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Review

A Survey of Vehicle-Enabled Control of Traffic for Freeway Flow in Partially Connected Environments

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ABSTRACT: Efficient freeway traffic control can alleviate congestion, improve operational efficiency, and enhance traffic safety. With the rapid development of Intelligent Transportation Systems (ITS) and connectivity technologies, Connected Vehicles (CVs), including Connected Automated Vehicles (CAVs) and Connected Human-Driven Vehicles (C-HDVs), are expected to coexist with conventional Human-Driven Vehicles (HDVs) on freeways for a considerable period. In partially connected traffic environments, CVs can provide historical and real-time Vehicle Trajectory Data (VTD) as mobile sensing sources and can also influence surrounding traffic as mobile actuators through vehicle guidance and cooperative control, thereby enabling Vehicle-Enabled Control of Traffic (VECT) for freeway flow. This paper systematically reviews recent advances in VECT under partially connected environments. The literature is organized into four categories according to the functional role of CVs and the level at which information, decisions, or control actions are generated: (1) vehicle-trajectory-enabled traffic state analysis, (2) vehicle-trajectory-enabled traffic control, (3) vehicle-guidance-enabled traffic control, and (4) collaborative vehicle–flow control. The review covers traffic state estimation, traffic state prediction, traffic anomaly detection, Variable Speed Limit (VSL) control, Ramp Metering (RM), vehicle trajectory planning, moving bottleneck control, and cross-scale coordination between macroscopic traffic regulation and microscopic vehicle guidance. Finally, key methodological challenges, deployment issues, and future research directions are discussed. This review provides a systematic framework for understanding how CVs enable freeway traffic analysis and control from sensing to actuation and coordinated vehicle–flow regulation.

KEYWORDS: freeway traffic control, vehicle-enabled control, vehicle trajectory data, connected vehicles, cooperative control, trajectory planning

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1. Introduction

Freeways, characterized by controlled access and limited entry and exit points, allow vehicles to travel at relatively stable and high speeds. They are considered a typical continuous-flow traffic scenario (National Academies of Sciences, 2022). With the rapid growth in passenger and freight demand, traffic congestion on freeways has become increasingly prominent. In the United States, particularly in Texas, nearly all of the top 100 most congested road segments are interstate highways or fully access-controlled freeways. Among them, the most congested segment is Interstate 610 (Harris County West Loop) in Houston, where the annual economic loss caused by congestion is estimated to reach approximately USD 166 million (Institute, 2025). In China, during major statutory holidays such as the Spring Festival and National Day, the proportion of congested mileage on the national freeway network reaches approximately 7.5% on average (AutoNavi, 2024).

Compared with freeway reconstruction or expansion, traffic control provides a more economical and feasible approach to congestion mitigation. Traditional freeway continuous-flow traffic control methods mainly include Variable Speed Limit (VSL) control (Lee et al., 2006), Ramp Metering (RM) (Zhang et al., 2001), and lane management (Yao et al., 2024). Most of these studies are based on macroscopic traffic flow data, which rely on infrastructure such as loop detectors, cameras, and radar. This leads to relatively high installation and maintenance costs and challenges in ensuring data reliability (Peng et al., 2025). With the rapid development of Intelligent Transportation Systems (ITS) and connectivity technologies, the emergence of Connected Vehicles (CVs) — including Connected Automated Vehicles (CAVs) and Connected Human-Driven Vehicles (C-HDVs)—has provided new opportunities for continuous-flow traffic control (Zhang et al., 2025). Compared with conventional Human-Driven Vehicles (HDVs), CVs can function as mobile sensors in traffic, providing historical and real-time Vehicle Trajectory Data (VTD), such as positions and speeds, and supporting traditional freeway traffic control. In a broad sense, CVs also include vehicles connected through ride-hailing platforms (e.g., Didi, or Grab) and navigation applications (e.g., Google Maps, AutoNavi, or Baidu Maps), which have made large-scale VTD increasingly available and accessible. They can also receive driving guidance, such as speed advisory and lane-changing guidance, to influence surrounding traffic and thereby improve operational efficiency (Qin et al., 2025) , as shown in Fig. 1. This has led many countries to place increasing emphasis on CV-related technologies and introduce supportive policies to accelerate CV deployment, providing strong momentum for the intelligent transformation of freeway traffic control (China, 2024; Commission, 2018; Transportation, 2024).

