

Microscopic control and optimization of connected and automated vehicles at highway on-ramp merging areas: a comprehensive review

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ABSTRACT: Highway ramp merging areas are critical bottlenecks affecting traffic safety and operational efficiency, where interactions between mainline and ramp vehicles often induce traffic conflicts, crashes, and delays. Connected and automated vehicles (CAVs), enabled by precise trajectory control and real-time cooperation, provide a promising solution for improving ramp merging operations. Existing reviews mainly compare algorithms or application scenarios, with limited attention to the physical process of ramp merging, in which longitudinal speed and spacing adjustments must be coordinated with lateral lane-changing motion to enter a safe mainline gap within a limited merging area. To examine how this motion is planned and realized, this paper develops a decision-planning and control-execution framework for reviewing CAV ramp merging strategies. The two functional modules are analyzed across individual-vehicle, general multi-vehicle, and platoon-based forms of vehicle organization, focusing on their technical methods, implementation, and effects on traffic performance. Their system-level organization is then compared under hierarchical cooperative, integrated, and hybrid control architectures. Finally, future research directions for CAV ramp merging control are identified.

KEYWORDS: Connected and automated vehicles, Mixed traffic, Ramp merging, Microscopic trajectory control, Vehicle coordination

1 Introduction

With accelerating urbanization, sustainable transportation planning has become increasingly important in urban development and transport policy (Kimuli et al., 2025). Meanwhile, growing travel demand is placing increasing pressure on available highway capacity, resulting in denser traffic and more frequent vehicle interactions. As automated vehicles enter increasingly complex traffic environments, road conditions and vehicle manoeuvres remain important factors in crash occurrence (Kurse et al., 2025). At the microscopic level, UAV-based vehicle trajectory data have been used to analyse traffic flow and accident risk under congested highway conditions (Berghaus et al., 2024), as well as to assess inter-vehicle safety distances and identify unsafe vehicle-interaction patterns in dense and heterogeneous traffic (Bhavsar et al., 2025). These capacity and vehicle-interaction problems are particularly evident at highway on-ramp merging areas, where ramp traffic merges into the mainline traffic flow. In these areas, intensive interactions between mainline and ramp vehicles can disturb traffic flow stability, reduce operational efficiency, and generate traffic conflicts such as rear-end and side-swipe collisions (Zhu et al., 2022a). Therefore, more refined and intelligent traffic flow control strategies are needed for ramp areas. Systematic investigation of such strategies is important for improving highway safety and operational efficiency and can also provide scientific support for traffic management policy development (Lu

and Liu, 2021).

Early research on ramp merging primarily focused on traditional methods such as ramp metering (Du et al., 2018; Kotsialos and Papageorgiou, 2004; Roncoli et al., 2015) and variable speed limit control (Carlson et al., 2010; Hegyi et al., 2005; Zhang and Ioannou, 2017; Zhang et al., 2017). The former optimizes main road traffic flow by adjusting the vehicle flow entering the highway on-ramp, while the latter improves traffic conditions through dynamic speed control. These methods have shown performance benefits under specific conditions; however, they are limited by the locality and latency of detection data, making it difficult to handle the dynamically changing and complex traffic scenarios. In recent years, with breakthroughs in vehicle intelligence, connectivity, and vehicle-infrastructure cooperation technologies, new solutions have emerged to address ramp-merging problems (Yue et al., 2022). Connected and automated vehicles (CAVs), with their precise trajectory control and real-time information exchange capabilities, have the potential to fundamentally transform transportation patterns (Zhu et al., 2022b). However, the transition from a traffic environment dominated by human-driven vehicles (HDVs) to the ideal stage of full CAV adoption will inevitably experience a prolonged and complex transitional period. In this context, the mixed traffic environment of HDVs and CAVs will become the norm for decades to come, presenting both new opportunities and challenges for the design of ramp control strategies (Lyu et al., 2021).

In studies on CAV cooperative control for ramp merging areas,

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existing literature has explored a wide range of technical approaches, including feedback control (Chen et al., 2021; Kim et al., 2023; Tajdari et al., 2022), optimal control (Fang et al., 2022; Jing et al., 2022; Ntousakis et al., 2016; Wei et al., 2022), and reinforcement learning (Lubars et al., 2021; Sheng et al., 2024; Zhao et al., 2022). Although these methods differ in formulation, they address the same fundamental problem: how to coordinate longitudinal and lateral vehicle motions under strict spatiotemporal constraints (Yang et al., 2023). The core challenge of ramp merging is not limited to vehicle-motion control; it also requires higher-level tactical decision making before these decisions are translated into local control actions. Typical decision-planning tasks include determining when and where to merge, which gap or lane to select, and what reference trajectory to follow, whereas control execution determines how speed, acceleration, steering, and trajectory tracking realize those decisions. Because the two functions differ in decision variables, inputs, update scales, and constraints, separating them analytically provides a clearer basis for reviewing vehicle-level on-ramp control.

Accordingly, the present review adopts decision planning and control execution as its two main functional perspectives. Studies are organized according to their primary functional emphasis, inputs and outputs, and vehicle organization rather than solely according to algorithm types, and complete vehicle-level methods are further examined through hierarchical cooperative, integrated, and hybrid control architectures. The review also compares safety guarantees, communication requirements, traffic and HDV assumptions, computational complexity, validation levels, and deployment nonidealities across representative studies. The main contributions are as follows:

(1) The decision-planning module and the control-execution module are separately reviewed at the individual-vehicle, general multi-vehicle, and platoon levels. The decision-planning module covers merging-sequence determination, gap selection, merging timing and position, and trajectory planning. The control-execution module covers speed control, steering control, and trajectory tracking under vehicle-dynamic and safety constraints.

(2) The mechanisms connecting decision planning and control execution are systematically analyzed through hierarchical, integrated, and hybrid control architectures. Beyond architectural classification, the review synthesizes representative studies in terms of safety guarantees, communication requirements, traffic and HDV assumptions, computational complexity, validation settings, and deployment limitations.

The remainder of this paper is organized as follows. Section 2 compares the present review with prior relevant review studies and describes the review scope, search methodology, screening procedure, and classification criteria. Section 3 reviews decision-planning studies at the individual-vehicle, general multi-vehicle, and platoon levels, and Section 4 reviews control-execution studies using the same vehicle-organization perspective. Sections 5, 6, and 7 examine hierarchical cooperative, integrated, and hybrid control architectures, respectively. Section 8 provides a cross-study comparison of methods and control architectures, mixed-traffic modelling and HDV behaviour representation, validation settings and performance metrics, practical deployment challenges, and the applicability of these methods to related multi-lane coordination scenarios. Section 9 summarizes the main conclusions and future research directions. The overall review framework is shown in Fig. 1.

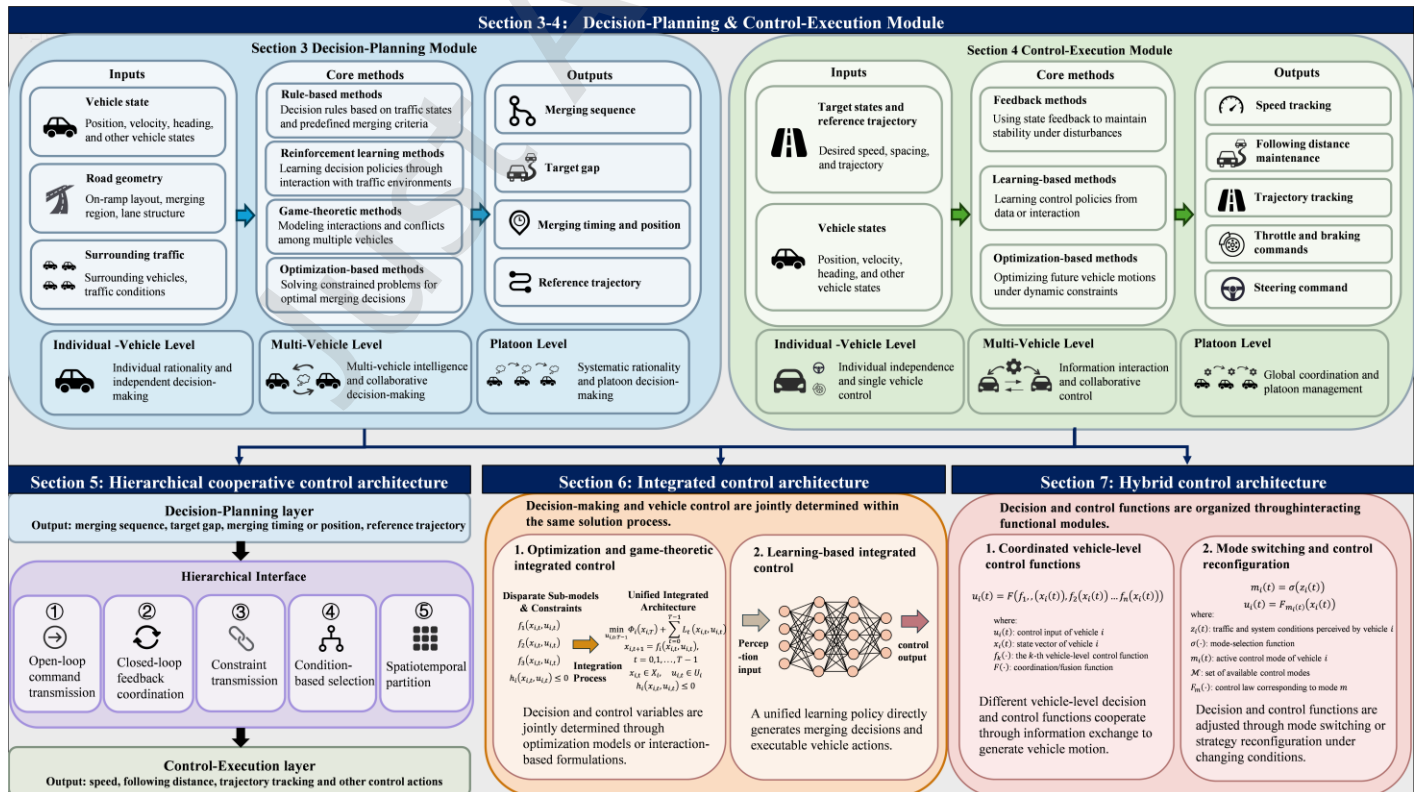


Fig. 1. The overall review framework

2 Review methodology and classification framework

To clarify the scope, positioning, literature sources, and classification basis of this review, this section first compares the present study with related reviews and explains its distinct analytical focus. The literature search and screening procedure is then described, followed by the classification criteria for functional

modules, vehicle organization, and control architectures.

2.1. Existing reviews and scope of this review

Recent reviews have examined CAV ramp merging and related automated-driving problems from the perspectives of merging scenarios, decision making and planning, vehicle control, driver behaviour, and method. **Table 1.** compares the five reviews most closely related to this study with the present review.

Table 1. Comparison of recent reviews and the present review

Study	Main focus	Distinction from the present review
Zhu et al. (2022a)	Road configuration and traffic composition.	Emphasizes road and traffic scenarios more than the underlying merging motion, particularly the coordination of longitudinal speed and spacing adjustment with lateral lane entry.
Garrido and Resende (2022)	General automated-driving decision and planning levels.	Offers a general automated-driving framework, but gives less attention to the restricted merging space and safety-critical vehicle interactions of on-ramp bottlenecks.
Liu et al. (2023)	Vehicle and CAV cooperative control techniques.	Covers vehicle control broadly, but provides less detailed differentiation and organization of the distinct motion behaviours involved in ramp merging.
Kherroubi and Aknine (2024)	Highway on-ramp driver-behaviour modelling.	Centres on HDV behaviour, with less attention to CAV-HDV interaction and cooperative control in mixed traffic.
Irshayyid et al. (2024)	RL-based lane changing, ramp merging, and platoon control.	Centres on reinforcement learning, with relatively limited comparison across other major categories of decision and control methods.
Present review	Decision planning and control execution for CAV ramp merging.	Takes longitudinal-lateral merging motion as the organizing basis and distinguishes its decision-planning and control-execution functions under different control architectures.

The five reviews explain merging scenarios, general automated-driving functions, vehicle-control techniques, human-driver behaviour, or reinforcement-learning methods, but they do not use the actual merging motion process as a common basis for organizing the literature. In a limited merging area, the ramp vehicle must regulate its longitudinal speed and spacing, interact with mainline vehicles to select or create a safe gap, and complete the lateral entry before the available space ends. The present review follows this process to distinguish what is determined through decision planning, what is realized through control execution, and how the two functions are organized under hierarchical, integrated, and hybrid control architectures.

2.2. Literature search and selection

The Web of Science Core Collection was used to identify relevant studies published between 1 January 2010 and 5 August 2026. The search terms were organized into three groups concerning vehicle technology, freeway on-ramp merging scenarios, and vehicle-level research:

TS = (("connected and automated vehicle*" OR "connected autonomous vehicle*" OR "automated vehicle*" OR "autonomous vehicle*" OR CAV OR CAVs) AND ("on-ramp" OR "on ramp" OR "freeway merg*" OR "highway merg*" OR "ramp merg*") AND (decision* OR planning OR control* OR coordination OR cooperation OR trajector* OR "gap selection" OR "merging sequence" OR "optimal control" OR "model predictive control" OR "reinforcement learning" OR platoon*))

The initial topic search identified 331 records. After restricting the publication period to the specified dates, the document types to

Articles and Proceedings Papers, and the language to English, 316 records entered the relevance assessment. We included studies that focused on vehicle-level CAV control during highway on-ramp merging. The scope covered microscopic vehicle interactions, cooperative merging, trajectory planning, and motion control in both fully automated and mixed traffic. We excluded studies on off-ramp diverging, service areas, toll plazas, work zones, or network-level traffic management. We assessed relevance according to the traffic scenario, vehicle type, and research focus, using the titles, abstracts, and full texts where necessary. Following this assessment, we retained 96 studies for the core review. These studies were then synthesized within a framework covering decision planning, control execution, and hierarchical, integrated, and hybrid control architectures.

2.3. Classification framework

To systematically organize the reviewed studies, three classification perspectives are adopted. First, Sections 3 and 4 organize studies according to their primary functional emphasis in decision planning or control execution. Second, studies are classified according to the organization of controlled vehicles as individual-vehicle, general multi-vehicle, or platoon-based approaches. Third, studies involving both decision and control functions or multiple vehicle-level control mechanisms are distinguished according to how these functions are coupled, namely hierarchical cooperative control, integrated control, and hybrid control. These perspectives respectively describe what function is emphasized, how the controlled vehicles are organized, and how decision and control mechanisms are connected.

