the smallest function value as the next intersection.

Step 5: Determine whether the route of the current vehicle will change the routes of other vehicles in PV. If it disturbs the route of vehicle u, move vehicle u from PV to RV, and record intersection i as the rescheduled node of vehicle u. If $v \in TV$, then Step 6. If $v \in RV$, go to Step 7.

Step 6: Let $i = m$; if $m = f_v$, delete v from TV. Skip to Step 3. Otherwise, go back to Step 4.

Step 7: If $RV \neq \varnothing$, then go to Step 8. Otherwise, go to Step 9.

Step 8: Select vehicle w corresponding to the first element in RV and update its route from the rescheduled node: update only the arrival time, collision avoidance scheme, and departure time of the rescheduled intersection and subsequent intersections. After updating, move w from RV to PV and return to Step 5.

Step 9: Output the final routes of all vehicles and stop.

6 Computational experiments

The numerical experiments serve two primary objectives. The first is to assess the performance of the model and algorithm introduced in this paper. The second is to evaluate the beneficial effect of the global scheduling mode on urban transportation. Three sets of experiments were designed to achieve these goals. The first set pertains to the initial cycle ($P = 1$), during which no scheduled vehicles are present in the road network. The second set utilizes results from the first set as scheduled vehicle schemes for the subsequent cycle (i.e., $P = 2$). For each set of experiments, we conducted 24 instances of eight small-scale scenarios to gauge the model's accuracy and the algorithm's efficiency. Additionally, we carried out 36 instances of 12 large-scale scenarios to compare the performance of the traditional A-star algorithm with that of our MASA. Furthermore, a third experiment aimed to assess the disparities between global and local scheduling modes. For this purpose, we generated 5 instances with varying numbers of vehicles within a predetermined network configuration. All the experiments were executed on a PC equipped with an Intel Core i7-10510U processor (4.1 GHz) and 12 GB of RAM. The MIP solver employed was CPLEX 12.8. Our algorithm was implemented in C++ using Visual Studio 2022.

6.1 Parameter settings

We created a simulated road network environment with the following characteristics. Four different road network scales are considered: 5 × 5 (five roads in the east–west direction and five roads in the north–south direction), 10 × 10, 20 × 20, and 30 × 30. Intersection collision avoidance decisions are determined based on the mixed prioritization rules for roads and vehicles, as previously outlined. To prevent collisions between vehicles of the same level entering the same intersection from different segments, it is essential to ensure that the levels of road segments connected to the same intersection are different. At most, each intersection can connect in four directions, and accordingly, the segments are categorized into 1–4 levels. The specific rules and diagrams for generating road segment levels are illustrated in Fig. 7 (where $link_{ij}$ represents that intersection j is connected by intersection