In recent years, the number of related studies has increased significantly. Existing studies generally predict that CVs will gradually dominate transportation systems. However, their full deployment still faces several challenges, including limited CV penetration,

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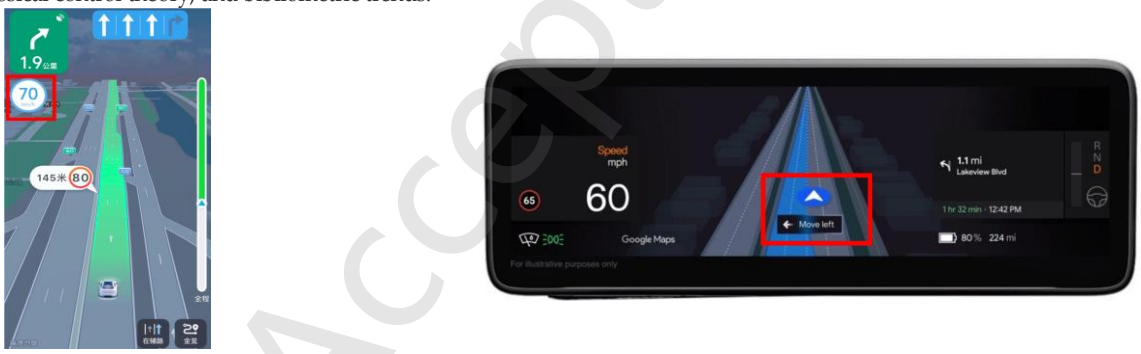
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communication uncertainty, heterogeneous vehicle behavior, and the integration of VTD with existing freeway control infrastructure. With the bidirectional information exchange capabilities of CVs, the concept of Vehicle-Enabled Control of Traffic (VECT) has been proposed (Li et al., 2023). Fig. 2 illustrates the evolution of VECT in response to changing traffic environments. The framework highlights the transition from HDV to CV traffic and organizes the reviewed studies into four categories: vehicle-trajectory-enabled traffic state analysis, vehicle-trajectory-enabled traffic control, vehicle-guidance-enabled traffic control, and collaborative vehicle–flow control.

VECT strategies for freeway flow have attracted widespread attention in recent years and have gradually become a research hotspot. Several review studies have systematically summarized traffic control strategies in partially connected environments. Li et al.(Li et al., 2023) reviewed mixed traffic control strategies mainly for urban road networks, particularly CAV-based coordinated signal control and trajectory planning at signalized intersections, where platoon-based cooperative control has also been investigated (Zheng et al., 2024c). Siri et al.(Siri et al., 2021) reviewed freeway traffic control methods developed over the past decades, with a primary focus on conventional traffic flow modeling, classical control theory, and bibliometric trends. Compared with these reviews, the present review differs in both scope and analytical perspective. It specifically focuses on vehicle-enabled freeway traffic control under partially connected environments and organizes the literature according to the functional role of CVs within a unified VECT framework, covering the progressive use of CVs from traffic sensing and flow-level regulation to vehicle-level actuation and cross-scale coordination. In addition, this review systematically considers partially connected conditions, methodological trade-offs, and practical deployment challenges across these research directions. This paper therefore provides a focused synthesis of VECT strategies for freeways and outlines potential research directions and development trends for future studies.

The rest of the paper is organized as follows. Section 2 provides an overview of the classification and evolution of VECT strategies for freeway flow and discusses their key characteristics. Sections 3–6 review four categories of VECT studies in partially connected environments: vehicle-trajectory-enabled traffic state analysis, vehicle-trajectory-enabled traffic control, vehicle-guidance-enabled traffic control, and collaborative vehicle–flow control. Section 7 discusses future research directions and challenges for VECT in partially connected environments.



（a） Speed advisory from Gaode Map app (AutoNavi)　　（b） Lane guidance from Google Maps

Fig. 1. Examples of vehicle guidance enabled by navigation applications.
Source: (a) adapted from Gaode Map app (AutoNavi); (b) adapted from Google Maps Live Lane Guidance (Google, 2025).