2.3.1 Functional modules classification

Studies were not organized according to algorithm types, because model predictive control, optimal control, reinforcement learning and other algorithms can contribute to either decision planning or control execution. Instead, Sections 3 and 4 organize studies according to their primary functional emphasis, identified mainly

from their decision variables and outputs, with inputs and relative update time scales used as supporting criteria. In this review, macro-level decision planning refers to the upper tactical function within a vehicle-level on-ramp merging system rather than network-level traffic-flow control. The criteria are summarized in **Table 2**.

Table 2. Classification criteria for the decision-planning and control-execution modules

Criterion	Decision-planning module	Control-execution module
Main question	What, when, and where should the vehicle merge?	How should the planned merging decision be executed?
Main inputs	Ego and surrounding-vehicle states, available gaps, lane information, predicted intentions or motions, and system objectives.	Current vehicle states, reference decisions or trajectories, vehicle-dynamic constraints, and disturbances.
Decision variables	Merging sequence π , target gap g^* , target lane l^* , merging time t_m , merging position s_m , and reference trajectory $r^{\text{ref}}(\tau)$.	Desired speed v^{des} , acceleration a , steering angle δ , torque T , spacing correction, and control-input sequence $u(\tau)$.
Main outputs	Tactical decisions and reference states or trajectories for subsequent execution.	Directly executable or immediately trackable vehicle-motion commands.
Time scale	Event-triggered or rolling planning horizon; updated when traffic interactions, available gaps, or merging conditions change.	Short-horizon optimization or continuous feedback cycle; updated more frequently according to state and tracking errors.
Trajectory role	Plans a future trajectory as a reference for subsequent execution.	Tracks the reference trajectory and generates the control inputs required to realize it.

The main output is used as the primary indicator of functional emphasis. A study is reviewed primarily from the decision-planning perspective when its main contribution concerns tactical merging decisions or reference trajectory generation, whereas it is reviewed primarily from the control-execution perspective when its main contribution concerns the generation or tracking of executable vehicle-motion commands. A study may contain functions from both modules; therefore, this organization indicates the dominant analytical emphasis rather than an exclusive assignment of the complete study.

2.3.2 Controlled object classification

Vehicle organization is classified according to how many vehicles are explicitly involved in the decision or control process and

whether their interactions follow a coordination relationship. Three forms are distinguished: individual-vehicle organization, general multi-vehicle cooperation, and platoon-based cooperation. Individual-vehicle organization focuses on the ego CAV, while surrounding vehicles mainly provide environmental information or interaction constraints. General multi-vehicle cooperation explicitly coordinates multiple vehicles without requiring a fixed platoon structure or role assignment. Platoon-based cooperation is treated as a more formally constrained form of multi-vehicle cooperation and requires an explicit longitudinal vehicle order, platoon roles, spacing relations, or platoon stability requirements. The classification criteria are summarized in **Table 3**.

Table 3. Classification criteria for vehicle organization

Criterion	Individual-vehicle organization	General multi-vehicle cooperation	Platoon-based cooperation
Vehicle organization	The ego CAV makes or executes its own decision; surrounding vehicles are not jointly controlled.	Multiple vehicles are explicitly coordinated without requiring a fixed platoon structure or role assignment.	A formally constrained subtype of multi-vehicle cooperation with explicit platoon membership, longitudinal order, roles, spacing, or platoon stability constraints.

Criterion	Individual-vehicle organization	General multi-vehicle cooperation	Platoon-based cooperation
Information sharing	Local perception and basic surrounding-vehicle or roadside states; no explicit reciprocal intention negotiation.	Vehicle states, intentions, plans, or objectives are shared through V2V/V2I or a coordinator.	Information related to platoon roles and structure, such as leader, predecessor, follower, spacing, or platoon states.
Coordination topology	No explicit inter-vehicle coordination topology.	Centralized, decentralized or multi-agent interaction.	Leader–follower, predecessor-following, bidirectional, queue-based, or virtual-platoon structure.

Vehicle organization was classified sequentially. A study was classified as individual-vehicle organization when only the ego CAV was optimized or controlled and surrounding vehicles primarily provided environmental information or interaction constraints. Studies involving explicit coordination among multiple ramp or mainline vehicles were classified as general multi-vehicle cooperation. Within this group, studies introducing an actual or virtual one-dimensional vehicle order, leader–follower or predecessor–follower relationships, longitudinal spacing, or platoon stability requirements were classified as platoon-based cooperation.

2.3.3 Control architecture classification

The last classification perspective concerns how decision-making and vehicle-control functions are organized to generate vehicle

motion. The classification is based on two criteria: the relationship between decision-making and control execution, and the process used to determine decision variables and control variables. A hierarchical architecture is identified when decision-making and control execution follow a sequential structure. An integrated architecture is identified when decision variables and control variables are determined within the same solution process. Hybrid architectures refer to microscopic control structures that do not follow either of these two organizations, where decision-making and control functions are combined through multiple interacting components rather than a fixed sequential hierarchy or a unified solving process. The classification criteria are summarized in **Table 4**.

Table 4. Classification criteria for hierarchical, integrated, and hybrid control architectures

Criterion	Hierarchical cooperative control architecture	Integrated control architecture	Hybrid control architecture
Decision-control relationship	Decision-making and control execution follow a clear sequential relationship. Decision variables are determined first and then provided to the control layer for execution.	Decision-making and control execution do not follow a predefined sequence. Decision variables and control variables are determined together within the same process.	Decision-making and control execution are not organized through a fixed sequential structure or a unified solving process. Decision components and control components interact through multiple functional mechanisms.
Solution process	Decision variables and control variables are determined separately. The control layer generates executable actions based on decisions, references, or constraints from the decision layer.	Decision variables and control variables are jointly optimized or generated within the same optimization, game, or learning framework.	Decision variables and control variables are determined through different but interacting functional components. These components may cooperate, switch, or modify each other during vehicle control.

3 Decision-making and planning module

This section reviews studies whose primary contribution or analytical focus lies in decision planning. Their main outputs specify what, when, and where a vehicle or vehicle group should merge, including merging sequence, target gap or lane, merging time or position, and reference trajectory. This section discusses

these studies mainly from the perspective of how tactical merging decisions and reference plans are generated, rather than how low-level commands are executed.

3.1. Individual-vehicle decision-making

Individual-vehicle decision planning treats one CAV as the decision maker, while surrounding mainline and ramp vehicles mainly provide traffic states, available gaps, and interaction

constraints rather than being jointly optimized with the ego CAV. Based on its own state, surrounding vehicle information, and roadside information, the CAV independently determines its merging behaviour. Typical decisions include target gap selection, lane changing or merging actions, merging time and position, and reference trajectories. The reviewed methods mainly include reinforcement learning and model-based optimization. Reinforcement learning adapts decisions through interaction with dynamic traffic, whereas model-based methods determine feasible decisions through explicit objectives and constraints.

When reinforcement learning is applied to individual-vehicle decision-making, a CAV is modelled as an individual agent that selects actions from the currently available traffic information and evaluates them through rewards associated with safety, travel efficiency, comfort, or energy consumption. The main differences among existing studies lie in the observation design, action space, and reward formulation. Actions may be continuous, such as longitudinal acceleration, or discrete, such as acceleration, deceleration, lane keeping, and merging. Eqs. (1) to (3) summarize the common finite-horizon reinforcement-learning structure used in representative on-ramp studies, such as Lin et al. (2020), Wang et al. (2021b), and Kherroubi et al. (2022).

Under a finite horizon Markov decision process, or a partially observable representation when the complete traffic state is not directly available, agent i seeks a policy that maximizes the expected cumulative discounted reward:

$$J(\pi_i) = \mathbb{E}_{\tau_i \sim \pi_i} \left[\sum_{t=0}^T \gamma^t R_i(s_{i,t}, a_{i,t}) \right] \quad (1)$$

The interaction trajectory of agent i over the finite decision horizon can be represented by the sequence of states, actions, and rewards:

$$\tau_i = (s_{i,0}, a_{i,0}, r_{i,0}, s_{i,1}, a_{i,1}, r_{i,1}, \dots, s_{i,T}) \quad (2)$$

At decision step t , the agent selects an action from its policy using the currently available information $o_{i,t}$:

$$a_{i,t} \sim \pi_i(\cdot | o_{i,t}) \quad (3)$$

In Eqs. (1) to (3), the variables are defined as follows:

- $J(\pi_i)$: The expected cumulative discounted return of policy π_i for agent i .
- π_i : The policy of agent i , which defines a mapping from available information to action selection.
- τ_i : The interaction trajectory of agent i , consisting of the sequence of states, actions, and rewards over the finite horizon.
- $\mathbb{E}_{\tau_i \sim \pi_i}[\cdot]$: The expectation over trajectories generated by following policy π_i .
- $\gamma \in [0, 1]$: The discount factor, which balances the importance of immediate versus future rewards.
- $R_i(s_{i,t}, a_{i,t})$: The instantaneous reward received by agent i after taking action $a_{i,t}$ in state $s_{i,t}$ at time t .
- $r_{i,t}$: The instantaneous reward at time t , typically defined as $r_{i,t} = R_i(s_{i,t}, a_{i,t})$.
- $s_{i,t}$: The local state of agent i at time t , which may include position, velocity, and other relevant information.
- $a_{i,t}$: The action executed by agent i at time t , such as acceleration, braking, or lane-change commands.
- $o_{i,t}$: The information available to agent i at time t for

decision-making, which may consist of the complete state, local observations, observation histories, or latent representations, depending on the original study.

- T : The terminal time step of the finite decision horizon.

The exact definitions of these variables therefore follow the corresponding source study.

Reinforcement learning studies mainly differ in how the ego CAV observes surrounding traffic, selects merging or lane-changing actions, and balances safety, efficiency, and comfort through the reward design. Lin et al. (2020) used deep deterministic policy gradient (DDPG) with longitudinal acceleration as the continuous action of the ego CAV, so the resulting decision determines whether the vehicle progresses to merge ahead of or behind the interacting mainline vehicle. The reward penalizes collision risk and jerk, and Pareto trade-off analysis was used to examine the balance between safety and passenger comfort. Triest et al. (2020) used reinforcement learning to select a temporally extended merging manoeuvre for the ego CAV, so the decision output specifies the high-level merging action to be maintained over several time steps. The temporally extended action design reduces the frequency of decision making, and the learned decisions were evaluated through successful and collision-free merging in simulated highway scenarios. He and Lv (2023) formulated ego-CAV merging as a constrained multi-objective reinforcement-learning problem in which the policy selects the merging behaviour according to safety, efficiency, and driver-preference requirements. The reward weights adjust the emphasis among these objectives while safety-related constraints remain active, allowing the selected merging decision to vary with the specified driving preference. Kherroubi et al. (2022) used an artificial neural network (ANN) at the roadside unit to predict mainline HDV behaviour and supplied the prediction to a twin delayed deep deterministic policy gradient (TD3) policy that selects the ego CAV's merging action. The predicted HDV behaviour is incorporated into the decision state, allowing the ego CAV to select the merging action based on both current traffic states and future HDV responses. Wang et al. (2021a) combined the hidden Markov model with Gaussian mixture regression (HMM-GMR) to identify latent vehicle interaction states, and then used reinforcement learning to select the ego CAV's merging action based on these states. The latent state representation distinguishes typical interaction patterns prior to action selection, so merging decisions are not confined to instantaneous traffic observations, but instead grounded in inferred vehicle interaction relationships. Wang et al. (2021b) used a deep Q-network (DQN) to let the ego CAV choose among acceleration, deceleration, and merging actions from its local traffic state, making the selected discrete action the direct decision output. The Q-values are learned from the subsequent safety and merging progress associated with each action, enabling the ego CAV to make the decision without jointly controlling surrounding vehicles.

Model-based decision methods explicitly determine merging-related variables through stated objectives and feasibility constraints. Sharma et al. (2022) used a feedback-feedforward linear quadratic regulator based on a multi-class, multi-lane traffic

model to generate lane-changing advisories for automated vehicles. The quadratic objective determines the advisory by penalizing deviations from the desired traffic state and excessive advisory effort. Liang et al. (2023) treated merging time and merging position as the ego CAV's primary decision variables and jointly generated a smooth reference trajectory for the selected merge. Acceleration and jerk terms shape the objective, while vehicle-motion and road constraints restrict the feasible decision set; the resulting merging plan and reference trajectory were evaluated in PreScan and Simulink co-simulation.

3.2. General multi-vehicle decision-making

General multi-vehicle decision coordination uses the states, intentions, predicted motions, available gaps, and other shared information of multiple ramp and mainline vehicles to determine merging decisions without requiring a persistent platoon structure. Based on these inputs, participating vehicles jointly or interactively determine outputs such as merging sequence, vehicle-gap assignment, lane-changing choices, merging time, and planned trajectory. The reviewed methods mainly include multi-agent reinforcement learning, optimization, and game-based decision models.

When multi-agent reinforcement learning is applied to multi-vehicle decision-making, each participating CAV is modelled as an agent that selects merging actions based on local observations and information received from interacting vehicles, while coordination is promoted through individual or shared rewards reflecting safety and traffic efficiency. Eqs. (4) to (6) provide a unified representation of information sharing and multi-agent decision-making synthesized from the studies discussed in this subsection, such as Liu et al. (2024), Guo et al. (2021), and Yang et al. (2025).

Assuming that vehicle i can obtain its local traffic observation and receive information from a defined set of communicating neighbours, its cooperative observation can be written as

$$o_{i,t} = g(o_{i,t}^{\text{local}}, \{m_{j \rightarrow i,t}\}_{j \in \mathcal{N}_i}) \quad (4)$$

where the local observation $s_{i,t}$ contains information directly available to vehicle i , $m_{j \rightarrow i,t}$ denotes the message received from a neighbouring vehicle j , $\mathcal{N}_i$ is the communication-neighbour set, and $g(\cdot)$ represents the information-fusion mechanism. Based on the fused observation, vehicle i selects its merging-related action according to

$$a_{i,t} \sim \pi_i(\cdot | o_{i,t}) \quad (5)$$

This representation assumes that the information required for action selection can be obtained from local sensing and the specified communication links. It does not require every participating vehicle to observe the complete traffic state.