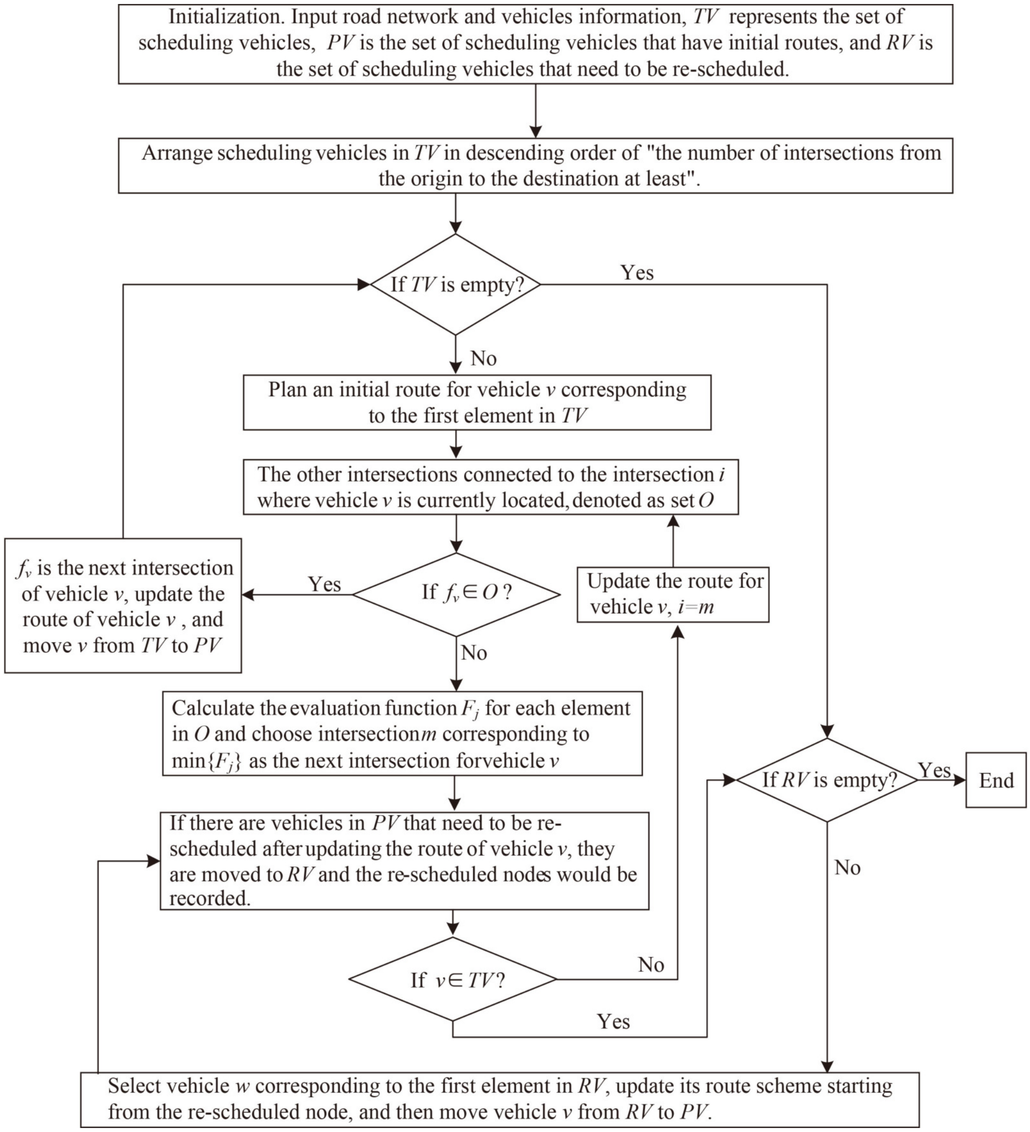

Fig. 6 Flowchart of our MASA.

i, $Level_{is}$ represents the level of road segment r_{is}, and $PossibleL^i$ represents the feasible level set of road segments connected by intersection i). L is set to 1.5 km, the *speed* is 15 m/s, wt is 10 s, pt is 20 s, and the direction penalty factor a is 0.3. The number of scheduling vehicles is set as {2,4,8,10,20,40,80,100}. (v) The cycle interval is set to 60 s. Vehicles are randomly generated with origins, destinations, and travel request times for scheduling.

6.2 Performance of the model

For small-scale instances, which include road network scales of 5 × 5 and 10 × 10 and scheduling vehicle scales of 2, 4, and 8, each problem size consists of three instances. We applied both the basic model and the model with valid inequalities in CPLEX, with a solution time limit of 300 s. Table 4 shows the results for P = 1 and P = 2. Instances that could not achieve lower bounds within 300 s using CPLEX were not included.

The columns in the table are structured as follows: *Instance* described as {the number of roads in the east–west direction}-{the number of roads in the north–south direction}-{the number of scheduling vehicles}-{the number of scheduled vehicles}-{the instance index}. For P = 2, specify that the number of scheduling vehicles is equal to the number of scheduled vehicles. Column *LB* denotes the lower bound obtained by CPLEX. Column *T* represents the solving time of CPLEX, and column *Gaps* are computed as (T1–T0)/T1 × 100 for P = 1 and P = 2, respectively. The result of instance 5-2-1 at P = 1 was used as the known information of the scheduled vehicles, for instance, 5-2-1 at P = 2.

When considering the number of scheduling vehicles within 10, we observed that two models were unable to obtain lower bounds within the 300 s time limit. Moreover, instances that did not have feasible solutions at P =

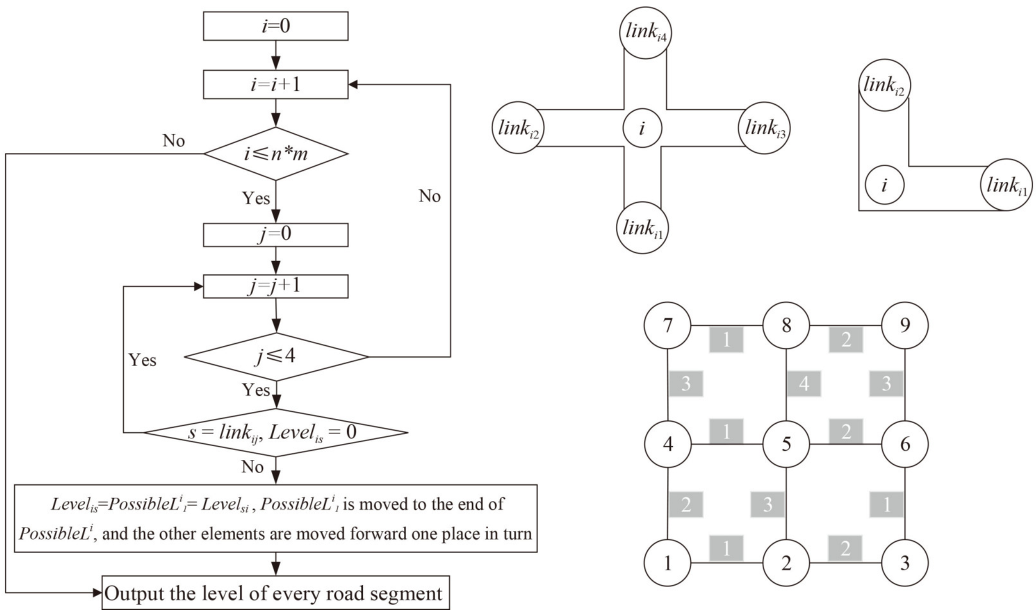

Fig. 7 Generation process of the road segment level.