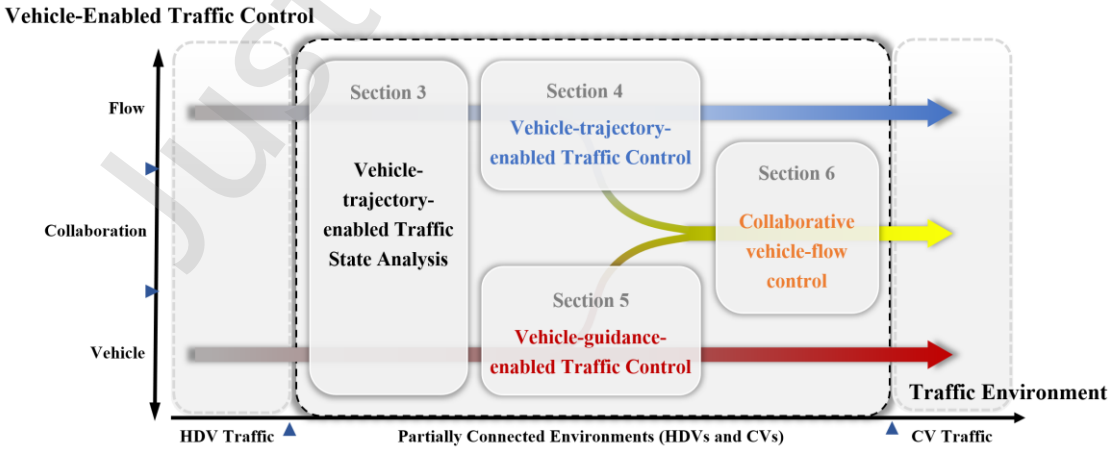


Fig. 2. Evolution of VECT research.

2. Glance at the evolution of highway traffic control techniques

Freeway traffic control has gradually expanded from infrastructure-centered regulation based on fixed detectors to vehicle-enabled approaches supported by VTD and vehicle guidance. In this review, VECT is discussed from four categories: vehicle-trajectory-enabled traffic state analysis, vehicle-trajectory-enabled traffic control, vehicle-guidance-enabled traffic control, and collaborative vehicle–flow control. To clarify the boundaries among these categories, the classification is based primarily on the functional role of connected vehicles and the level at which the resulting decision or control action is generated. It is therefore not determined simply by whether VTD is used. Specifically, the four categories represent traffic state analysis without direct control

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actions, flow-level traffic control, vehicle-level guidance, and coordinated control across flow and vehicle levels, respectively, as summarized in Table 1.

Table 1 further clarifies the distinctions among the four categories by comparing the role of CVs, the information used, and the resulting control level. Vehicle-trajectory-enabled traffic state analysis uses VTD either independently or as a supplement to local/partial flow measurements. It aims to estimate or predict traffic states over a wider range and detect traffic anomalies, without generating control strategies. Vehicle-trajectory-enabled traffic control combines VTD with control-area flow measurements to support adaptive flow-level control strategies, such as VSL and RM. In vehicle-guidance-enabled traffic control, CVs serve not only as mobile detectors but also as actuators. These methods generate vehicle guidance strategies, such as speed advisory and lane-changing guidance. Collaborative vehicle–flow control integrates the two control levels by coordinating adaptive flow-level control strategies with vehicle guidance strategies.

Compared with existing surveys that mainly organize studies according to control strategies, methodological approaches, or application scenarios, VECT provides a complementary functional taxonomy. It is built upon two fundamental capabilities of CVs: (1) generating VTD and serving as mobile sensing units, and (2) acting as traffic actuators that can directly influence individual vehicle behavior and aggregate traffic flow. Based on these capabilities, VECT organizes studies according to the functional role of CVs and the level at which information, decisions, or control actions are generated. This establishes clearer boundaries among traffic sensing, flow level regulation, vehicle level control, and coordinated vehicle flow control.

The relationship between VECT and related concepts is also distinct. Traffic control based on CVs is a broader technology centered concept that encompasses approaches exploiting CV data, communication, or control capabilities, including traffic state estimation, driver guidance, infrastructure control, and coordinated vehicle and infrastructure control (Guo et al., 2019; Li et al., 2023). VECT therefore provides a more structured functional organization within this broader field. Cooperative traffic control, in contrast, is defined primarily by coordination among multiple traffic participants or control entities through information exchange and coordinated decision making (Guériau et al., 2016; Zhang et al., 2022a), and its relationship with VECT is one of partial overlap rather than inclusion. Cooperation is not required for VECT, because VTD can support traffic state analysis or flow level control without cooperative decision making. Conversely, cooperative traffic control also includes vehicle to vehicle cooperation, infrastructure coordination, and other cooperative applications outside the scope of VECT.