During multi-agent learning, the actions of different vehicles jointly affect traffic-state transitions and rewards. When joint training information is available, a centralized-training representation can evaluate the joint state information and joint actions while allowing individual vehicles to make their own decisions during execution:

$$Q_{\text{joint}}(s_t, a_t) = \mathbb{E} \left[\sum_{\tau=t}^T \gamma^{\tau-t} R_{\text{global}}(s_\tau, a_\tau) \mid s_t, a_t \right] \quad (6)$$

where s_t and a_t denote the joint information and joint action used during training. This formulation assumes that joint

information can be accessed during training, while decentralized decision making uses the information available to each vehicle during operation. The specific observation variables, communication topology, reward function, and training architecture follow the corresponding source study.

In Eqs. (4) to (6), the newly introduced variables are defined as follows:

- $o_{i,t}^{\text{local}}$: The local observation information of vehicle i at time t , directly obtainable via onboard sensors.
- $m_{j \rightarrow i,t}$: The message sent by neighbouring vehicle j to vehicle i at time t , which may include the neighbour's state, intention, etc.
- $\mathcal{N}_i$: The set of communication neighbours of vehicle i .
- $g(\cdot)$: The information-fusion function that integrates local observations and neighbour communication messages into a cooperative observation.
- $Q_{\text{joint}}(s_t, a_t)$: The joint action-value function, which evaluates the expected cumulative return of executing joint action a_t under joint state s_t .
- $R_{\text{global}}(s_\tau, a_\tau)$: The global reward function, computed based on joint states and joint actions during training, used to guide the overall optimization objective of the multi-agent system.

Multi-agent reinforcement-learning methods determine coordinated merging decisions through the action and reward design of several interacting vehicles. Liu et al. (2024) represented vehicle interactions with a graph and used multi-agent reinforcement learning to determine coordinated merging decisions for participating CAVs in multilane mixed traffic. The group reward combines traffic efficiency and safe interaction, and tests at different CAV penetration rates examine how the learned decisions change as the proportion of controllable vehicles varies. Pan et al. (2021) used model-based reinforcement learning to decide CAV lane-changing actions within an integrated highway-control environment that also represents ramp metering, speed control, recommendations to HDVs, and driver compliance. The decision objective evaluates the combined traffic effect of the CAV lane-changing choices. Guo et al. (2021) used a shared multi-agent learning framework to determine coordinated merging actions for automated vehicles interacting with HDVs. Shared interaction information affects the action selected by each participating vehicle, and evaluation in mixed merging traffic examines how the learned decisions change when HDVs and automated vehicles coexist. Yang et al. (2025) introduced priority sequential inference so that interacting vehicles make their merging and lane-changing choices in a prescribed order rather than simultaneously. Later vehicles condition their decisions on earlier choices, which reduces mutually incompatible actions in dense interactions.

Optimization and game-based methods determine multi-vehicle decisions through explicit system objectives or interacting utilities. Ramezani and Ye (2019) used an optimization-based strategy to generate lane-changing advisories for multiple automated vehicles according to the current traffic state. The optimization determines how the participating vehicles should adjust their lane choices so that their individual lane-changing

decisions collectively improve the distribution of vehicles across lanes. Jing et al. (2025) modelled the coupled merging choices of CAVs and HDVs as a stochastic potential game and solved the resulting decision problem through decentralized optimization. Each vehicle's utility contributes to the potential function, allowing mixed-traffic interaction preferences to affect the final merging outcome without a single central scheduler. Jiang et al. (2021) used instantaneous virtual trajectories to predict future interactions and then assigned each ramp vehicle to a feasible gap in the mainline stream, making vehicle-gap pairing the main multi-vehicle decision output. The prediction and pairing process determines which mainline gap each ramp vehicle should use, and the strategy was evaluated in a VISSIM network constructed from I-35 field data.

3.3. Platoon-based decision planning

Platoon-based decision planning uses vehicle states, arrival information, available gaps, platoon roles, and spacing requirements to organize ramp and mainline vehicles into an actual or virtual one-dimensional order and determine their merging plan. The resulting decisions may include platoon establishment, vehicle order, target-gap assignment, entry time or merging position, desired intra-platoon spacing, and reference trajectories. Unlike general multi-vehicle coordination, these decisions are made under explicit platoon relationships such as leader-follower order, prescribed spacing, or platoon membership.

The reviewed studies mainly use rule- or state-based planning, optimization and scheduling, and learning-based decision methods. Rule-based approaches determine platoon organization and gap allocation from predefined safety and coordination conditions, whereas optimization and learning methods determine these decisions from explicit objectives or learned policies.

For rule-based platoon planning, Eqs. (7) to (9) summarize recurring gap-feasibility and spacing-adjustment mechanisms used in representative merging studies such as Marinescu et al. (2012), Karbalaieali et al. (2020), and Zhu et al. (2024). These formulations assume that the vehicles defining the target gap can be identified, their longitudinal motion can be measured or predicted over the planning horizon, and the platoon order is maintained during merging.

$$\begin{aligned} C_{\text{merge}}(t) &= 1 \Rightarrow d_f(\tau) \geq d_f^{\text{safe}}(\tau), \\ d_r(\tau) &\geq d_r^{\text{safe}}(\tau), \\ d_{j,j-1}(\tau) &\geq d_{j,j-1}^{\text{safe}}(\tau), \quad j = 2, \dots, M, \\ d_{\text{gap}}(t) &\geq L_{\text{platoon}}(t) + d_f^{\text{safe}}(t) + d_r^{\text{safe}}(t), \\ \tau &\in [t, t + T_m] \end{aligned} \quad (7)$$

The variables in Eq. (7) are defined as follows:

- $C_{\text{merge}}(t)$: Merging permission flag; a value of 1 indicates that merging is allowed.
- $d_f(\tau)$, $d_r(\tau)$: Longitudinal clearances between the front and rear boundaries of the merging platoon and the leading and following vehicles of the target gap.
- $d_f^{\text{safe}}(\tau)$, $d_r^{\text{safe}}(\tau)$: Corresponding safety distance thresholds.
- $d_{j,j-1}(\tau)$: Actual spacing between vehicle j and its predecessor $j - 1$ within the platoon.
- $d_{j,j-1}^{\text{safe}}(\tau)$: Required safe spacing between vehicle j and its predecessor $j - 1$.

- $L_{\text{platoon}}(t)$: Total platoon length, including vehicle lengths and desired internal spacings.
- T_m : Merging planning horizon length.
- M : Total number of vehicles in the platoon.

Eq. (7) represents longitudinal feasibility for the planned merge. Additional lateral, dynamic, sensing, or communication constraints are introduced when required by the corresponding study. When the desired intra-platoon spacing is adjusted at the planning level, the spacing deviation and the corresponding gap-revision trigger can be represented by Eqs. (8) and (9):

$$e_{j,t} = d_{j,j-1}(t) - d_{j,j-1}^{\text{des}}(t), \quad j = 2, \dots, M \quad (8)$$

$$C_{\text{gap}}(t) = \mathbb{I}\left(\max_{j=2,\dots,M} |e_{j,t}| > \delta\right) \quad (9)$$

The variables in Eqs. (8) and (9) are defined as follows:

- $e_{j,t}$: Spacing deviation between actual and desired spacing for vehicle j at time t .
- $d_{j,j-1}^{\text{des}}(t)$: Desired spacing between vehicle j and its predecessor $j - 1$ at time t .
- $C_{\text{gap}}(t)$: Gap adjustment trigger flag; a value of 1 indicates that the desired gap should be revised.
- $\mathbb{I}(\cdot)$: Indicator function; equals 1 if the condition is satisfied and 0 otherwise.
- δ : Tolerance threshold for spacing deviation.

Rule-based and state-based methods determine platoon organization and merging decisions through predefined states, slots, or cost-based selection rules. Marinescu et al. (2012) reserved mainline slots for ramp vehicles and used rule-based slot allocation to decide each ramp vehicle's acceptable gap and entry order. The slot rule gives the decision directly without repeated numerical optimization, but it requires the relevant vehicle arrival and slot information to be available. Han et al. (2022) combined finite-state transitions with a genetic fuzzy system to decide platoon establishment, the merging position, and the cooperative merging action associated with the current traffic state. The finite-state structure makes the decision stages explicit, while the fuzzy rules provide adaptation within the predefined state and rule set. Karbalaieali et al. (2020) compared candidate platoon-merging options using a dynamic travel-time cost and selected the option with the lower system travel burden. The decision method therefore chooses among merging alternatives through an interpretable cost comparison, and its reported performance was evaluated in VISSIM.

Optimization and scheduling methods explicitly determine platoon size, vehicle order, target-gap assignment, or entry time from system objectives and feasibility constraints. Zhu et al. (2024) optimized platoon size and matched each resulting ramp-vehicle group with an available spatiotemporal gap in a multilane merging environment. The decision jointly determines how many ramp vehicles should be grouped and which gap should serve that group, so it depends on the availability of predicted or known spatiotemporal gaps. Kumaravel et al. (2021) formulated the arrivals of mainline and ramp platoons as a decentralized scheduling problem and decided their entry times without one centralized optimizer. The schedule determines inter-platoon order while retaining each platoon's internal order, which distributes computation but still requires the participating groups

to share sufficient arrival information. Shi et al. (2021b) used graph search to evaluate candidate merging sequences together with their motion plans and selected the solution with the lowest search cost. The method reduced fuel consumption compared with the first-come-first-served baseline, although its computational burden increased with the number of candidate sequences.

Learning-based methods use traffic observations, vehicle roles, and reward functions to adjust platoon-related decisions such as desired spacing or cooperative merging actions. Eqs. (10) to (15) summarize recurring role-dependent observations, reward components, and spacing-related terms used in representative learning-based platoon studies, such as Yadavalli et al. (2023) and He and Lv (2023b).

$$a_{i,t} \sim \pi_i(\cdot | o_{i,t}, r_i) \quad (10)$$

Here, r_i denotes the predefined role of agent i (e.g., leader or follower). A leader and a follower can therefore use different policy mappings, while predecessor information is represented as a communicated message rather than assuming that the predecessor's current action is always directly observable:

$$a_{i,t} \sim \begin{cases} \pi_{\text{leader}}(\cdot | o_{i,t}), & r_i = \text{leader}, \\ \pi_{\text{follower}}(\cdot | o_{i,t}, m_{i-1 \rightarrow i,t}), & r_i = \text{follower}, \end{cases} \quad (11)$$

The variables in Eqs. (10) and (11) are defined as follows:

- r_i : Predefined role of agent i (leader or follower).
- π_{leader} : Policy mapping for leader vehicles.
- π_{follower} : Policy mapping for follower vehicles.
- $m_{i-1 \rightarrow i,t}$: Communication message sent by predecessor $i-1$ to following vehicle i at time t , which may contain the predecessor state, planned action, or other communicated information according to the topology used in the source study.

At the reward level, a generic platoon objective can combine system performance, individual safety or comfort, and platoon maintenance:

$$R_{\text{platoon}}(s_t, a_t) = \alpha R_{\text{global}}(s_t) + \beta \sum_{i=1}^M R_{\text{local},i}(s_{i,t}, a_{i,t}) + \eta R_{\text{maintenance}}(s_t) \quad (12)$$

The variables in Eq. (12) are defined as follows:

- R_{platoon} : Platoon-level reward function.
- R_{global} : Global platoon performance reward, such as average speed and total fuel consumption.
- $R_{\text{maintenance}}$: Spacing-maintenance reward, penalizing spacing deviations.
- α, β, η : Weight coefficients for the respective reward components, set by the specific study.

Eq. (12) exposes a recurring reward structure only; the actual terms and weights differ across the reviewed learning methods.

A common platoon spacing-maintenance term penalizes deviation from the desired pairwise spacing:

$$R_{\text{maintenance}}(s_t) = - \sum_{i=2}^M (d_{i,t} - d_{i,t}^{\text{des}})^2 \quad (13)$$

Here, $d_{i,t}$ is the actual spacing between vehicle i and its predecessor at time t , and $d_{i,t}^{\text{des}}$ is the desired spacing. The desired spacing can depend on speed, time headway, vehicle role, or

merging phase rather than being a single fixed constant.

For a predecessor-following communication topology, one representative observation structure is:

$$o_{i,t} = (o_{i,t}^{\text{local}}, m_{i-1 \rightarrow i,t}), \quad i \geq 2 \quad (14)$$

Here, $o_{i,t}^{\text{local}}$ is the local observation of vehicle i (already defined in Section 3.2). Eq. (14) assumes a front-to-rear predecessor-following topology and should not be generalized to multi-predecessor, bidirectional, leader-broadcast, or switching communication structures.

Motion-consistency penalties can also be added to a learning objective. For example, a local smoothness penalty is:

$$L_{\text{smooth}}(s_t) = \sum_{i=2}^M (\Delta a_{i,t} - \Delta a_{i-1,t})^2 \quad (15)$$

$$\Delta a_{i,t} = a_{i,t} - a_{i,t-1}$$

Here, $\Delta a_{i,t}$ is the acceleration change of vehicle i at time t , and L_{smooth} is the motion smoothness penalty term. Minimizing Eq. (15) promotes similar acceleration changes between adjacent vehicles and can improve motion smoothness, but it does not by itself establish string stability.

Learning-based platoon planning uses the reward to adapt desired gaps or other platoon decisions as traffic conditions change. Yadavalli et al. (2023) used DDGP to decide the desired intra-platoon gap so that an entering ramp vehicle can be accommodated within the moving platoon. The continuous gap decision is conditioned on traffic-state information and is rewarded according to overall traffic-flow performance, so the method adapts the planned spacing rather than prescribing a fixed insertion gap. He and Lv (2023b) used multi-agent actor-critic learning to determine role-dependent cooperative decisions for a platoon of connected electric vehicles. The group reward combines merging cooperation, traffic efficiency, and energy use, while role-dependent observations and shared information keep the decisions of leader and follower vehicles coordinated.

Across Section 3, the main trade-off is therefore not simply between algorithms but between assurance, information demand, and adaptability. Rule-based planning methods have low computation and clear logic but limited generalization; optimization methods expose safety and dynamic constraints but become more expensive with additional vehicles and candidate sequences; and learning methods can adapt to complex interactions but rely on representative training and usually provide empirical rather than formal safety evidence.