Table 4 Results for small-scale instances

Instance	The model with valid equalities				The model				Gap 1/%	Gap 2/%
	P = 1		P = 2		P = 1		P = 2			
	LB0/s	T0/s	LB0/s	T0/s	LB1/s	T1/s	LB1/s	T1/s		
5-2-1	920	0.22	640	0.42	920	0.33	640	1.89	33.33	77.78
5-2-2	640	0.13	740	0.44	640	0.17	740	0.78	23.53	43.59
5-2-3	500	0.08	640	0.77	500	0.09	640	0.89	11.11	13.48
5-4-1	1880	5.06	1980	6.91	1880	4.06	1980	13.59	–24.63	49.15
5-4-2	1080	0.58	1140	2.97	1080	2.92	1140	9.03	80.14	67.11
5-4-3	1360	4.16	1220	2.83	1360	1.38	1220	30.88	–201.45	90.84
5-8-1	3140	300	/	/	3140	300	/	/	0	/
5-8-2	2600	300	/	/	2600	300	/	/	0	/
5-8-3	3040	300	/	/	3040	300	/	/	0	/
10-2-1	2140	2.53	1020	15.88	2140	2.86	1020	12.55	11.54	–26.53
10-2-2	1220	0.56	1040	13.8	1220	2	1040	50.34	72	72.59
10-2-3	1940	2.69	1540	21.45	1940	5.67	1540	51.77	52.56	58.57
10-4-1	3180	14.08	2560	300	3180	199.2	2500	300	92.93	0
10-4-2	2580	46.59	2980	300	2580	52.16	2900	300	10.68	0
10-4-3	3280	42.88	1840	300	3280	34.39	1800	300	–24.69	0
10-8-1	7860	300	/	/	7860	300	/	/	0	/
10-8-2	6340	300	/	/	6340	300	/	/	0	/
10-8-3	3840	300	/	/	3840	300	/	/	0	/

1 could not be utilized as known information for P = 2. Consequently, we tested 12 instances at P = 2. Based on the results presented in Table 4, the following conclusions can be drawn:

(i) Valid inequalities noticeably enhance model efficiency:

In terms of solution quality, valid inequalities did not have a significant effect, and they improved only the lower bounds for a few instances, such as “10-4-1.” This could be attributed to the inherent complexity of the problem. However, valid inequalities play a crucial role in enhancing solution efficiency. For P = 1, among the 12 instances where optimal solutions were found, the average solving time was 25.44 s. After incorporating valid inequalities, this time was reduced to 9.96 s, representing a 61% improvement in efficiency. For P = 2, among the nine instances with optimal solutions, the efficiency improved by 62% after valid inequalities were included.

(ii) The number of scheduled vehicles significantly impacts the model complexity:

When P = 1 is considered, the model obtains optimal solutions for 12 instances and lower bounds for 18 instances. The largest problem that could be solved was "10-4." However, for P = 2, the model could only find optimal solutions for nine instances and lower bounds for 12 instances. The maximum problem size that could be addressed was either "5-4" or "10-2." The primary difference between these two scenarios was the number of scheduled vehicles. Hence, increasing the number of scheduled vehicles is a key factor complicating the problem.

6.3 Performance of the MASA

This subsection aims to evaluate the performance of our algorithm by solving 72 instances of P = 1 and P = 2. First, we apply the MASA to solve small-scale instances and compare the results with the model's results, as reported in Table 5. Additionally, our algorithm is utilized to address large-scale instances, and the results are presented in Table 6. Finally, we select several large-scale instances of P = 2 and employ the traditional A-star algorithm to solve them; the results are shown in Fig. 9. In Table 5, the bold parts indicate optimal or provably optimal solutions.

The results obtained from the small-scale instances demonstrate that our algorithm can efficiently produce high-quality solutions. For the 21 instances where the model achieved optimal solutions, our algorithm also obtained optimal solutions for 20 of them. Furthermore, for the nine instances where the model could only provide lower bounds, our algorithm produced solutions identical to their lower bounds. This not only confirms the optimality of these solutions but also underscores the high solution quality of our algorithm. Notably, our algorithm was able to solve all small-scale instances within 0.005 s. Compared to the model, our algorithm exhibited greater efficiency and stability. These results indicate that the algorithm is capable of meeting the scheduling requirements of the road network.

However, when dealing with large-scale instances, the problem complexity is significantly elevated to the extent that obtaining a lower bound within the specified time using CPLEX becomes unfeasible. Therefore, we resort to calculating a lower bound for one of the relaxation problems derived from the basic model, specifically focusing on Eqs. (37)–(39), which pertains to the minimum necessary travel time for all vehicles. The results of this approach are displayed in Table 6. In this table, "*Ideal Results*" refers to the results of the relaxation problem,