Table 1. Four categories of VECT studies

Category	Role of CVs	Input		Output	
		Flow level	Vehicle level	Flow level	Vehicle level
Vehicle-trajectory-enabled traffic state analysis	Mobile detector	Local/partial flow measurements	VTD	Estimated/predicted traffic states over a wider range (e.g., TSE, TSP, TAD)	——
Vehicle-trajectory-enabled traffic control	Mobile detector	Control-area flow measurements	VTD	Adaptive flow-level control strategies (e.g., VSL, RM)	——
Vehicle-guidance-enabled traffic control	Mobile detector and actuators	Control-area flow measurements	VTD	——	Vehicle guidance strategies (e.g., speed advisory, lane-changing guidance)
Collaborative vehicle-flow control	Mobile detector and actuators	Control-area flow measurements	VTD	Adaptive flow-level control strategies (e.g., VSL, RM)	Vehicle guidance strategies (e.g., speed advisory, lane-changing guidance)

The evolution of vehicle-trajectory-enabled traffic state analysis for freeway flow is illustrated in Fig. 3. Traffic State Estimation (TSE) refers to the estimation or reconstruction of prevailing traffic conditions from available observations (Wang and Papageorgiou, 2005). Early studies primarily relied on first-order models, such as the LWR model(Lighthill and Whitham, 1955) and the Cell Transmission Model (CTM) (Daganzo, 1994), as well as higher-order models, including the Payne model (Payne, 1971) and METANET(Papageorgiou et al., 1990), to describe traffic flow dynamics and congestion propagation. With the deployment of CVs, the scale of VTD has increased significantly. Some studies rely on traffic flow theory to represent traffic state evolution, using methods such as fundamental diagram models (Anuar et al., 2015) and Lagrangian traffic flow models (Zheng et al., 2018). Other studies infer traffic states from observed data through statistical or probabilistic methods, including linear regression (Chen et al., 2003) and Bayesian estimation (Kyriacou et al., 2023). More recent data-driven approaches further apply machine learning techniques, such as random forests (Zhang and Yang, 2020), XGBoost (Mussah and Adu-Gyamfi, 2022), and Graph Neural Networks (GNNs) (Xue et al., 2024), to extract latent patterns from VTD. To reduce reliance on high-quality VTD and improve physical consistency, model–data hybrid approaches have also been adopted, where traffic flow knowledge is incorporated as prior information or constraints to support data-driven learning (Raissi et al., 2019).

Traffic State Prediction (TSP) refers to the forecasting of future traffic conditions based on current and/or historical traffic information. Early studies focused on statistical models, such as the Historical Average method (Kreer, 1976), ARIMA models (Ahmed and Cook, 1979),

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exponential smoothing (Chan et al., 2012), and grey prediction models (Guo et al., 2013), to capture macroscopic traffic flow patterns. The field then moved toward ML methods, including Support Vector Regression (SVR) (Wu et al., 2004), K-Nearest Neighbors (Wang et al., 2011a), and random forest regression (Hou et al., 2017), which were introduced to model complex patterns in large-scale VTD. The temporal nature of VTD has also motivated the use of DL models, including Artificial Neural Networks (ANN)(Park et al., 1998), Backpropagation (BP) networks (Wang et al., 2008), Recurrent Neural Networks (RNN) (Jiang et al., 2015), Gated Recurrent Units (GRU) (Fu et al., 2016), Long Short-Term Memory (LSTM) networks (Ma et al., 2015), and GNNs (Diehl et al., 2019), in TSP.

Traffic Anomaly Detection (TAD) can be regarded as a special branch of TSE. As early as the 1960s, the United States adopted Automatic Incident Detection (AID) techniques to identify traffic incidents (Du et al., 2023b). Early studies relied on macroscopic traffic parameters, such as occupancy (Levin and Krause, 1978)and flow-density relationships (Willsky et al., 1980), or derived features, including double exponential smoothing values (Petty et al., 2002) and smoothed detector occupancy (Stephanedes and Chassiakos, 1993), which were compared with predefined thresholds to detect anomalies. With the availability of VTD, some studies have extracted microscopic features, such as headway and traffic wave propagation speed (Asakura et al., 2017), to improve detection accuracy. Another line of research applies statistical models, including the Standard Normal Deviate (SND) algorithm (Dudek et al., 1974), ARIMA models (Ahmed and Cook, 1982), the Generalized Extreme Studentized Deviate (GESD) test (Luan et al., 2021), and multi-model particle filters (Wang et al., 2016), to identify anomalies via confidence intervals. More recently, VTD has been widely incorporated into ML frameworks, including supervised (Zhang and Taylor, 2006), semi-supervised (Lin et al., 2020), and unsupervised learning (Kinoshita et al., 2015), as well as Reinforcement Learning (RL) (He et al., 2023), achieving significant improvements in large-scale traffic monitoring scenarios.