4 Control and execution module

This section reviews studies whose primary contribution or analytical focus lies in control execution, namely how a given merging decision, target state, or reference trajectory is converted into executable vehicle motion. The discussion here is restricted to the controlled variables, control law or optimization, feedback or safety mechanism, and execution-side validation rather than the upstream decision process.

4.1. Individual-vehicle control execution

Individual-vehicle control execution focuses on how the ego CAV realizes a given merging decision or reference trajectory while surrounding vehicles remain external traffic participants. The controller generates executable speed, acceleration, steering, torque,

or trajectory-tracking commands from the ego vehicle state, tracking error, vehicle dynamics, and relevant safety constraints. Individual-vehicle control methods mainly include optimal or model-predictive control and learning-based execution. Model-based methods expose the tracking or energy cost, vehicle dynamics, and actuator constraints, whereas learning-based methods are characterized by the executable action space and reward design.

At the individual-vehicle control level, model-based methods convert efficiency, energy use, comfort, and tracking requirements into an explicit limited-horizon constrained optimal-control problem. The following formulation is a generic discrete-time representation synthesized from recurring structures in the optimal-control and model-predictive-control studies discussed in this subsection, such as Liu et al. (2025), Qiang et al. (2025), and Gao et al. (2022). Individual studies use different vehicle models, cost terms, horizons, terminal conditions, and solvers. Assuming that a discretized vehicle model and a current state estimate are available, the objective is

$$\min_{\mathbf{u}_{i,0:T-1}} J_i = \Phi_i(\mathbf{x}_{i,T}) + \sum_{t=0}^{T-1} L_i(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}) \quad (16)$$

The control sequence is subject to the study-specific vehicle dynamics,

$$\mathbf{x}_{i,t+1} = f_i(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}), \quad t = 0, \dots, T-1 \quad (17)$$

admissible state and actuator sets,

$$\mathbf{x}_{i,t} \in \mathcal{X}_i, \quad \mathbf{u}_{i,t} \in \mathcal{U}_i \quad (18)$$

and additional path constraints such as collision avoidance, road boundaries, comfort, or merging requirements:

$$\mathbf{h}_i(\mathbf{x}_{i,t}, \mathbf{u}_{i,t}) \leq 0 \quad (19)$$

The variables in Eqs. (16) to (19) are defined as follows:

- $\mathbf{x}_{i,t}$: The state vector of vehicle i at time t , such as position, velocity, heading angle, etc.
- $\mathbf{u}_{i,t}$: The control input of vehicle i at time t , such as acceleration, steering angle, etc.
- J_i : The scalar performance index (total cost) to be minimized.
- $\Phi_i(\mathbf{x}_{i,T})$: The terminal cost function, penalizing or rewarding the state at the end of the horizon.
- $L_i(\mathbf{x}_{i,t}, \mathbf{u}_{i,t})$: The running cost function, integrating multiple objectives such as travel time, energy consumption, and comfort.
- $f_i(\cdot)$: The discrete-time state transition function describing vehicle dynamics.
- $\mathcal{X}_i$: The admissible state constraint set, such as speed limits.
- $\mathcal{U}_i$: The admissible input constraint set, such as acceleration bounds.
- $\mathbf{h}_i(\cdot)$: The path constraint function, encoding safety, comfort, or merging-specific requirements.

These Eqs. assume that the relevant dynamics and constraints can be represented over the selected horizon. They do not imply global optimality, recursive feasibility, or closed-loop stability unless those properties are separately established in the corresponding study.

Optimal-control and model-predictive methods compute the ego CAV's executable motion from an explicit cost function, vehicle model, and motion constraints. Xia et al. (2024) controlled the ego

CAV's lane-changing motion by tracking a quasi-uniform B-spline reference through a quadratic-programming formulation after the target lane had been fixed. The objective penalized tracking and smoothness errors, while geometric and dynamic constraints kept the executed path inside the feasible road and vehicle envelope. Liu et al. (2025) used short-horizon model predictive control to regulate the torque required by an automated electric vehicle to follow an energy-efficient reference motion. The controller optimizes the torque input online from the current vehicle state and reference motion while enforcing state and actuator constraints during execution. Qiang et al. (2025) used finite-time MPC with feedback correction to control the ramp vehicle toward a prescribed merging state within a fixed horizon. The cost penalized tracking error and control effort, and the terminal constraint required the ego vehicle to reach the assigned merge state within the allowed time. Gao et al. (2022) formulated ego-vehicle trajectory execution as a constrained optimal-control problem and used Legendre pseudospectral discretization to solve for the continuous control history. The optimization minimizes trajectory cost while enforcing vehicle dynamics, input limits, and path constraints throughout the merge.

Learning-based execution directly maps the ego CAV's observed state to executable motion commands and is distinguished by its action space, reward, and safety mechanisms. Zhao et al. (2022) controlled the ego CAV's lateral motion by tracking a quintic lane-change reference with a dedicated lane-keeping agent. A priority-based safety mechanism checks the generated commands before execution and prevents unsafe actions from being sent to the vehicle. Liu et al. (2022) used discrete Soft Actor-Critic to generate executable merging commands for the ego CAV and added a motion-predictive safety controller that forecasts near-term collision risk. When an action is predicted to be unsafe, the safety controller replaces it before execution, and the tested traffic-density scenarios reported collision-free operation. He et al. (2023) trained a constrained adversarial reinforcement-learning controller to maintain ego-vehicle control performance when observations and operating conditions are perturbed. Tests with measurement noise, observation noise, and changes in road adhesion directly evaluate robustness when the execution environment differs from nominal training. Zhang et al. (2023) used parameter-sharing independent proximal policy optimization (IPPO) so that the ego CAV policy outputs lane-keeping, lane-changing, acceleration, and deceleration commands. The reward directs these executable actions toward safe and efficient high-speed merging, while parameter sharing reduces duplicated policy training across vehicles without requiring their controls to be jointly optimized at execution.

4.2. General multi-vehicle control execution

General multi-vehicle control coordination simultaneously regulates executable motion variables of several ramp and mainline vehicles without requiring a fixed platoon structure. The controlled variables include acceleration, speed, steering, spacing, or trajectories, and inter-vehicle coupling enters through relative-state feedback, shared constraints, common objectives, communicated observations, or jointly optimized motion. General

multi-vehicle control methods include feedback control, constrained optimization and multi-agent reinforcement learning. Their main differences are what motion variables are controlled, how interaction errors or shared constraints enter the controller, what communication is required, and how much online computation is needed to generate executable commands.

In general multi-vehicle control, feedback methods use inter-vehicle spacing, velocity, or cooperative-gap errors to generate executable vehicle commands. Representative implementations discussed in this subsection define such errors and feedback laws under different information topologies, safety constraints, and vehicle models, such as Chen et al. (2021), Liu et al. (2023), and Pan et al. (2025). For N interacting vehicles, define the stacked state as

$$\mathbf{X}_t = [\mathbf{x}_{1,t}^\top, \mathbf{x}_{2,t}^\top, \dots, \mathbf{x}_{N,t}^\top]^\top, \quad \mathbf{x}_{i,t} \in \mathbb{R}^{n_x} \quad (20)$$

Let $\mathbf{X}_t^d$ denote the desired cooperative relation, which may encode desired spacing, relative velocity, or another cooperative motion objective. A generic cooperative error is

$$\mathbf{e}_t = \mathcal{E}(\mathbf{X}_t, \mathbf{X}_t^d) \quad (21)$$

where the mapping $\mathcal{E}$ is controller-specific and may contain pairwise spacing, velocity, or trajectory-tracking errors. A generic feedback controller then generates the executable input of vehicle i as

$$\mathbf{u}_{i,t} = \mathbf{K}_i(\mathbf{e}_t, \mathbf{x}_{i,t}) \quad (22)$$

The variables in Eqs. (20) to (22) are defined as follows:

- $\mathbf{X}_t$: The stacked state vector of all N vehicles at time t .
- $\mathbf{x}_{i,t}$: The state vector of vehicle i at time t .
- N : The total number of interacting vehicles.
- n_x : The dimension of the state vector of a single vehicle.
- $\mathbf{X}_t^d$: The desired cooperative relation, encoding objectives such as desired spacing, relative velocity, or other formation requirements.
- $\mathbf{e}_t$: The cooperative error vector, representing the deviation between the current stacked state and the desired cooperative relation.
- $\mathcal{E}(\cdot)$: The error mapping function, defined by the specific controller, which may incorporate pairwise spacing errors, velocity errors, trajectory-tracking errors, or combinations thereof.
- $\mathbf{u}_{i,t}$: The control input of vehicle i at time t .
- $\mathbf{K}_i(\cdot)$: The feedback control law of vehicle i , which maps the cooperative error and the vehicle's own state to an executable control input.

Eq. (22) describes only the structural relationship between feedback error and control input. Stability, robustness, constraint satisfaction, and string stability depend on the particular controller $\mathbf{K}_i$, communication topology, and vehicle dynamics.

String stability cannot be established from the generic feedback relations in Eqs. (20)–(22) alone; it must be evaluated using a specified inter-vehicle propagation model and an appropriate stability criterion. Chen et al. (2021) transformed the on-ramp merging problem into a multiple-predecessor virtual car-following system and designed a unidirectional multi-leader communication topology. For the idealized linear longitudinal control structure considered in that study, the velocity-propagation relation and a representative sufficient frequency-domain criterion for practical

string stability are given by:

$$V_i(s) = \sum_{k=1}^{N_i} Q_k(s) V_{i-k}(s) \quad (23)$$

$$\sum_{k=1}^{N_i} \|Q_k(j\omega)\|_\infty \leq 1$$

The variables in Eq. (23) are defined as follows:

- $V_i(s)$: Velocity response of vehicle i in the Laplace domain.
- $Q_k(s)$: Transfer function from the k -th predecessor to the current vehicle.
- N_i : Number of predecessors from which vehicle i can obtain information within its communication topology.
- ω : Angular frequency in frequency-domain analysis.
- $\|\cdot\|_\infty$: Infinity norm used to express the upper bound on the frequency-domain gain.

Eq. (23) applies to the linearized longitudinal multi-predecessor structure for which these transfer functions are defined. It should not be generalized directly to nonlinear, heterogeneous, switching-topology, or nonzero-initial-condition platoons. Such cases require the stability definition and proof adopted in the corresponding original study.

Feedback and robust-control methods generate executable multi-vehicle motion from inter-vehicle states, motion errors, or cooperative safety constraints. Chen et al. (2021) transformed the merge into a virtual car-following system and used distributed feedforward and feedback longitudinal control, together with local lateral control, to regulate the spacing and speed of the participating vehicles. The control law uses communicated predecessor information, and practical string stability was established for the longitudinal dynamics under the specified information topology. Liu et al. (2023) used a safety-critical cooperative controller to regulate the longitudinal motion of interacting CAVs during on-ramp merging in mixed traffic. Control barrier functions and control Lyapunov functions were incorporated into an online quadratic program to generate vehicle control inputs while enforcing collision-avoidance requirements and updating the control according to surrounding HDV motion. Pan et al. (2025) used spatial-enhanced adaptive robust control to regulate the longitudinal and lateral motions of multiple CAVs during on-ramp merging. Spatially dependent safety constraints define the allowable vehicle motion near the merging conflict region, while a Lyapunov-based min-max controller compensates for time-varying vehicle-dynamics uncertainties and regulates the corresponding tracking errors.

Optimization-based multi-vehicle control solves the trajectories or control inputs of several participating vehicles within explicit dynamic and safety constraints. Han et al. (2023) jointly computed executable CAV trajectories in mixed traffic while surrounding HDVs were represented by Gipps and heuristic behaviour models. The controller therefore optimizes CAV motion against explicit human-driver responses, but its execution quality remains dependent on how well those HDV models represent actual behaviour. Xie et al. (2017) centrally optimized the trajectories of cooperating vehicles under common safety and traffic-efficiency objectives. The centralized controller was connected to a test platform integrating VISSIM, MATLAB, and

Car2X, providing a communication-enabled simulation of multi-vehicle trajectory execution. Hu and Sun (2019) used event-triggered longitudinal control to regulate the immediate speed and spacing responses of mainline and ramp CAVs during the merge. The controller is activated by the prescribed event condition rather than continuously, so execution depends on timely detection of the interaction state that triggers the control update. Zhou et al. (2019b) formulated the longitudinal motions of a facilitating mainline vehicle and a ramp vehicle as coupled state-constrained optimal-control problems under congestion. The control objective creates sufficient merging space while the constraints limit excessive deceleration and keep both vehicle trajectories dynamically feasible. Wang et al. (2022) jointly optimized the longitudinal motions of a downstream mainline vehicle and the ramp vehicle so that the two controlled trajectories reach a safe merging condition. The objective reduces disturbance around the merging conflict while vehicle-dynamic and spacing constraints bound both executable trajectories. Wang et al. (2024) used MPC to control the longitudinal and lateral motion of cooperating CAVs while tracking an assigned lane-changing trajectory and desired headway. The MPC cost penalizes tracking error and control effort, and vehicle-dynamic constraints restrict the executable motion throughout the manoeuvre. Wang et al. (2025) used online speed replanning with an ultra-local vehicle model and MPC to generate speed commands and added compensation for vehicle-to-vehicle packet drops. The controller updates the command from measured input-output behaviour rather than a detailed plant model, allowing communication loss to be tested directly within the closed control loop.

Multi-agent reinforcement-learning control directly generates executable actions for several interacting vehicles from learned cooperative policies. Li et al. (2023) used communication-based Soft Actor-Critic to control the longitudinal accelerations of multiple vehicles from shared interaction information. The reward combines safe spacing and traffic efficiency so that the learned acceleration commands open a usable merging gap, but execution depends on the availability of the communicated neighbour information. Schester and Ortiz (2021) used multi-agent DDPG in continuous state and action spaces to coordinate the longitudinal motion of multiple vehicles. The reward was designed to promote safe and efficient merging, and simulations under different merging-distance settings showed successful coordinated merging in the tested cases. Peng et al. (2025) used a multi-agent deep deterministic policy gradient algorithm to generate cooperative merging motions for multiple CAVs, allowing the participating vehicles to adjust their merging trajectories according to multi-vehicle interaction states. Global and individual rewards are jointly designed to account for both the overall performance of the merging area and the local motion objectives of individual CAVs.