Table 5 Results for small-scale instances

Instance	P = 1				P = 2			
	The model with valid equalities		MASA		The model with valid equalities		MASA	
	LB0/s	T0/s	Obj1	Calculation_Time1/s	LB0/s	T0/s	Obj1	Calculation_Time1/s
5-2-1	920	0.22	920	0.003	640	0.42	640	0.002
5-2-2	640	0.13	640	0.002	740	0.44	740	0.002
5-2-3	500	0.08	500	0.003	640	0.77	640	0.002
5-4-1	1880	5.06	1880	0.003	1980	6.91	1980	0.002
5-4-2	1080	0.58	1080	0.003	1140	2.97	1140	0.002
5-4-3	1360	4.16	1360	0.004	1220	2.83	1220	0.002
5-8-1	3140	300	3140	0.003	/	/	2600	0.002
5-8-2	2600	300	2600	0.003	/	/	1980	0.003
5-8-3	3040	300	3040	0.003	/	/	2580	0.003
10-2-1	2140	2.53	2140	0.002	1020	15.88	1020	0.002
10-2-2	1220	0.56	1230	0.002	1040	13.8	1040	0.002
10-2-3	1940	2.69	1940	0.002	1540	21.45	1540	0.002
10-4-1	3180	14.08	3180	0.003	2560	300	2560	0.002
10-4-2	2580	46.59	2580	0.004	2980	300	2980	0.002
10-4-3	3280	42.88	3280	0.003	1840	300	1840	0.002
10-8-1	7860	300	7860	0.003	/	/	4920	0.005
10-8-2	6340	300	6340	0.004	/	/	5950	0.003
10-8-3	3840	300	3840	0.003	/	/	6050	0.003

Table 6 Results for larger-scale instances

Instance	P = 1					P = 2				
	Ideal Results	Obj	Calculation_Time /s	Turn_Time	Wait_Time	Ideal Results	Obj	Calculation_Time/s	Turn_Time	Wait_Time
10-10	7106.67	7113.33	0.003	140.00	6.67	6373.33	6376.67	0.003	140.00	3.33
10-20	13726.67	13733.33	0.005	326.67	6.67	14293.33	14300.00	0.006	326.67	6.67
20-10	15260.00	15263.33	0.012	193.33	3.33	14046.67	14046.67	0.009	180.00	0.00
20-20	29073.33	29080.00	0.010	373.33	6.67	27240.00	27250.00	0.010	340.00	10.00
20-40	54866.67	54893.33	0.313	733.33	26.67	55713.33	55733.33	0.017	746.67	20.00
20-80	102900.00	102996.67	0.026	1466.67	96.67	113366.67	113460.00	0.023	1466.67	93.33
20-100	138006.67	138110.00	0.034	1806.67	103.33	138906.67	139030.00	0.030	1806.67	143.33
30-10	17153.33	17153.33	0.020	186.67	0.00	20493.33	20493.33	0.020	193.33	0.00
30-20	39980.00	39986.67	0.026	380.00	6.67	39953.33	39956.67	0.021	386.67	10.00
30-40	84106.67	84116.67	0.032	773.33	10.00	80033.33	80043.33	0.028	733.33	10.00
30-80	165946.67	166026.67	0.040	1480.00	80.00	162100.00	162160.00	0.044	1443.33	83.33
30-100	194446.67	194553.33	0.049	1880.00	106.67	202600.00	202680.00	0.050	1900.00	80.00

"*Turn_Time*" represents the total turning time, and "*Wait_time*" denotes the total waiting time incurred by collision avoidance measures for all scheduling vehicles. The table reveals the following findings:

(i) The gap between the results produced by the algorithm and the ideal results is within 1% for the majority of instances.

(ii) Our algorithm can solve all large-scale instances within 0.05 s.

Figure 8 presents the results for each instance at $P = 2$. The labels "*20_ATT*" (or "*30_ATT*") and "*20_AWT*" (or "*30_AWT*") indicate the average drive time and average waiting time per vehicle for different instances when the road network scale is 20 × 20 (or 30 × 30), respectively. Several observations can be made from this figure. The total time per vehicle in the road network exhibits minimal variation at the same road network scale. However, as the road network scale increases, the waiting time per vehicle noticeably increases. An increase in vehicle density leads to a substantial increase in the unit collision avoidance time.

Figure 9 provides a visual representation of the differences in waiting time (ΔWait_Time) and solution time (ΔT) between the results obtained by our algorithm and those obtained by the traditional A-star algorithm. A comparison between the two algorithms reveals the following key improvement in our algorithm: Our algorithm primarily focuses on reducing the collision avoidance time. Since we established a regular road network environment with consistent segment lengths, there was no significant difference in pure travel time between the two algorithms. Additionally, our algorithm incorporates optimization strategies to calculate the evaluation function, which has a minimal effect on the computational time. Consequently, our algorithm boasts high efficiency, affirming the rationality and feasibility of using the A-star algorithm to address global scheduling problems in traffic networks.

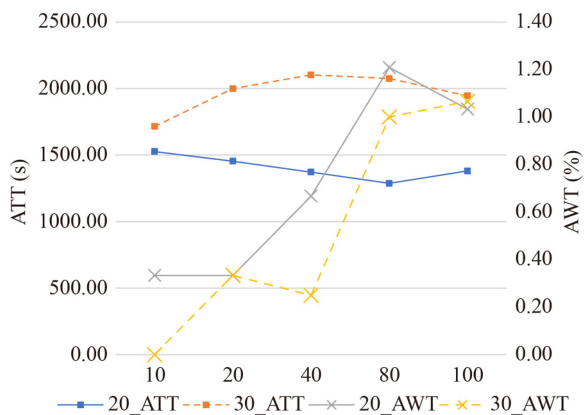

Fig. 8 Results of instances with different road network scales and vehicle numbers.