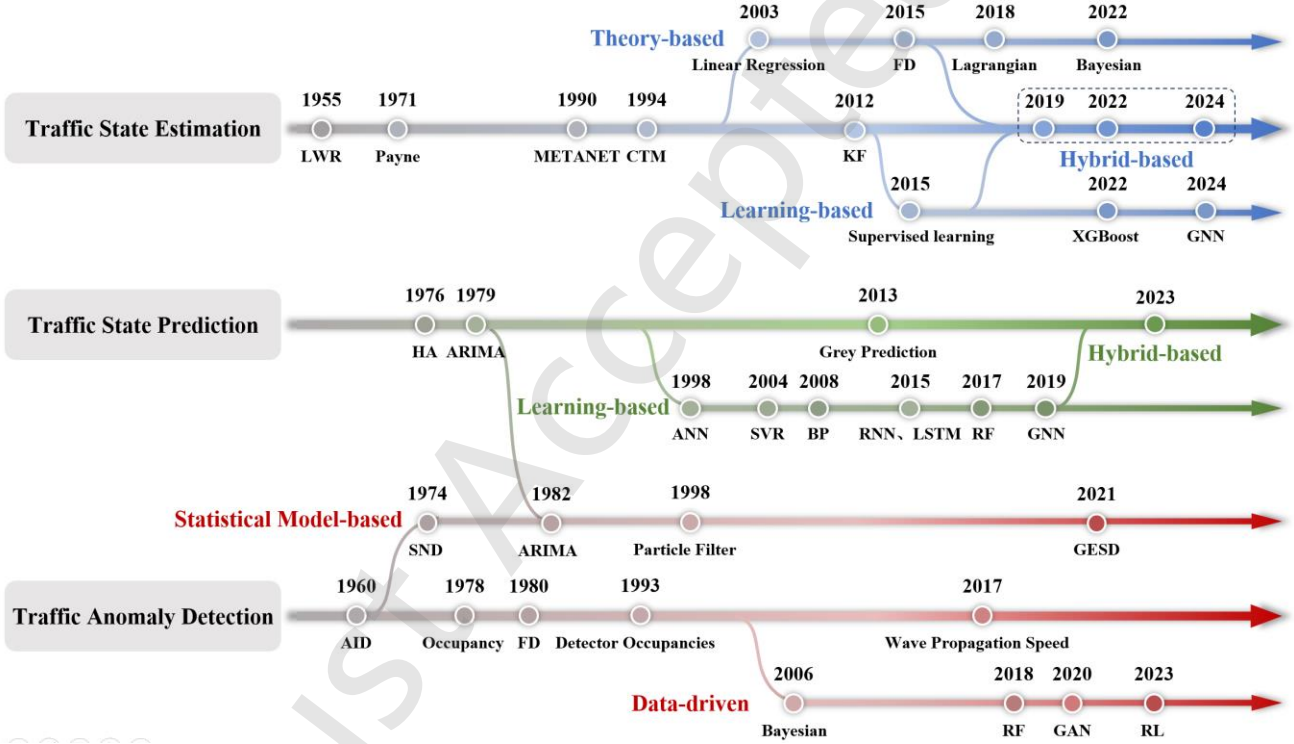


Fig. 3. The evolution of vehicle-trajectory-enabled traffic state analysis for freeway flow

The evolution of vehicle-trajectory-enabled traffic control for freeway flow is illustrated in Fig. 4. These methods mainly utilize VTD to regulate traffic flow at the macroscopic or mesoscopic level, and can be broadly classified into VSL and RM (Vrbanić et al., 2021). Early VSL methods primarily relied on open-loop control(Lee et al., 2004) and feedback control(Smulders, 1990) to adjust speed limits, but they suffered from delayed responses and limited control accuracy. With the development of CV technology, VTD has been leveraged to calibrate macroscopic and mesoscopic traffic flow models, such as car-following models(Wang and Ioannou, 2011b), METANET(Fang et al., 2019), and CTM (Hadiuzzaman, 2014), thereby improving control accuracy and stability. In recent years, RL methods have been widely applied to VSL control(Kušić et al., 2018), as they can learn control policies without relying on fully specified traffic-flow models (e.g., Q-learning(Li et al., 2017) and R-MART(Zhu and Ukkusuri, 2014)). Among them, multi-agent cooperative approaches, such as distributed Q-learning(Wang et al., 2019) and W-learning(Kušić et al., 2020), enable coordinated control over long freeway segments through multiple agents, and have emerged as a research focus.