4.3. Platoon-based control execution

Platoon-based control regulates ramp and mainline vehicles after an explicit one-dimensional order, platoon role, or spacing relationship has been established. The main control outputs are platoon-member speed, acceleration, spacing correction, and trajectory-tracking commands, with particular emphasis on maintaining the assigned vehicle order and longitudinal safety

during merging. Platoon control mainly uses feedback or robust control and predictive or optimal control. Feedback methods convert platoon spacing or velocity errors directly into vehicle commands, while predictive and optimal methods compute member trajectories subject to assigned merge states, intra-platoon spacing, vehicle dynamics, and input constraints.

Feedback and robust-control methods regulate a platoon through explicit spacing relations and safety constraints. Huang et al. (2019) used distributed linear feedback under bidirectional communication to control the relative motion of mainline and ramp CAVs organized as a virtual platoon. The controller generates feedback inputs from inter-vehicle spacing errors and shared neighbouring states, allowing the vehicles to coordinate their longitudinal motion according to the prescribed virtual order. Meng et al. (2022) designed a spatial-dependent robust constraint-following controller to regulate platoon motion during merging. Collision avoidance is imposed as a spatial constraint within the control law, so robustness and safety are handled directly during execution rather than only through a planning rule.

Predictive and optimal-control methods compute executable trajectories for platoon members from an already assigned group structure or merging target. Xue et al. (2022) used MPC to track planned merging nodes and regulate inter-vehicle motion within the platoon. The objective keeps each member close to its assigned merge state while spacing and input constraints maintain coordinated group motion. Zhao et al. (2021) used vehicle-level MPC to regulate the microscopic trajectories of CAVs after the desired group organization had been assigned. The controller therefore focuses on executing the given platoon target while enforcing vehicle-level motion constraints. Xue et al. (2023) solved analytical optimal-control problems for each local platoon after the temporary vehicle order had been established in dense traffic. The controller computes coordinated longitudinal motion for the members of each group, using the temporary platoon structure to reduce the number of vehicles coupled in each control problem.

Overall, model-based feedback and optimal control provide clearer stability or constraint-based assurances but depend on accurate models and, for cooperative formulations, reliable shared states. Learning-based controllers offer flexible nonlinear policies with low inference cost after training, yet their safety and generalization are typically verified only in simulation and lack formal mathematical guarantees. The diversity of traffic demand, CAV penetration, vehicle models, baselines, and validation platforms also means that numerical improvements reported by different studies should not be ranked directly across papers.

Building upon the functional analyses of decision planning and control execution, this review further examines how these functions are organized within complete vehicle-level control systems. Sections 5–7 distinguish three architectures: hierarchical control, in which decision-making and control execution remain sequentially separated; integrated control, in which decision variables and control variables are determined within the same solution process; and hybrid control, in which decision and control functions are organized through multiple interacting components without a fixed sequential structure or a unified solving process.

5 Hierarchical cooperative control architecture

Hierarchical cooperative control divides highway on-ramp merging into two connected levels, namely the decision layer and the control layer, where the decision layer operates before the control layer in a sequential manner. The decision layer determines the cooperative arrangement of vehicles during merging and typically outputs the merging sequence, target gap, merging time and position, and reference trajectory. The control layer then converts these results into executable longitudinal and lateral control actions through speed, acceleration, and steering regulation. The main difference among hierarchical approaches lies in the type of information transmitted from the decision layer to the control layer and whether the execution state of the control layer is used to update the upper-level decision. According to the dominant inter-layer interaction mechanism, hierarchical cooperative control is classified into five typical forms: open-loop command transmission, closed-loop feedback coordination, constraint transmission, condition-triggered strategy selection, and spatiotemporal partitioning. These five forms are shown in Fig. 2.

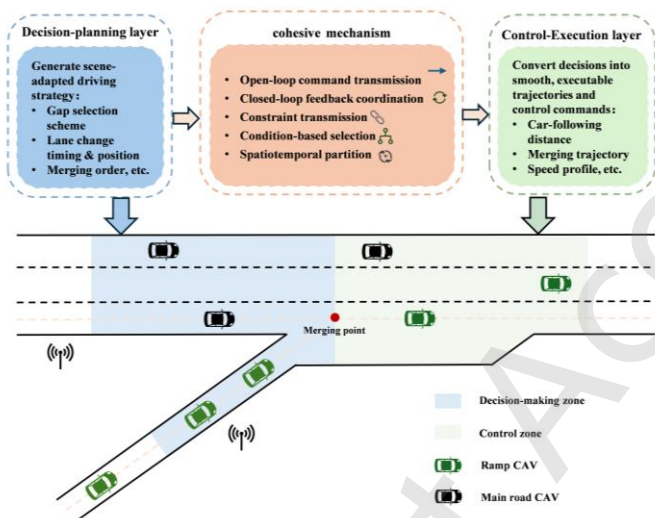


Fig. 2. Hierarchical cooperative control architecture diagram

Open-loop command transmission adopts a one-way connection between the two layers. After the decision layer determines the cooperative decision, the result is passed directly to the control layer, which executes the corresponding vehicle motion. Within the current decision cycle, the execution result is not returned to the decision layer to revise the original decision. The main characteristics of this form are a clear inter-layer relationship and a simple interface, although the decision layer has limited ability to respond immediately to actual vehicle execution. Kimura et al. (2022) used reinforcement learning to decide the target merging position and timing, then passed these values directly to an MPC controller for execution. The lower controller follows the received target without sending feasibility information back to revise the upper decision in the same cycle. Li et al. (2024) selected the target gap and lateral reference first, then transmitted them to a lower vehicle-motion controller in multilane mixed traffic. The execution scenarios were informed by real Delft trajectory data, providing a more realistic traffic basis for the one-way decision transfer. Hu et al. (2021) scheduled the merging sequence at a roadside unit and sent that order to a distributed robust constraint-

following controller. The lower controller accounts for time-varying vehicle-dynamics uncertainty, while the sequence itself remains the command received from the upper layer. Chen et al. (2023) used multi-agent reinforcement learning to issue high-level cooperative instructions, screened the selected instruction with a safety supervisor, and then sent it to a proportional-integral-derivative controller. Human-driven vehicles were represented with the Intelligent Driver Model and the Minimizing Overall Braking Induced by Lane Changes model, allowing the command chain to be tested in explicit mixed-traffic behaviour.

Closed-loop feedback coordination adopts a bidirectional connection between the two layers. The decision layer passes the current decision results to the control layer, while the control layer returns vehicle states, tracking deviations, or execution feasibility during implementation. The decision layer then updates subsequent decisions according to this feedback. The two layers therefore form a continuous process of decision making, execution, feedback, and revision, allowing upper-level decisions to adapt to actual vehicle motion and improving consistency between decision making and control. Milanese et al. (2011) generated the merging reference at an infrastructure controller and used fuzzy longitudinal controllers on the vehicles, with vehicle-to-infrastructure feedback returning the current execution state. The closed-loop system was tested with three production vehicles in real-road experiments. Sun et al. (2020) used dynamic programming to decide the cooperative order and fed lower trajectory costs back into the sequencing calculation. The feedback was evaluated under different human car-following models, including Gipps and the Intelligent Driver Model, so the upper decision could be revised according to the cost of actual downstream motion. Shen et al. (2018) generated candidate cooperative plans with heuristic rules and evaluated their lower-level execution cost before fixing the final plan. This repeated cost check allows infeasible or inefficient candidates to be discarded before the command is committed. Chen et al. (2021) repeatedly coordinated an upper manoeuvre-planning optimization with a lower trajectory controller as new vehicle states became available. The upper plan is therefore updated during execution rather than being transmitted only once at the beginning of the merge. Chen et al. (2022) extended the same repeated planning and control coordination to on-ramps with several mainline lanes. Additional lane alternatives are evaluated in the upper layer, while state feedback continues to revise the planned manoeuvre during execution. Hou et al. (2023) used repeated updates of anticipated positions and cooperating vehicles in a multilane mixed-traffic merging framework. The planning layer is recalculated from the updated traffic state, then the revised command is passed to the motion layer for the next control cycle. Wu et al. (2025) combined deep reinforcement-learning path planning with MPC execution and added a reject and request mechanism between the two layers. When the lower layer detects that a plan is risky or infeasible, it sends that result back so the planner can generate another candidate. Li et al. (2025) coupled upper platoon and sequence decisions with lower following and lane-changing execution while explicitly considering large vehicles. The execution response of different vehicle classes feeds into the feasibility of the planned

organization, so the hierarchy can account for vehicle-size effects during repeated coordination. The comparison of open-loop and closed-loop coordination between the decision-making and control layers is shown in Fig. 3.

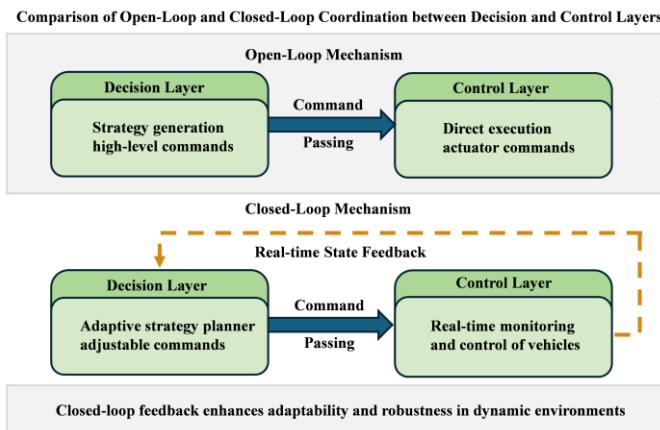


Fig. 3. Comparison of open-loop and closed-loop coordination between decision and control layers

Constraint transmission connects the two layers primarily through boundary conditions. Instead of prescribing a complete vehicle motion process, the decision layer specifies the ordering relationships, admissible time ranges, safety boundaries, or terminal conditions that must be satisfied during control execution. The control layer then determines the detailed vehicle motion within the resulting feasible region. In this form, the decision layer defines the overall boundaries of the merging process, while the control layer retains a certain degree of freedom to optimize vehicle motion within those boundaries. Letter and Elefteriadou (2017) determined the merging order first and then optimized longitudinal trajectories with that order fixed as a lower-level boundary condition. Safe-headway and vehicle-dynamic constraints define the feasible trajectory set used to execute the selected sequence. Tang et al. (2022) used a mixed-integer tactical optimization to determine vehicle order and flexible merging positions, then passed the resulting critical states to a continuous motion-planning problem. The lower solver therefore searches only trajectories that satisfy the discrete sequence and merge-location decisions received from the upper layer. Chen and Yang (2024) determined lane allocation and merging sequence before using those results as terminal conditions for numerical trajectory optimization. The terminal states restrict the lower solver to trajectories that reach the selected lane and order at the planned merge. Wu et al. (2022) transmitted merging order and terminal arrival time to a lower controller derived from the Pontryagin maximum principle. The fixed arrival condition links scheduling to the energy and motion calculation performed at the execution level. Liu et al. (2023) used constrained proximal policy optimization to select the target lane, then passed that lane decision to an optimal-control problem that balances travel time, energy consumption, and emissions. The lower problem keeps the chosen lane fixed while optimizing the continuous motion needed to reach it. Wang et al. (2025) used a virtual-platoon organization to determine sequence and gap relations for multilane mainline and dual-lane ramp merging, then imposed these relations on the lower trajectory generator. The trajectory solver preserves the

received order and gap constraints while computing feasible vehicle motion in the more complex road geometry.

Condition-triggered strategy selection adopts a strategy-switching connection driven by traffic states. The decision layer determines the appropriate merging strategy or operating mode according to the current traffic conditions and passes the selected strategy to the control layer. When the traffic state changes and a new triggering condition is satisfied, the decision layer selects another strategy and the control layer correspondingly changes its execution mode. The main inter-layer connection therefore lies in strategy selection and switching according to traffic conditions, rather than in the continuous transmission of detailed motion references. Liu et al. (2022) used a dueling double deep Q-network to choose the target lane and then activated a time and energy optimal controller for the selected manoeuvre. The discrete lane decision determines which continuous trajectory problem is solved next. Ding et al. (2020) adjusted sequence scheduling according to CAV penetration and surrounding vehicle type before generating cooperative CAV motion. Human-driven longitudinal behaviour was represented with the Gipps model, so the selected control organization changes as the traffic composition changes. Du et al. (2024) identified HDV driving style with a Gaussian mixture model and support vector machine, used an incomplete-information game to decide right of way, and activated lower deep reinforcement-learning intervention when cooperation was insufficient. The detected driver style and game result therefore determine when the learned control response is invoked. Yang et al. (2023a) selected virtual-platoon connection modes for different CAV and HDV combinations and then switched among CACC, adaptive cruise control, and merging-speed control. The active motion controller is chosen from the detected vehicle combination and traffic condition rather than remaining fixed throughout the merge. Li et al. (2024a) adjusted speed guidance according to driver style and the observed execution rate, then used the measured response to update subsequent guidance. The human-response model was supported by a naturalistic-driving experiment with 50 participants, providing data for the condition-dependent guidance logic.

Spatiotemporal partitioning connects the decision and control layers by separating their main responsibilities across different road regions, time periods, or stages of the merging process. The two layers mainly operate in different regions or stages, and the decision results produced in an earlier stage provide the basis for control execution in a subsequent stage. Compared with methods that maintain continuous inter-layer information exchange, this form reduces the need for continuous coordination between the decision and control layers during merging execution, although later control execution becomes more dependent on the continued validity of earlier decisions. Shi et al. (2021a) divided the merging area into spatial zones, completed lane-changing and trajectory decisions upstream, and started speed tracking after those decisions were fixed. The interface is therefore created by road location: planning ends in the upstream zone and execution begins in the downstream zone. Shi et al. (2023b) used a dynamic conflict graph upstream to schedule merging sequence and lane changes, then performed optimal trajectory

generation and platoon tracking downstream. The road segment itself separates the tactical scheduling problem from the later motion-control problem.

These five hierarchical interfaces therefore represent different balances between modularity and responsiveness. Open-loop transmission has the lowest cross-layer overhead but the weakest adaptation after a command is issued; closed-loop feedback

improves consistency at the cost of bidirectional communication and latency; constraint transmission offers explicit feasibility but can require heavier optimization; condition-triggered control adapts modes but depends on reliable classification and switching logic; and spatiotemporal partitioning reduces coupling but may act on stale decisions. Their characteristics are summarized in

Table 5.