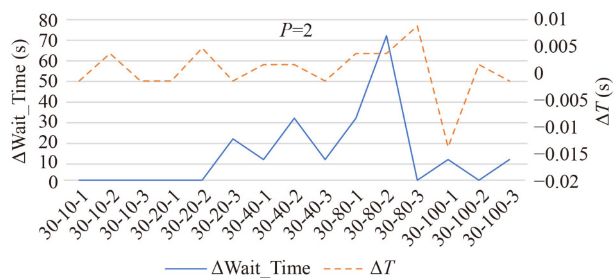

Fig. 9 Comparison between our MASA and the traditional A-star algorithm.

6.4 Results considering cross-region vehicles

Vehicles entering the road network from a boundary intersection can be categorized into two distinct groups: The first group comprises vehicles originating from a boundary intersection. These vehicles follow the same global scheduling approach as those originating from non-boundary intersections within the road network. They are scheduled on a fixed cycle, similar to other vehicles in the network. The second group includes vehicles with origins and destinations in different regions, and these vehicles enter the current region from a boundary intersection. To illustrate this, consider the scenario shown in Fig. 10: a vehicle's origin is intersection 18 in Sub-region 1, and its destination is intersection 7 in Sub-region 2. In this case, the traffic system in Sub-region 1 will select the first intersection along the shortest path from the origin to the destination, which also marks the boundary of the next region. In this example, intersection 16 is in Sub-region 2 (or intersection 20 is in Sub-region 1).

The system then plans the vehicle's route from intersection 18 in Sub-region 1 to intersection 16 in Sub-region 2. Additionally, the vehicle's expected arrival time (AI) at intersection 16 is determined. If $AT \in [T_{m-1}, T_m)$, where T_{m-1} is the previous scheduling cycle and T_m is the upcoming one, the cross-region vehicle will be included in the set of scheduling vehicles for cycle T_{m-1} in Sub-region 2.

Consequently, the scheduling vehicles for cycle T_{m-1} in Sub-region 2 include both vehicles that submitted travel requests during the time interval $(T_{m-2}, T_{m-1}]$ and vehicles that will enter the current region from other regions within the time interval $[T_{m-1}, T_m]$. The transportation system of Sub-region 2 uses the starting time (AI) and starting location (intersection 16) determined by Sub-region 1 as input information. For the other vehicles originating within Sub-region 2, the starting time is T_{m-1}, and their starting locations correspond to their respective origins.

In this subsection, we address 30 instances of $P = 1$ with a varying road network scale of {20 × 20, 30 × 30} and a scheduling vehicle scale of {10, 20, 40, 80, 100}. The size of each problem was tested with three different instances. Notably, we introduced cross-region vehicles into these instances, where the proportion of cross-regional vehicles to the total vehicle scale was set at 0.2. For cross-region vehicles whose origin is not within the current region, there is no guarantee that they can depart at the T_m moment. The time needed to reach the current region affects the arrival time and collision avoidance decisions at subsequent intersections. To account for this, we modeled their behavior using a Poisson distribution with $\lambda = 30$, considering a cycle interval of 60 s. This represents the expected time for a cross-region vehicle to reach the first boundary intersection. The results are summarized in the following table, with "proportion of cross-regional vehicles = 0" indicating instances without cross-regional vehicles and "proportion of cross-regional vehicles = 0.2" representing instances with cross-regional vehicles. The results demonstrate the effectiveness of the algorithm even when cross-regional vehicles are introduced into the scenarios, highlighting its versatility and robustness.

6.5 Comparison of the global scheduling mode and local scheduling mode based on large-scale instances

To further demonstrate the effect of the global scheduling mode on urban traffic efficiency, this study conducted experiments with a fixed road network scale and compared the traffic efficiency of the two scheduling modes. Based on data from the Beijing Municipal Commission of Transport for the Labor Day holiday in 2023, traffic on Beijing's highways reached 13.88 million vehicles, with a daily average of nearly 2.78 million vehicles and a peak day of 3.02 million vehicles (Beijing Municipal Commission of Transport, 2023). Taking this as the benchmark, the number of vehicles entering the road network per minute ranged between 1930 and 2097.