RM is designed to regulate the inflow rate of vehicles entering from ramps in order to alleviate mainline congestion(Papageorgiou and Kotsialos, 2002). Early studies mainly adopted feedback control methods, such as the ALINEA(Hadjsalem et al., 1990) algorithm and its variants (e.g., PI-ALINEA (Wang et al., 2014)). These methods effectively improve traffic efficiency by maintaining macroscopic indicators, such as downstream occupancy at bottlenecks, near critical levels(Vrbanić et al., 2021). Control foresight has been enhanced through optimal control frameworks based on macroscopic traffic flow models (Papamichail et al., 2010). As the scale of VTD has increased, the RM control paradigm has gradually shifted from flow-level management to vehicle-level coordination (Xie et al., 2017), improving both traffic efficiency and control stability. In recent years, the introduction of RL methods (e.g., Q-learning(Rezaee et al., 2012)) has enabled RM to establish adaptive and cooperative decision-making

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frameworks based on VTD. More recently, Deep Reinforcement Learning (DRL) methods, such as Deep Q-Networks (DQN) (Wang et al., 2017) and Deep Deterministic Policy Gradient (DDPG)(Wang et al., 2022a), have been used to extract complex traffic state representations and support coordinated control of multiple ramps and large-scale freeway networks.

The evolution of vehicle-guidance-enabled traffic control for freeway flow is illustrated in Fig. 5. Early studies mainly focused on local vehicle guidance in bottleneck areas, using rule-based strategies to mitigate merging conflicts and improve vehicle interactions (Schmidt and Posch, 1983). Subsequent studies incorporated vehicle kinematics and traffic flow dynamics into trajectory planning, enabling guidance strategies to account for constraints on speed, acceleration, safety spacing, and merging behavior (Ran et al., 1999). With the development of control-oriented modeling, Model Predictive Control (MPC) and optimal control frameworks were increasingly used to generate vehicle guidance over larger freeway segments (Cao et al., 2013); (Ghiasi et al., 2019). Depending on the formulation of the control problem, these frameworks can be implemented through different mathematical representations and solution techniques, such as mixed-integer nonlinear programming (MINLP) for constrained optimization problems (Zhou et al., 2019) and Hamiltonian-based approaches for analytical optimal control problems (Ghiasi et al., 2019). To better exploit latent features in VTD, some studies have employed ML methods, such as Bayesian linear regression (Le et al., 2025) and multi-agent reinforcement learning (MARL) approaches (Zhu et al., 2021), demonstrating stronger capabilities in policy learning and generalization under high-dimensional and nonlinear traffic environments.

A small number of CVs can be guided to act as moving bottlenecks, reducing dependence on high CV penetration rates while shaping the spatiotemporal distribution of downstream arrivals through their influence on surrounding vehicles. This concept can be traced back to the idea of moving bottlenecks (Gazis and Herman, 1992) , and the emergence of CVs enables the practical implementation of such methods. One line of research develops macroscopic analytical models, such as MPC (Piacentini et al., 2018) and CTM (Cicic et al., 2018), to characterize the impact of CVs acting as moving bottlenecks on overall traffic flow. Alternatively, other studies take a microscopic perspective by transforming the system-level optimization problem into trajectory planning problems for CVs, either at the individual level (Larsson et al., 2021) or platoon level(Vishnoi et al., 2024; Zheng et al., 2023). To better capture the coordination among multiple moving bottlenecks, RL methods have been introduced, such as Trust Region Policy Optimization (TRPO) (Vinitsky et al., 2018), DQN(Ko et al., 2020), and Proximal Policy Optimization (PPO) (Suriyarachchi et al., 2022). These approaches learn optimal policies through agent – environment interactions and can directly generate optimal control actions based on the current state, thereby further improving the real-time performance and effectiveness of arrival distribution control.