Table 5. Hierarchical interface mechanisms and representative studies

Hierarchical interface mechanism	Representative studies	Typical decision-layer methods	Typical control-layer methods
Open-loop command transmission	Kimura et al. (2022) Li et al. (2024) Hu et al. (2021) Chen et al. (2023)	Deep reinforcement learning; rule-based heuristic algorithms; multi-agent deep reinforcement learning	Model predictive control; distributed robust control; proportional–integral–derivative control
Closed-loop feedback coordination	Milanes et al. (2011) Sun et al. (2020) Shen et al. (2018) Chen et al. (2021) Chen et al. (2022) Hou et al. (2023) Wu et al. (2025) Li et al. (2025)	Dynamic programming; discrete optimization; deep reinforcement learning; game-theoretic optimization	Fuzzy logic control; feedback control; optimal control; model predictive control
Constraint transmission	Letter and Eleftheriadou (2017) Tang et al. (2022) Chen and Yang (2024) Wu et al. (2022) Liu et al. (2023) Wang et al. (2025)	Rule-based decision methods; mixed-integer programming; cooperative game methods; constrained proximal policy optimization	Optimal control; control based on Pontryagin's minimum principle; receding-horizon optimization
Condition-triggered strategy selection	Liu et al. (2022) Ding et al. (2020) Du et al. (2024) Yang et al. (2023a) Li et al. (2024)	Reinforcement learning; rule-based strategy switching; game-theoretic decision methods	Optimal control; adaptive cruise control; proportional–integral–derivative control
Spatiotemporal partitioning	Shi et al. (2021a) Shi et al. (2023b)	Graph-based optimization; heuristic tree search; dynamic conflict graph decomposition	Optimal trajectory control; control based on Pontryagin's minimum principle

6 Integrated control architecture

Integrated control addresses how vehicles merge and how they move within the same solution framework, rather than determining the merging decision first and then passing it to a separate controller. In highway on-ramp merging, the merging order, target gap, merging time, merging position, or lane choice directly affects the required speed, acceleration, and trajectory, while the motion that a vehicle can actually achieve also limits the feasible merging decisions. Integrated control therefore considers these two types of variables together during the solution process, so that merging decisions are determined together with vehicle motion. Existing studies mainly follow game-theoretic and integrated optimization approaches, as well as learning-based integrated control in which vehicle behaviour is generated by a unified policy.

Game-theoretic and interaction-based methods determine

merging choices and motion responses within the same vehicle interaction process. The merging behaviour of ramp vehicles and the yielding, acceleration, or deceleration responses of mainline vehicles are incorporated into the payoff formulation, allowing decision and control to influence each other. Fukuyama (2020) used a dynamic game and a time-expanded decision diagram to couple yielding, acceleration, priority, and merging-position choices over time. The game produces both the interaction outcome and the longitudinal trajectory leading to that outcome within the same decision process. Zhang et al. (2025) combined a Stackelberg game with sampling-based motion planning so that the predicted response of surrounding drivers changes the candidate trajectories considered by the CAV. Driver aggressiveness is identified as part of the interaction model, and the final plan is selected from trajectories that already reflect the leader-follower response. Nishi et al. (2019) used multipolicy decision

making together with passive actor-critic learning to evaluate candidate merging locations and the vehicle behaviour required to reach them.

Integrated optimization methods solve merging order, time, position, or lane choice together with vehicle speed and acceleration in a single optimization problem subject to safety, road, and vehicle-dynamics constraints. Zhou et al. (2019a) formulated related optimal-control problems for the mainline facilitating vehicle and the ramp vehicle, with merging time and location emerging from the same solution as the trajectories. A recursive implementation updates the analytical solution as the vehicles approach the merge rather than fixing the conflict point in advance. Mu et al. (2021) formulated rolling-horizon cooperative merging as a mixed-integer nonlinear programming problem in which platoon organization and multi-vehicle trajectories are optimized together. The objective evaluates the coordinated system over each horizon while safety, vehicle dynamics, and merging feasibility constrain the solution, and event-triggered replanning updates it online. Shi et al. (2023a) inserted motion feasibility and control cost directly into the search for merging sequences under flexible merging positions. A sequence is therefore preferred only when the trajectories required to execute it remain feasible and have acceptable motion cost. Chen et al. (2024) optimized merging sequence and continuous-time trajectories with mixed-integer nonlinear programming and reduced the combinatorial search space with an integrated solution strategy. Runtime was evaluated under several demand levels and Next Generation Simulation (NGSIM)-based arrival patterns, showing how the reduced search affects online computational complexity.

Reinforcement learning-based integrated control uses a unified policy to generate merging behaviour and vehicle control actions directly from traffic states, with a common reward function evaluating safety, efficiency, and motion performance. Wang and Chan (2017) used a long short-term memory network to encode the interactive traffic history and a deep Q-learning policy to select the vehicle action for the merge. The reward evaluates the consequences of the action over the interaction process, so merging behaviour and executable motion are learned together rather than connected through a separate planner. Lin et al. (2022) used Soft Actor-Critic to coordinate the merging behaviour of a plug-in hybrid electric vehicle with its power-split control. Safety and traffic-progress terms are optimized together with energy use, so the policy chooses vehicle motion and power-system operation under one reward. Dong et al. (2022) used reinforcement learning with hindsight experience replay to control both a ramp vehicle and an assisting mainline electric vehicle. The common reward includes safety, traffic efficiency, and battery-health objectives, coupling the cooperative merge with the energy condition of the two vehicles. Song et al. (2026) used hybrid-action Soft Actor-Critic to output a discrete lane-changing action and continuous longitudinal acceleration from one policy. The hybrid action design allows lane choice and longitudinal motion to be learned in one policy, and the method was validated with California real-traffic data rather than only synthetic arrivals.

Multi-agent learning extends integrated control to multiple ramp and mainline vehicles and coordinates their merging,

yielding, and motion behaviours through shared rewards or integrated value functions. Zhou et al. (2022) used distributed multi-agent deep reinforcement learning to generate longitudinal accelerations for interacting CAVs. The reward combines safety, traffic efficiency, and energy objectives, so cooperative merging behaviour emerges from the same policy that produces the executable acceleration. Li et al. (2024) combined Nash-equilibrium reasoning with double Q-learning for mainline and ramp interactions in mixed traffic. The game payoff shapes the learned action values, allowing the final executable action to reflect the anticipated response of the other vehicle. Shi et al. (2026) used the multi-agent framework to learn longitudinal adjustment, lane actions, and inter-vehicle cooperation together. Its reward explicitly combines safety, traffic efficiency, and comfort, keeping the tactical lane choice and the continuous motion response inside the same learned coordination process.

7 Hybrid control architecture

Hybrid control differs from hierarchical control, where decision information is generated first and then transmitted to the control layer for execution, and from integrated control, where decision variables and control variables are determined within the same solution process. Instead, hybrid control organizes decision and control functions through multiple interacting components within the same vehicle-level control framework. These components may directly influence longitudinal or lateral vehicle motion and can cooperate, switch, or modify their roles according to the requirements of the merging process.

Coordinated vehicle-level control functions combine multiple decision and control functions with different roles within the same merging process. These functions address different aspects of merging and coordinate vehicle motion through information exchange. Unlike hierarchical architectures, where decisions are transmitted from a decision layer to a control layer in a sequential manner, this form maintains relatively independent functional modules that jointly contribute to decision adjustment and vehicle execution. Yang et al. (2023b) represented the interacting vehicles as a virtual platoon and used one control law for conventional same-lane following and another for cross-lane merging-speed regulation. The two controllers operate during the same merging process, with their outputs determined by the current relationship between the connected vehicles. Yang et al. (2025a) used separate reinforcement-learning modules for ramp-mainline merging control and proactive mainline lane-changing control in heterogeneous multilane traffic. Each module has its own action logic, and their outputs are coordinated so that mainline lane changes can create better conditions for the ramp vehicle. Yang et al. (2025b) retained separate merging control for the outer-lane ramp interaction and lane-changing control for multilane traffic redistribution. The two control functions were evaluated together under heterogeneous traffic and different CAV penetration rates, showing how lateral redistribution changes the subsequent merging control demand. Liu et al. (2026) combined cooperative longitudinal merging control with a separate lateral lane-balancing mechanism driven by dynamically estimated lane capacity. The longitudinal controller regulates the immediate merge while the lateral mechanism redistributes CAVs across

lanes as available capacity changes. Jing et al. (2026) formulated decentralized longitudinal and lateral vehicle-control problems and used feedback linearization to make both motion channels tractable. The two controllers remain separately defined but exchange the vehicle state needed to complete the same cooperative merge.

Mode switching and control reconfiguration adjust the organization of decision and control functions according to the merging stage or current system condition. Stage-based switching changes the active mode when the merging task progresses between different operating phases, while control reconfiguration modifies the original control strategy when communication degradation, information loss, or other operating changes occur. Wang et al. (2021) used one controller for ramp merging and another for subsequent platoon operation, with a smooth switching law connecting the two operating stages. The switch is triggered by the vehicle's progress through the merging process so that the control input changes continuously when responsibility moves from the merging controller to the platoon controller. Scholte et al. (2022) coordinated CACC, gap-opening, transitional, and MPC control states when inserting a cooperative vehicle into a platoon. MATLAB and Simulink experiments explicitly tested communication delay, sensor noise, leader disturbance, and controller switching, so the mode-transition logic was evaluated under several non-ideal conditions. Liu et al. (2023) used a nominal cooperative-driving mode when communication was available and activated fault-tolerant control modes after communication degradation or failure was detected. The fallback logic changes the controller according to communication status, allowing vehicle motion to continue without assuming that the original cooperative information remains available.

Overall, although hierarchical, integrated, and hybrid control architectures organize decision making and vehicle control in

different ways, they still face common challenges in complex traffic interactions, communication uncertainty, real-time computation, and practical deployment, and Section 8 addresses these challenges in detail.

8 Cross-study comparison and synthesis

Sections 3–7 review how decision planning and control execution are implemented in CAV ramp merging under different methods and control architectures. Building on these findings, Section 8 synthesizes the reviewed studies following a progression from methodological comparison to practical application. It first compares the methods and architectures to clarify how decision planning and control execution are organized (Section 8.1). The analysis then focuses on studies involving both CAVs and HDVs, examining how mixed traffic flow behaviour is modelled and how different assumptions affect control (Section 8.2). The focus subsequently shifts from method design to supporting evidence by comparing validation settings and performance metrics (Section 8.3), followed by an assessment of the remaining challenges to practical deployment (Section 8.4). Finally, Section 8.5 compares on-ramp merging with related multi-lane coordination scenarios to clarify the applicability and limitations of the reviewed methods.

8.1. Comparative analysis of methods and architectures

This subsection compares the implementation characteristics of different decision methods, control methods, and architectures for on-ramp merging tasks and discusses their applicable conditions. The selected studies represent major approaches reviewed in Sections 3–7 and are included when they explicitly define decision variables, control objectives, or architectural connections. The comparison focuses on six aspects: decision or control mechanisms, safety guarantees, communication requirements, traffic assumptions, computational complexity, and practical deployment limitations.

Table 6. Comparative analysis of methods and architectures

Method or architecture	Representative studies	Main decision or control mechanism	Safety guarantees	Communication requirements	Traffic assumptions	Computational complexity	Main practical limitation
Optimization-based decision planning	Liang et al. (2023); Shi et al. (2021b); Jiang et al. (2021)	Explicitly optimizes merging time, position, sequence, gap, or a reference trajectory; pairing methods evaluate feasible vehicle-gap relations.	Collision, minimum-spacing, state, input, terminal, and feasibility constraints can be written explicitly.	Ranges from local state exchange to centralized multi-vehicle information.	Often assumes modelled vehicle responses and known or predicted surrounding states.	Online nonlinear, mixed-integer, graph-search, or pairing computation grows with vehicles and candidate decisions.	Real-time scalability and sensitivity to prediction or model error.
Reinforcement learning decision planning	Lin et al. (2020); Wang et al. (2021a); Wang et al. (2021b); Liu et al. (2024)	Learns merge, gap, lane, or high-level actions from observations; reward functions combine safety,	Mainly reward penalties, constrained learning, action screening,	Can use local observation only or shared multi-agent states, depending on the formulation.	Can represent nonlinear interactions, but performance depends on	High offline training cost; online policy inference is usually light.	Generalization on and formal safety guarantees outside the training

Method or architecture	Representative studies	Main decision or control mechanism	Safety guarantees	Communication requirements	Traffic assumptions	Computational complexity	Main practical limitation
		efficiency, comfort, and sometimes energy.	or an external safety supervisor.		training traffic and HDV behaviour.		distribution.
Game-based and interaction-aware decision planning	Jing et al. (2025); Du et al. (2024)	Models how another vehicle may yield, compete, or respond; decision utility changes with the predicted opponent response.	Safety enters utility, feasible-action sets, or downstream motion constraints.	Requires observation or estimation of the interacting vehicle state and sometimes behavioural type.	Designed for strategic CAV and HDV interaction rather than independent surrounding traffic.	Repeated game solution or behavioural inference adds online computation.	Accuracy depends on the assumed response model and identified driver type.
Feedback and robust control execution	Chen et al. (2021); Huang et al. (2019); Hu et al. (2021)	Computes acceleration, speed, spacing, or lateral correction from tracking and inter-vehicle errors.	Stability analysis, robust bounds, explicit spacing constraints, and disturbance attenuation.	Distributed implementations require neighbouring states; some use fixed platoon communication topology.	Best suited to clearly defined reference states or cooperative relations.	Low to moderate online burden because the control law is evaluated directly.	Model uncertainty, communication quality, and maintaining the assumed interaction topology.
Model predictive and optimal control execution	Xia et al. (2024); Xue et al. (2022); Zhao et al. (2021)	Optimizes executable trajectories or control inputs over a limited or analytical horizon under vehicle dynamics.	Hard state and input constraints, collision constraints, terminal conditions, and feasibility checks.	Cooperative formulations often require predicted or shared states and reference decisions.	Usually relies on calibrated vehicle dynamics and a defined planning horizon.	Repeated online optimization; burden increases with horizon length and number of controlled vehicles.	Meeting real-time deadlines while preserving feasibility under changing traffic.
Learning-based control execution	Liu et al. (2022); Li et al. (2023); Chen et al. (2023)	Directly outputs acceleration or other motion commands; reward functions penalize collision and reward progress, smoothness, or cooperation.	Safety supervisor, action replacement, reward penalties, or constrained training are commonly added.	Local observations may suffice for ego control; cooperative policies often share neighbour information.	Can accommodate complex mixed traffic if represented during training.	Large training cost with relatively low online inference cost.	Safety certification, transfer to unseen traffic, and dependence on the simulator used for training.
Hierarchical cooperative architecture	Milanes et al. (2011); Tang et al. (2022); Kimura et al. (2022); Sun et	Separates tactical decisions from motion execution and passes commands,	Can combine upper-level feasibility with lower-	Open-loop interfaces require less exchange; closed-loop coordination	Supports full CAV and mixed traffic, but interface assumptions	Splits one large problem into modules, although	Interface delay, stale commands, and inconsistency