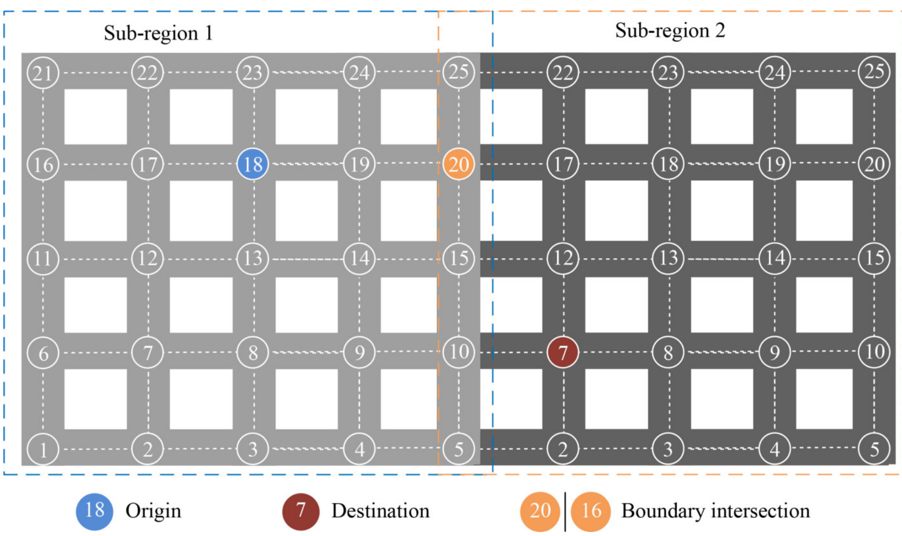

Fig. 10 Routes for cross-regional vehicles.

Table 7 Results of different proportions of cross-regional vehicles

Instance	Proportion of cross-regional vehicles = 0				Proportion of cross-regional vehicles = 0.2			
	Obj	Calculation_ Time/s	Turn_Time/s	Wait_Time/s	Obj1	Calculation_ Time/s	Turn_Time1/s	Wait_Time1/s
20-10	15263.33	0.01	193.33	3.33	14046.67	0.01	180.00	0.00
20-20	29080.00	0.01	373.33	6.67	27250.00	0.01	340.00	10.00
20-40	54893.33	0.31	733.33	26.67	55733.33	0.02	746.67	20.00
20-80	102996.67	0.03	1466.67	96.67	113460.00	0.02	1466.67	93.33
20-100	138110.00	0.03	1806.67	103.33	139030.00	0.03	1806.67	143.33
30-10	17153.33	0.02	186.67	0.00	20493.33	0.02	193.33	0.00
30-20	39986.67	0.03	380.00	6.67	39956.67	0.02	386.67	10.00
30-40	84116.67	0.03	773.33	10.00	80043.33	0.03	733.33	10.00
30-80	166026.67	0.04	1480.00	80.00	162160.00	0.04	1443.33	83.33
30-100	194553.33	0.05	1880.00	106.67	202680.00	0.05	1900.00	80.00

In these experiments, five different scheduling vehicle scales were tested: 500, 1000, 2000, 3000, and 4000, while the road network scale was fixed at 20 × 20. The local scheduling mode involves selecting the optimal route with at most one turn between the vehicle's origin and destination and is identified as the optimal local route. As shown in Fig. 11, the origin (intersection 13) and destination (intersection 12/18/9) of the vehicle are on the same east–west or north–south route, and the straight route was chosen as the optimal route. If the vehicle's origin and destination allowed for two optimal routes, one was randomly selected with a probability of 0.5 as the final driving route. The experiments involved counting the number of vehicles passing through each road segment in one cycle, and the results are presented in Table 8 and Table 9. Figure 12 illustrates the variation in the difference in the number of vehicles passing through each intersection in each cycle for both the global and local scheduling modes.

"*V_Num*" denotes the total vehicle scale, "*Vehicle_number*" represents the number of vehicles passing through an intersection in the local scheduling mode minus that in the global scheduling mode, "*Cycle*" is the cycle with the values [0, 100], and "*Intersection*" denotes the intersection number with the value [1,400]. Table 8 and Table 9 analyze the vehicle numbers of all road segments and the central road segments in the two modes (the area enclosed by 8–12 rows and 8–12 columns in the 20 × 20 road network is defined as the central area, and the road segments in this area are the central road segments): *Average*, *Max-min* and *Var* denote the mean, maximum-minimum difference and variance of the number of vehicles passing, respectively. *The average gap* indicates the average difference between the traffic flows in two scheduling modes and is calculated as (*Local_Average* – *Global_Average*)/*Local_Average*.

The analysis of the results, as shown in the figure and tables, reveals several key findings:

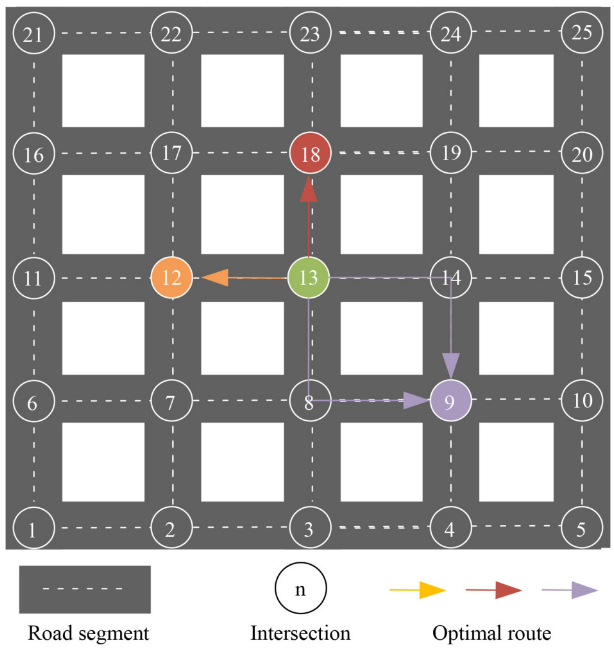

Fig. 11 Optimal routing in local scheduling mode.