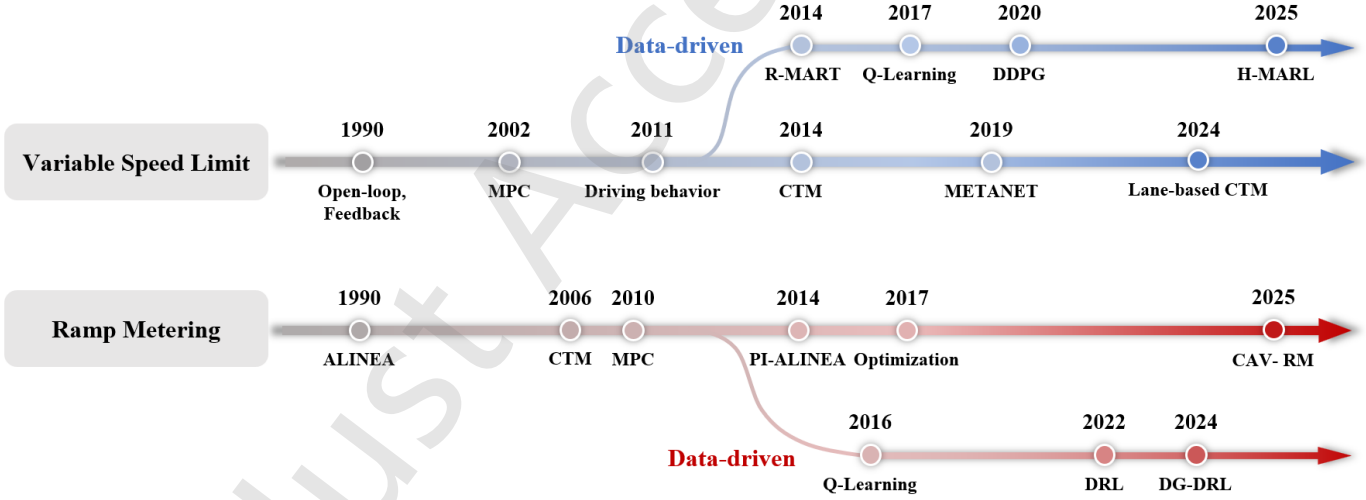


Fig. 4. The evolution of vehicle-trajectory-enabled traffic control for freeway flow

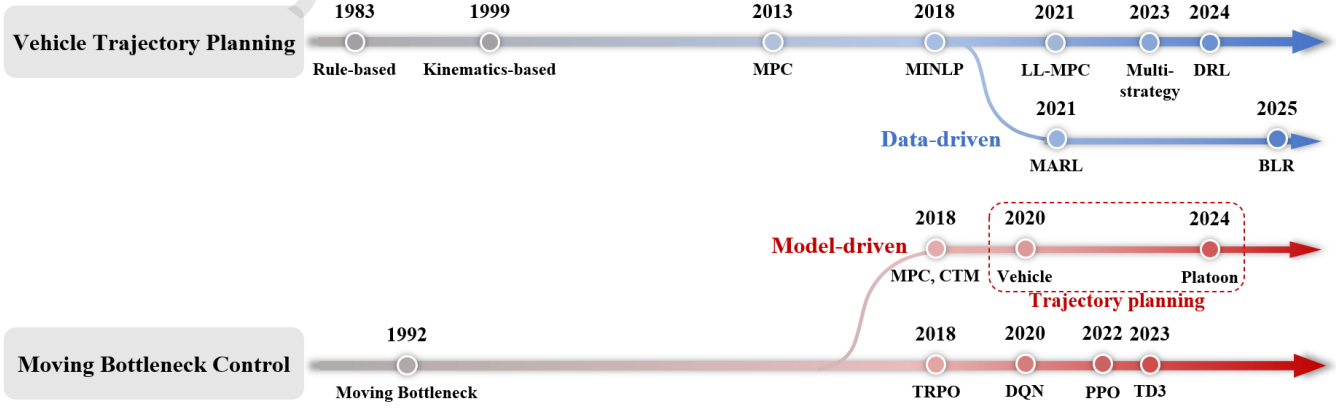


Fig. 5. The evolution of vehicle-guidance-enabled traffic control for freeway flow

Recent studies have increasingly focused on collaborative vehicle–flow control in freeway scenarios. This line of research aims to clarify

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the interaction mechanisms between vehicle-level control and traffic flow evolution, and to explore effective coordination between macroscopic and microscopic control strategies. However, to the best of our knowledge, only a limited number of studies have been reported, as illustrated in Fig. 6. Early studies primarily focused on urban intersections, where coordinated control systems integrating trajectory planning and signal timing were developed to improve overall traffic efficiency(Malakorn et al., 2010). In freeway environments, existing studies primarily focus on on-ramp areas, addressing merging conflicts between high-speed mainline traffic and low-speed ramp traffic (Kherroubi et al., 2022). Riccardo et al. (Scarinci et al., 2017) proposed a coordinated strategy that integrates RM with microscopic vehicle cruise control. In this approach, mainline vehicles actively create gaps for lane changing, while ramp signals regulate the release of ramp vehicles, enabling more efficient merging operations. Fan et al. (Fan et al., 2025) investigated the impact of CV penetration rates on macroscopic traffic flow characteristics and microscopic control strategies under different traffic demand conditions. In their framework, RM regulates ramp inflow while coordinated trajectories are optimized for ramp and mainline CVs.