Method or architecture	Representative studies	Main decision or control mechanism	Safety guarantees	Communication requirements	Traffic assumptions	Computational complexity	Main practical limitation
Integrated architecture	al. (2020)	feedback, constraints, or triggered mode information across the interface.	level stable or constrained control.	requires feedback and reliable cross-layer information.	differ by implementation.	repeated feedback can add computation and latency.	y between planned and executable motion.
	Zhou et al. (2019b); Mu et al. (2021); Zhang et al. (2025); Song et al. (2026)	Determines tactical and executable variables in the same optimization, game, or learning process.	Explicit integrated optimization can impose hard constraints; learned integrated policies mainly use reward and training-based safety.	Often requires richer interaction information because decision and motion variables are coupled.	Used in cooperative and interactive mixed-traffic settings.	Can be high for mixed discrete-continuous optimization or high during policy training.	Scalability, solver or training burden, and validation under communication and behavioural uncertainty.
	Scholte et al. (2022); Yang et al. (2025a); Yang et al. (2025b); Liu et al. (2023); Wang et al. (2021)	Retains multiple identifiable vehicle-level controllers that cooperate, switch, or correct one another during merging.	Safety can be assigned to a dedicated supervisor, fallback controller, or constrained controller within the set.	Different controllers may depend on different V2X information, making availability and switching logic important.	Useful when traffic mode, lane function, or communication changes during operation.	Each controller can remain moderate, but coordination and switching logic add implementation complexity.	Controller consistency, switching transients, and safe degradation when information is lost.

Table 6. indicates clear differences among methods in terms of safety guarantees, information requirements, and computational processes. Optimization-based methods can directly incorporate collision constraints, vehicle dynamics constraints, and feasibility conditions, providing explicit safety descriptions. However, their computational requirements may increase rapidly with the number of vehicles and optimization variables. Learning-based methods can capture complex traffic interactions and generate control actions, but their reliability depends strongly on reward design, safety supervision, and training coverage. Feedback control and model predictive control rely heavily on vehicle state information, while model predictive control can handle more constraints at the cost of continuous online optimization.

Regarding communication requirements, distributed cooperative methods usually require neighbouring vehicle information exchange, while integrated approaches often need richer interaction information because decision and motion variables are considered together. Different methods

also rely on different traffic assumptions. Some are designed for CAV cooperation, whereas others consider mixed CAV and HDV environments. In terms of computation, optimization and integrated methods mainly face online solving pressure, while learning methods face training costs and adaptation problems under unseen conditions. Therefore, method selection should consider not only control performance but also whether safety constraints, communication conditions, and practical vehicle environments can support implementation.

8.2. Mixed traffic flow behaviour modelling

This subsection analyses how existing studies construct mixed traffic environments and how HDV behaviour representation affects CAV control and performance evaluation. The reviewed studies are selected from representative works in Sections 3–7 involving mixed traffic validation and are categorized according to HDV modelling approaches and traffic composition. The comparison considers mixed traffic settings, HDV behaviour

representation, the role of HDV information in CAV decision-making and control, and sensitivity under different traffic conditions.

Table 7. Mixed traffic flow behaviour modelling

Dominant mixed-traffic pattern	Studies	Mixed-traffic and penetration setting	HDV behaviour representation	Role in CAV decision or control	Sensitivity examined
Rule-based microscopic HDV motion	Triest et al. (2020); Wang et al. (2021b); Liu et al. (2022); Han et al. (2023); Zhou et al. (2019a); Sun et al. (2020); Chen et al. (2023); Ding et al. (2020)	Mixed merging, congested traffic, and several density or penetration settings.	Simulator or rule behaviour, kinematic prediction, Gipps car following, Intelligent Driver Model (IDM), and Minimizing Overall Braking Induced by Lane Changes (MOBIL). Artificial neural network prediction, Hidden Markov	Provides surrounding trajectories, feasible gaps, interaction constraints, or safety predictions used by the CAV decision or execution process.	Traffic density and demand, CAV penetration, and alternative car-following assumptions.
Data-driven, latent-state, and driver-style representation	Kherroubi et al. (2022); Wang et al. (2021a); Li et al. (2024a); Du et al. (2024); Zhang et al. (2025)	CAVs interact with human-driven traffic; some studies use naturalistic driving or human-in-the-loop evidence.	Model with Gaussian Mixture Regression, naturalistic driver-style labels, Gaussian mixture model with support vector machine classification, and aggressiveness identification.	Predicted behaviour or driver style becomes an observation, an interaction parameter, or a guidance input.	Prediction accuracy, driver style, aggressiveness, compliance, participant differences, and scenario variation.
Primarily game-based interactive response	Jing et al. (2025); Li et al. (2024)	Mixed CAV and HDV interactions in which surrounding responses influence the selected merge action.	Stochastic potential-game response and Nash-based interaction representation rather than a fixed car-following model.	Couples the expected response of surrounding traffic with the CAV action, priority, or trajectory choice.	Interaction conditions, traffic composition, and response assumptions.
Penetration and traffic-composition analysis without a dedicated HDV predictor	Ramezani and Ye (2019); Pan et al. (2021); Guo et al. (2021); Liu et al. (2024); Yang et al. (2025); He and Lv (2023b); He et al. (2023); Li et al. (2023); Peng et al. (2025); Yang et al. (2023a); Li et al. (2025); Hou et al. (2023); Mu et al. (2021); Yang et al. (2025a); Yang et al. (2025b); Liu et al. (2026)	Heterogeneous or mixed traffic with changes in penetration, demand, density, traffic flow, vehicle class, or CAV and HDV spatial composition.	HDVs remain uncontrolled agents or are represented through the traffic simulator, heterogeneous vehicle classes, traffic-flow states, or dynamic-capacity descriptions; no separate HDV behaviour predictor is the main model.	Changes the proportion and location of controllable vehicles, available gaps, lane capacity, observed interactions, or which CAV control module is activated.	CAV penetration, demand, density, flow, speed, compliance, vehicle composition, and CAV and HDV spatial arrangement.

Table 7. shows that HDVs play different roles across existing studies. Some methods model HDVs as dynamic participants whose behaviours need to be predicted or considered through car-following models, driving-style recognition, or interaction models. Other studies mainly evaluate cooperative performance by changing CAV penetration rates or traffic composition, where HDVs are treated as uncontrolled background traffic. These differences directly influence the information available to CAVs and the scope of control actions. Therefore, reported

improvements should be interpreted together with the corresponding HDV representation rather than being attributed solely to the control method. Future studies should further improve the consistency between HDV behaviour models and real driving interactions.

8.3. Validation settings and performance metrics

This subsection examines how existing studies validate control performance and discusses the comparability of reported results under different validation conditions. The included studies are

selected according to unified criteria, including explicit baselines, extractable quantitative results, and sufficient validation descriptions, while higher-level experimental studies are additionally included to reflect validation maturity. The comparison considers validation platforms, traffic demand, CAV composition, baseline methods, evaluation metrics, and validation levels. For cross-study comparison, this review defines five

validation levels: L1, numerical or traffic simulation; L2, empirical-data-calibrated or replay-based simulation; L3, human-in-the-loop or naturalistic driving experiments; L4, hardware-in-the-loop or vehicle-in-the-loop validation; and L5, real-vehicle closed-loop road testing. Higher levels indicate greater validation realism, and no L4 study was identified in the reviewed literature.

Table 8. Validation settings and performance metrics

Method or architecture category	Study	Validation platform or data	Traffic demand and CAV composition	Baseline	Metrics and quantitative within-study result	Level
Section 3: Optimization-based decision planning	Shi et al. (2021b)	Numerical CAV merging simulation	Platoon/CAV merging cases	First-in-first-out (FIFO)	Fuel consumption about 20% lower than FIFO in the reported case	L1
	Kumaravel et al. (2021)	VISSIM with COM real-time control	Mainline 1060 veh/h; ramp 720 veh/h; 900 s	Stop-and-yield baseline	Travel time -54.3%, fuel -57.8%, delay -88.92%, average speed +63.53%	L1
Section 3: Reinforcement-learning decision planning	Triest et al. (2020)	NGSIM-informed trajectory replay; repeated held-out tests	127 held-out interactions; mixed human traffic	Low-level RL; slot method; MML-PGM	Collision rate: 4.2% versus 9.9%, 12.9%, and 60.0% for the three comparators	L2
	Liu et al. (2024)	Mixed-traffic simulation	Easy/medium/hard traffic; CAV penetration 0.25-1.0	D3QN-based comparator	At full CAV penetration, fuel -11.4% to -14.1% and travel time -5.7% to -7.7% across tested density modes	L1
	Xia et al. (2024)	Multi-lane traffic simulation	Mainline 1000-1800 veh/h/lane; ramp 400-1200 veh/h; 25 scenarios, 20 runs each	Existing lane-changing model	Lane changes -16.66% and driving delay -7%	L1
	Xue et al. (2022)	Numerical hierarchical MPC simulation	Multiple on-ramp vehicles; normal and heavy mainline flow	Baseline merging controller	Case III: energy -16.23%, travel time -33.64%; heavy-flow case: energy -64.47%, travel time -12.03%	L1
Section 4: Model predictive and optimal control execution	Liu et al. (2025)	Numerical electric-vehicle merging simulation	Various merging scenarios	Baseline and PBHMC	Energy consumption -29.6% versus Baseline and -19.4% versus PBHMC	L1
	Liu et al. (2022)	Gym-like highway simulation	Easy, medium, and hard density modes; mixed traffic	ACKTR, PPO, A2C, and discrete SAC variants	Safety-enhanced SAC reported zero collisions in tested modes; average speed 27.47/25.51/25.01 m/s across the three density modes	L1
	Zhao et al. (2022)	SUMO simulation	Automated on-ramp merging scenarios	TTC-based method and TD3-based method	Versus TTC baseline: average travel time -8.3% and emergency-braking rate -65.4%	L1
Section 4: Learning-based control execution	Li et al. (2023)	Heavy-traffic simulation	Representative case about 1200 veh/h per stream; cooperative CAV traffic	Four RL/control baselines	Reported travel-time reduction up to 56.9% with zero conflicts in the tested case	L1

Method or architecture category	Study	Validation platform or data	Traffic demand and CAV composition	Baseline	Metrics and quantitative within-study result	Level
Section 5: Hierarchical cooperative architecture	Ding et al. (2020)	Microscopic traffic simulation	Multiple demands; CAV penetration from 0% to 100%	Uncoordinated / lower-penetration cases	At 30% CAV: throughput up to +4.9%, delay -45.9%, fuel -34.7%	L1
	Sun et al. (2020)	Microscopic mixed-traffic simulation	Mixed CAV-HDV traffic; penetration varied	100% HV / non-cooperative mixed traffic	At high CAV penetration, throughput about +18%; cooperative decision adds about 10-15% in reported cases	L1
	Kimura et al. (2022)	Numerical merging simulation	10,000 trials with varied initial interaction states	Comparison merging policy	Merge success 99.2% versus 73.4%	L1
	Yang et al. (2023a)	Traffic simulation	Typical mainline and ramp demand 650 veh/h each; CAV penetration 0.1-0.9 and pure CAV	No cooperative control	Safety indicators reduced by roughly 30-60% in mixed traffic and about 90% in the pure-CAV case	L1
	Shi et al. (2021a)	SUMO and Python	Demand 800-2000 veh/h; multiple demand splits and safety gaps	Case 0/Case 1 without full lane-change cooperation	At 2000 veh/h, Case 1 delay -70.3% versus Case 0; cooperative lane-change case further reduced delay 38.3% and raised speed 18.2% versus Case 1	L1
	Chen et al. (2021)	MATLAB-based numerical evaluation	135 on-ramp scenarios with varied demand/configuration	FIFO-based hierarchical benchmark	Reported system-performance gains of at least about 13% in the tested comparisons; computation time also reported	L1
	Tang et al. (2022)	Numerical hierarchical-control simulation	Multiple mainline-ramp demand ratios	Fixed-merging-position hierarchical control	Delay reduction advantage reached about 64% in low ramp-demand-ratio cases	L1
	Wu et al. (2022)	Traffic simulation	Increasing vehicle demand in cooperative merging zone	No control and FIFO control	Optimized control: energy -13.2% and travel time -50.4% versus no control	L1
	Milanes et al. (2011)	Real-road closed-loop experiment with three production vehicles	Congested on-ramp merging; three equipped production vehicles	No standardized numerical baseline used for cross-study evidence	Demonstrated closed-loop automated merging and limited disturbance to mainline traffic; no directly comparable percentage improvement was reported	L5
	Li et al. (2024a)	Naturalistic-driving experiment with 50 participants plus simulation	Urban-expressway on-ramp; heterogeneous driving styles and observed human execution responses	Did not meet all three strict quantitative-comparison criteria	Naturalistic data supported driving-style identification and closed-loop speed-guidance response; included for its L3 experimental evidence rather than for percentage ranking	L3