(i) For the same vehicle density, the global scheduling mode yields lower mean values, maximum and minimum differences, and variance in road segment traffic flow than does the local scheduling mode. This indicates that vehicle allocation is more balanced in the global mode, leading to less traffic flow fluctuations and similar traffic levels across road segments. In contrast, the local scheduling mode results in higher values for all these statistical indicators, with a significantly greater variance, especially when the vehicle scale exceeds 2000. This suggests that the local mode is more prone to congestion, which aligns with current urban traffic patterns.

(ii) Under varying vehicle densities, the global scheduling mode consistently reduces the average traffic flow by approximately 50% compared to the local scheduling

Table 8 Traffic flow statistics of each road section under the two scheduling modes

Vehicle number	Average		Average gap	Max-min		Var	
	Global	Local		Global	Local	Global	Local
500	4.87	9.25	47.30%	17.00	24.00	9.53	21.76
1000	8.79	17.20	48.88%	31.00	42.00	29.72	62.97
2000	17.68	34.76	49.13%	58.00	83.00	112.46	226.86
3000	26.64	52.69	49.43%	84.00	125.00	270.04	506.63
4000	34.87	69.56	49.87%	97.00	156.00	424.62	798.33

Table 9 Traffic flow statistics of each central road section under the two scheduling modes

Vehicle number	Average		Average gap	Max-min		Var	
	Global	Local		Global	Local	Global	Local
500	6.42	11.02	41.77%	12.00	17.00	6.34	14.10
1000	12.71	22.96	44.64%	14.00	23.00	11.18	29.77
2000	24.28	47.41	48.78%	29.00	62.00	34.18	201.28
3000	36.58	65.79	44.40%	25.00	66.00	41.18	175.40
4000	46.58	86.33	46.05%	38.00	79.00	98.78	357.72

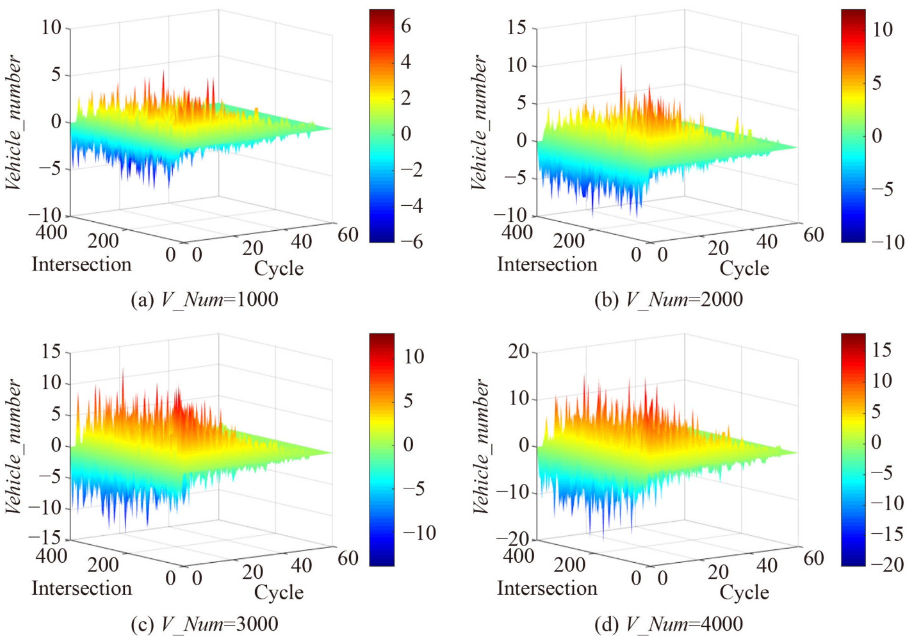

Fig. 12 Spatiotemporal traffic variation maps.

mode. In the local scheduling mode, as the vehicle count increases from 500 to 4000, both the mean and variance in the traffic flow increase significantly, by 60.31 and 776.57, respectively. However, the increase in the global scheduling mode is only 30.00 and 415.09. Consequently, the global scheduling mode provides more substantial benefits in equalizing traffic flow and reducing the risk of congestion, especially in high-density road networks.

(iii) Table 9 indicates that the traffic flow on central road segments is generally higher in both scheduling modes, particularly at high vehicle densities. Central road traffic flow is increasing rapidly, making it more challenging to manage. However, when comparing the traffic flow in central road segments between the two scheduling modes *(local_average – global_average)*, the difference is more pronounced, with the average value increasing by 3.27. Furthermore, the global scheduling mode achieves a more significant reduction in traffic flow fluctuations on central road segments, averaging 77.35%, while the local scheduling mode achieves a 51.86% reduction. These findings demonstrate that the global scheduling mode more effectively regulates traffic flow in central segments, improving traffic flow balance and reducing congestion risks, especially on local roads.

In summary, the global scheduling mode is proven to be more effective at balancing traffic flow, minimizing congestion risks, and enhancing resource allocation across road segments. This approach offers significant improvements over local scheduling and addresses existing congestion issues more effectively.

Additional experiments were conducted to assess the performance of the global scheduling mode under different levels of autonomous vehicle penetration (25%, 50%, and 75% of the total number of autonomous vehicles, respectively) (for instance, "*Vehicle_number* = 2000"). In the new experiments, several assumptions are considered. First, human-driven vehicles randomly select the shortest paths based on the local scheduling mode without considering collision avoidance with other human-driven vehicles. Second, after determining the paths of human-driven vehicles, paths for autonomous vehicles are planned based on the global scheduling mode, with autonomous vehicles unilaterally avoiding human-driven vehicles.

The results of these experiments are presented in Table 10, where "*PenRate*" represents the penetration rate of autonomous vehicles, "*Max*" denotes the maximum value, "*Avg*" represents the mean value, and "*Var*" indicates the variance. The "gap" is calculated as the average vehicle count on all road segments minus the count on central road segments. The observations from these experiments are as follows: (i) As the proportion of human-driven vehicles decreases (with a higher penetration rate of autonomous vehicles), the difference in average traffic flow between all road segments and central road segments gradually diminishes. This finding suggests that the global scheduling mode effectively balances traffic flow across road segments. (ii) A gradual increase in the variance difference indicates that the global scheduling mode is particularly effective at reducing traffic flow imbalances between road segments. This further highlights the mode's ability to mitigate traffic flow fluctuations.

7 Conclusions and future research

Automated driving represents a transformative shift in the transportation landscape, with profound implications for the automotive industry, transportation systems, and urban development. While its widespread adoption is still on the horizon, research into development methods and control modes for automated driving is crucial. Such research can aid traffic managers in establishing strategic plans for the eventual implementation of fully autonomous driving. These plans can guide the development of essential infrastructure and accelerate progress in automated driving and intelligent transportation systems. With this perspective in mind, our paper conducts a comprehensive examination of urban automated driving traffic from a management standpoint.

This paper initiates this investigation by analyzing the current state of automated driving and subsequently proposes a novel global scheduling mode designed for future automated driving traffic. The operational mechanisms, processes, prerequisites, and relevant regulations governing this mode are elaborated upon. To facilitate a deeper understanding of the scheduling mode, it is formally defined as a scientific problem, accompanied by the introduction of a mixed-integer programming model. Additionally, a MASA is introduced to address this problem. Computational experiments are conducted to assess the efficacy of the AVGSP formulation and the efficiency of the heuristic.

Furthermore, through an analysis of road network operations under both global and local scheduling modes, the paper highlights the substantial advantages offered by the global scheduling mode in terms of reducing traffic flow and ensuring the equitable allocation of road resources. These findings provide valuable insights for future urban transportation and urban planning initiatives. Although this research strives to comprehensively address the complexities of urban automated driving traffic, there are inherent limitations that need to be acknowledged:

(i) Urban traffic networks are dynamic and continuously evolving systems subject to changes in both time and space. The mathematical model and algorithm developed in this paper primarily focus on determining initial scheduling schemes for newly entering vehicles within a single cycle. Future research should explore real-time updates and optimization of driving routes for scheduled vehicles. This could involve the establishment of fixed cycles for route updates or the introduction of traffic flow thresholds at intersections, triggering route updates when thresholds are reached. These strategies could significantly enhance the dynamic optimization of urban road networks.

Table 10 Traffic flow with different autonomous vehicle penetration rates

Vehicle number = 2000	*PenRate* = 0		*PenRate* = 0.25		*PenRate* = 0.5		*PenRate* = 0.75		*PenRate* = 1	
	Avg	*Var*	*Avg*	*Var*	*Avg*	*Var*	*Avg*	*Var*	*Avg*	*Var*
All road segments	34.76	226.86	17.38	67.32	17.38	75.92	17.41	90.84	17.68	112.46
Central road segments	47.41	201.28	24.58	28.22	25.04	32.16	24.54	26.96	24.28	34.18
Gap	–12.65	25.58	–7.20	39.10	–7.66	43.76	–7.13	63.87	–6.60	78.28

(ii) Collision avoidance at intersections is a central concern in this research. However, this paper assumes that there are only two lanes with opposing directions between every pair of intersections, leading to the consideration of 34 collision scenarios. In reality, road networks often feature multiple lanes between intersections, with varying lane counts on different road segments. This complexity necessitates the development of collision avoidance rules that are adaptable to diverse road conditions. Future studies should account for these complex road scenarios, potentially by determining the maximum number of vehicles in a particular direction that can occupy an intersection based on lane counts. By combining road segment-level and lane-level congestion, a system for establishing vehicle priority order could be developed.

(iii) Future research could further explore the principles and methods of urban road network partitioning. Additionally, the classification and configuration of urban road segments and autonomous vehicles warrant more in-depth investigation. Furthermore, understanding the interaction mechanisms between autonomous vehicles, intelligent roadside devices, pedestrians, and other elements within the urban environment should be a focal point of research in this field.

Competing Interests The authors declare that they have no competing interests.

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