Method or architecture category	Study	Validation platform or data	Traffic demand and CAV composition	Baseline	Metrics and quantitative within-study result	Level
Section 6: Integrated architecture	Mu et al. (2021)	Rolling-horizon numerical testbeds	Mixed testbeds including 9 CAVs + 4 HDVs and a 51-CAV case	BARON, BONMIN, COUENNE, SCIP	Heuristic runtime about 2.63 s in a benchmark where general solvers required hundreds of seconds	L1
	Shi et al. (2023b)	SUMO continuous-flow simulation	About 120 s continuous traffic with multi-lane conflict graph	SUMO default and DCG without lane changing	Total travel delay 15.1 s versus 34.2 s and 78.3 s for the two comparators	L1
	Chen et al. (2024)	NGSIM I-80 arrival patterns plus numerical optimization	45-min replay; varying mainline and ramp CAV counts	MCTS-DA, VROCP, FTOCP	Same optimal delay as MCTS-DA with much lower computation; per-trigger computation difference versus faster alternatives was about 0.1 s while delay was lower	L2
	Dong et al. (2022)	Numerical experiments plus I-880 trajectory-data test	Multiple ramp inflows; connected electric vehicles	SRL and PRL baselines	At 5 s/veh ramp inflow, throughput +18.2%/+13.0% versus SRL/PRL; mainline energy consumption improved by 15.9%/32.8%	L2
	Lin et al. (2022)	Powertrain and merging co-simulation	Plug-in hybrid CAV merging scenarios	Two sequential optimization baselines	Co-optimization maintained zero collisions while a sequential design showed 25% power-saturation occurrence; energy/jerk trade-offs were also improved	L1
	Song et al. (2026)	SUMO plus PeMS-calibrated California Highway 580 scenarios	Mainline 1000-1800 veh/h; ramp 200-600 veh/h; two real-data time windows	No control, PID, PASAC, MPDQN	Versus no control: waiting time -96.2% (-51.3% real-data case), merging time -73.9% (-42.6%), TTC-risk rate -87.5% (-26.3%)	L2
Section 7: Hybrid architecture	Zhang et al. (2025)	Simulation plus human-in-the-loop experiment	Interactive on-ramp merging with different driver-aggressiveness and interaction conditions	Did not meet all three strict quantitative-comparison criteria	Human-in-the-loop tests validated the coupled decision and trajectory-planning behaviour; included for its L3 experimental evidence rather than for percentage ranking	L3
	Yang et al. (2025b)	Calibrated Python traffic simulation	Total flow 2500 and 3500 veh/h; CAV penetration varied	Non-cooperative control and ramp-metering groups	Cooperative control reduced TET 30-60% at penetration 0.4-0.5 and >80% above 0.7; delay reduced 15-50% in congested cases	L1

Table 8. shows that existing studies have accumulated extensive performance evaluation results, but these results are strongly influenced by experimental settings and cannot be directly ranked across different methods. Variations in traffic demand, CAV penetration, HDV models, baseline strategies, and evaluation metrics can significantly affect reported improvements. Meanwhile, simulation-based validation remains dominant, whereas field experiments, naturalistic driving studies, and real-vehicle closed-loop

tests remain limited. Future research should therefore pay greater attention to consistent evaluation conditions and higher-level validation to improve the interpretability of reported results.

8.4. Practical deployment challenges

This subsection evaluates how existing studies consider deployment-related non-ideal factors and identifies major gaps between current methods and real-world applications. All core studies are considered, and only factors explicitly modelled, tested,

or validated in the original studies are counted, while issues mentioned only as future work are excluded. The comparison covers communication reliability, perception uncertainty, vehicle

execution uncertainty, real-time computational capability, fault degradation strategies, hardware-in-the-loop and vehicle-in-the-loop validation, and real-vehicle closed-loop validation.

Table 9. Practical deployment challenges

Deployment factor	Coverage in 96 studies	Studies counted	How it was explicitly tested	Interpretation of current evidence
Communication delay	2/96 (2.1%)	Wang et al. (2021); Scholte et al. (2022).	Communication delay was incorporated into string-stability analysis or introduced into the simulated communication and control loop.	Delay has been examined explicitly in only two studies, and its interaction with packet loss and sensing errors remains insufficiently tested.
Packet loss or communication failure	2/96 (2.1%)	Wang et al. (2025); Liu et al. (2023).	One study introduced V2V packet drops and a compensation method; the other simulated random communication failures and reconnection.	Existing evidence covers packet drops and communication-failure modes, but combined communication and sensing faults have not been systematically evaluated.
Sensing or observation noise	4/96 (4.2%)	Triest et al. (2020); Jing et al. (2025); He et al. (2023); Scholte et al. (2022).	Gaussian observation noise, random sensing errors, adversarial observation perturbations, or predefined sensor-noise profiles were introduced into decision or control processes.	Noise robustness has been tested in only a small number of studies, mainly through simulation and with different noise definitions.
Dedicated positioning error	0/96 (0%)	None identified	No reviewed study treated localization bias, drift, or position-error distributions as a separate validation factor.	Dedicated positioning-error validation remains absent. General observation noise and reported trajectory-data accuracy should not be counted in this category. Actuator lag is modelled more often than communication or positioning errors, but it is usually examined independently of other implementation imperfections.
Explicit actuator lag	6/96 (6.3%)	Qiang et al. (2025); Wang et al. (2022); Xue et al. (2022); Chen et al. (2021); Hou et al. (2023); Scholte et al. (2022).	First- or third-order actuator, engine, or driveline dynamics were represented using explicit time constants. Hou et al. additionally sampled heterogeneous inertial lags.	
Vehicle-model uncertainty or injected physical disturbance	8/96 (8.3%)	Liang et al. (2023); He et al. (2023); Pan et al. (2025); Hu et al. (2021); Hou et al. (2023); Zhou et al. (2019a); Yang et al. (2025b); Scholte et al. (2022).	The studies considered uncertain vehicle dynamics, road-adhesion or mass changes, heterogeneous inertial lag, leader-trajectory disturbances, or acceleration and speed-update perturbations.	Model uncertainty and physical disturbances receive more attention than communication faults, but the tested disturbance definitions and magnitudes differ substantially.
Explicit numerical computation-time or deadline test	20/96 (20.8%)	He and Lv (2023b); Yadavalli et al. (2023); Gao et al. (2022); Xia et al. (2024); Liu et al. (2025); Liu et al. (2023); Wang et al. (2025); Chen et al. (2023); Chen et al. (2021); Sun et al. (2020); Tang et al. (2022); Letter and Elefteriadou (2017); Chen and	Numerical solver, decision, control, or inference time was reported. Several studies compared it with the sampling, updating, or replanning interval.	Computation time is reported in about one fifth of the studies, but hardware, problem size, and timing definitions differ. End-to-end deadlines covering sensing, communication,

		Yang (2024); Shi et al. (2023a); Chen et al. (2024); Shi et al. (2023b); Mu et al. (2021); Zhang et al. (2025); Zhou et al. (2019a); Li et al. (2024).	computation, and actuation are rarely evaluated.
Explicit communication-degraded fallback mode	1/96 (1.0%)	Liu et al. (2023).	Communication-failure detection triggers a transition from nominal cooperative control to fault-tolerant control and reconnection modes. The speed planners were compiled and executed on a real-time platform connected to traffic, vehicle, and communication simulations. Three production vehicles were used in a closed-loop on-ramp merging experiment on an actual road.
Hardware-in-the-loop or vehicle-in-the-loop validation	1/96 (1.0%)	Wang et al. (2025).	A predefined degraded operating mode remains exceptional, and operation under complete V2X unavailability has not been widely demonstrated. Hardware-in-the-loop evidence is limited to one study, and no vehicle-in-the-loop experiment was identified.
Real-vehicle closed-loop field validation	1/96 (1.0%)	Milanes et al. (2011).	This is the clearest L5 validation in the reviewed corpus, but it remains a single early demonstration.

Table 9. reveals that deployment-related considerations remain limited in current studies. Some works have investigated communication delay, communication failures, or vehicle dynamics disturbances, but most studies still examine these factors individually rather than considering interactions among perception, communication, computation, and execution uncertainties. In addition, studies with explicit safety degradation strategies, hardware-in-the-loop and vehicle-in-the-loop validation, and real-vehicle closed-loop testing remain rare. Therefore, future on-ramp CAV control research should move beyond performance improvement under ideal conditions toward reliability evaluation under realistic operating environments.

8.5. Application scenarios and applicability

In this review, platoon refers to a one-dimensional longitudinal vehicle string coordinated primarily through spacing and speed control, as discussed in Sections 3.3 and 4.3. In contrast, formation in this subsection denotes a two-dimensional multi-lane arrangement requiring coordinated longitudinal and lateral positioning.

On-ramp merging and general multi-lane coordination share three basic tasks: arranging the relative order or target positions of multiple vehicles, planning collision-free multi-vehicle motion, and executing the coordinated motion at vehicle level. In this section, formation refers specifically to a two-dimensional multi-lane spatial arrangement with coordinated longitudinal and lateral relative positions, which differs from the one-dimensional platoon concept used in Sections 3.3 and 4.3. Marjovi et al. (2015) represented a multi-lane vehicle convoy with a graph and used distributed control to maintain coordinated motion while vehicles joined or left the group. Wu et al. (2021) formulated cooperative sorting as a path-finding problem in a discrete time-space grid and used integer linear programming to reduce the total sorting time. Cai et al. (2022) considered lane preference and performed target assignment and collision-free path planning at the upper level,

followed by trajectory planning and tracking at the lower level. Cai et al. (2023) used a closely related two-level structure, but represented vehicle relations in relative coordinates and evaluated the method in a lane-drop bottleneck, where vehicles must reorganize their longitudinal and lateral positions before the available lane set changes. These two studies therefore connect formation assignment and path planning with the decision-planning function. Cai et al. (2024) extended multi-lane formation control to mixed traffic containing both CAVs and HDVs. The study shows that multi-lane formation methods can retain CAV coordination even when some surrounding vehicles are not directly controllable. Firoozi et al. (2021) generated smooth, dynamically feasible, and collision-free trajectories for tight multi-lane spatial reconfiguration and then used an online hierarchical controller to select and execute the manoeuvre.

The substantive difference between on-ramp merging and general multi-lane coordination lies in the constraints imposed on their common coordination tasks. General multi-lane formation and vehicle sorting mainly rearrange vehicles that are already travelling within the same road system, whereas on-ramp merging must insert a separate ramp traffic stream into the mainline stream. The acceleration lane and merging region also provide a finite spatial opportunity, so merging order, target gap, merging time, and vehicle trajectories must be coordinated before that space is exhausted. In addition, the target of on-ramp control is an acceptable gap bounded by a leading and a following mainline vehicle, rather than only a desired relative vehicle position. When the existing gap is insufficient, controllable mainline vehicles may need to enlarge or create it through speed adjustment. Mixed traffic adds a further constraint because an HDV may form one boundary of the target gap but cannot be commanded by the cooperative controller. General multi-lane methods are therefore directly useful for vehicle ordering, collision-free multi-vehicle path planning, and coordinated trajectory execution, but their application to on-ramp

merging requires additional treatment of two-stream convergence, target-gap selection and creation, limited merging space, and uncertain HDV responses. These task constraints are the main substantive distinction between on-ramp merging and general multi-lane coordination.

9 Conclusions and future prospects

This review focuses on microscopic control of connected and automated vehicles at highway on-ramp merging areas. A functional framework based on decision planning and control execution was first established, followed by an analysis of how these two functions are organized under hierarchical, integrated, and hybrid control architectures. Different approaches were then compared in terms of mixed traffic, safety guarantees, communication requirements, computational complexity, validation levels, and practical deployment. The main conclusions are as follows:

First, the available evidence does not demonstrate that any single control method or architecture is optimal under all conditions. Rule-based methods may be better suited to situations with clear merging rules and limited online computation. Model-driven approaches may be preferable when vehicle dynamics and safety constraints can be formulated explicitly. Learning-based methods may be useful when vehicle interactions are complex and difficult to represent with fixed rules or analytical models. Game-theoretic methods may be appropriate when the decisions of ramp and mainline vehicles depend on one another, particularly in merge-sequence determination and target-gap selection. At the architectural level, hierarchical control may be suitable when decision planning and control execution can be clearly separated. Integrated control may be appropriate when decision and control variables need to be solved together, while hybrid control may be useful when multiple control mechanisms operate jointly or switch with operating conditions. Method selection should therefore consider computational resources, implementation requirements, and performance indicators.

Second, the reviewed studies do not provide a universal CAV penetration threshold for effective cooperative merging. Cooperative merging capability in mixed traffic depends not only on the CAV penetration rate but also on the spatial distribution of cooperative CAVs, uncertainty in HDV behaviour, traffic demand, and control settings. Consequently, the same CAV penetration rate may lead to very different merging outcomes; therefore, its effect should be interpreted jointly with the other factors listed above.

Third, the main challenge for practical CAV merging control is no longer limited to controller design itself. Closed-loop reliability under sensing, communication, computation, and vehicle-execution imperfections has become equally important. Existing studies still provide limited joint validation of these non-ideal factors. Practical evaluation should therefore examine whether safe and stable merging can still be maintained under incomplete information, communication degradation, limited computation, and vehicle-execution errors.

Based on these findings, three directions deserve further attention:

First, future research should further investigate the influence of vehicle heterogeneity on cooperative merging control mechanisms.

Existing studies have considered CAV-HDV mixed traffic and differences in vehicle behaviour, but vehicle heterogeneity is still mainly represented as a traffic characteristic, behaviour-model parameter, or control condition (Kherroubi et al., 2022; Wang et al., 2021a; Du et al., 2024). The relationship between differences in vehicle dynamics, size, and motion capability and the resulting merging decisions, control strategy selection, and decision-control organization remains insufficiently explored. Future research can further explore adaptive cooperation methods based on vehicle characteristics, allowing vehicle differences to play a more direct role in merging decision and control processes, thereby improving the adaptability of control methods in complex mixed-traffic environments.

Second, more attention should be given to dynamic allocation of authority between decision planning and control execution. Studies such as Kherroubi et al. (2022), Wang et al. (2021a), Du et al. (2024), and Zhang et al. (2025) have incorporated behaviour prediction, driving style, and interaction information into merging decisions, while the roles of decision planning and control execution usually remain fixed. Future methods could adjust their respective authority according to uncertainty in HDV behaviour and surrounding traffic. More specific merging targets can be imposed under stable conditions, while greater real-time flexibility can be left to the control layer as uncertainty increases. Under high-risk conditions, the control layer should also be able to revise or terminate an earlier decision.

Third, future research should investigate online selection of control architectures based on traffic state. Existing studies have already demonstrated the feasibility of switching controllers according to merging stages or operating conditions. Wang et al. (2021), Scholte et al. (2022), and Liu et al. (2023), for instance, explored stage-dependent switching, transitions between control states, and control adjustment under communication degradation. However, these changes are still mainly performed within a predefined architecture. A further step is to select among hierarchical, integrated, and hybrid architectures according to traffic density, interaction intensity, the number of controllable vehicles, communication quality, and available computational resources.

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