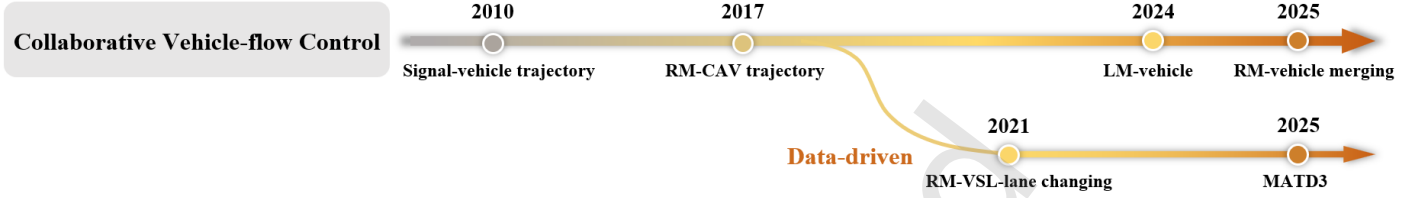


Fig. 6. The evolution of collaborative vehicle-flow control for freeway flow

Current studies increasingly exploit VTD and vehicle-level guidance while addressing the limited observability and controllability of conventional HDVs. However, studies conducted in partially connected environments differ substantially in their assumptions regarding vehicle connectivity, sensing, and control capability. Accordingly, this review characterizes such environments using several common dimensions, including the functional role and control authority of CVs, the penetration and spatial distribution of connected or controllable vehicles, VTD quality, communication reliability, and driver compliance and behavioral uncertainty. These dimensions provide a consistent basis for comparing the applicability, robustness, computational requirements, and deployment feasibility of different VECT approaches. Based on this framework, the following sections systematically review existing VECT approaches in freeway scenarios.

3. Vehicle-trajectory-enabled traffic state analysis for freeway flow

The core idea of vehicle-trajectory-enabled traffic state analysis for freeway flow is to use VTD, either independently or as a supplement to local/partial flow measurements, to characterize traffic conditions over a wider range. Unlike the three control-oriented categories discussed subsequently, this category does not directly generate traffic- or vehicle-level control strategies. Instead, it focuses on estimating prevailing traffic states, predicting their future evolution, and detecting traffic anomalies.

Freeway traffic differs from urban traffic in its continuous-flow operation, limited access points, and stronger longitudinal propagation of traffic disturbances. Traffic states are therefore largely shaped by interactions along the mainline and by localized bottlenecks such as ramps, lane reductions, and merging areas. Urban traffic, in comparison, is more strongly influenced by signal timing, intersection interactions, turning movements, and route choices. These characteristics make corridor-level state reconstruction and disturbance propagation particularly important for freeway TSE and TSP.

In partially connected environments, only a fraction of vehicles can be observed, making the available VTD inherently sparse and incomplete. Non-uniform vehicle sampling, measurement errors, missing observations, and communication-induced data loss may further reduce the representativeness and reliability of VTD. The central challenge is therefore to infer traffic states over a wider range from local/partial flow measurements and limited vehicle observations. Depending on the research objective, existing studies can be broadly divided into three categories: TSE, which reconstructs prevailing traffic conditions; TSP, which predicts their future evolution; and TAD, which identifies deviations from normal traffic patterns, as illustrated in Fig. 7. Table 2 summarizes the reviewed studies, most of which were published within the last decade.

3.1 Traffic state estimation

TSE aims to reconstruct prevailing spatiotemporal traffic states, such as speed, density, flow, and congestion patterns, from partially observed traffic information. In freeway applications, this reconstruction typically focuses on continuous traffic states along mainline corridors and the spatial evolution of congestion and traffic waves, with ramps and bottlenecks acting as important boundary conditions or disturbance sources. Compared with fixed detectors, VTD provides continuous vehicle-level observations over space; however, only a subset of vehicles is observable in partially connected environments, making reliable reconstruction challenging, particularly under low penetration rates or when trajectories are unevenly sampled, noisy, or incomplete. Existing methods address this partial-observability problem through four main approaches: traffic-flow-theory-based, statistical-model-based, ML-based, and physics-guided or hybrid methods. These approaches differ primarily in how they exploit traffic-flow assumptions, observed data, and prior knowledge to compensate for missing information.

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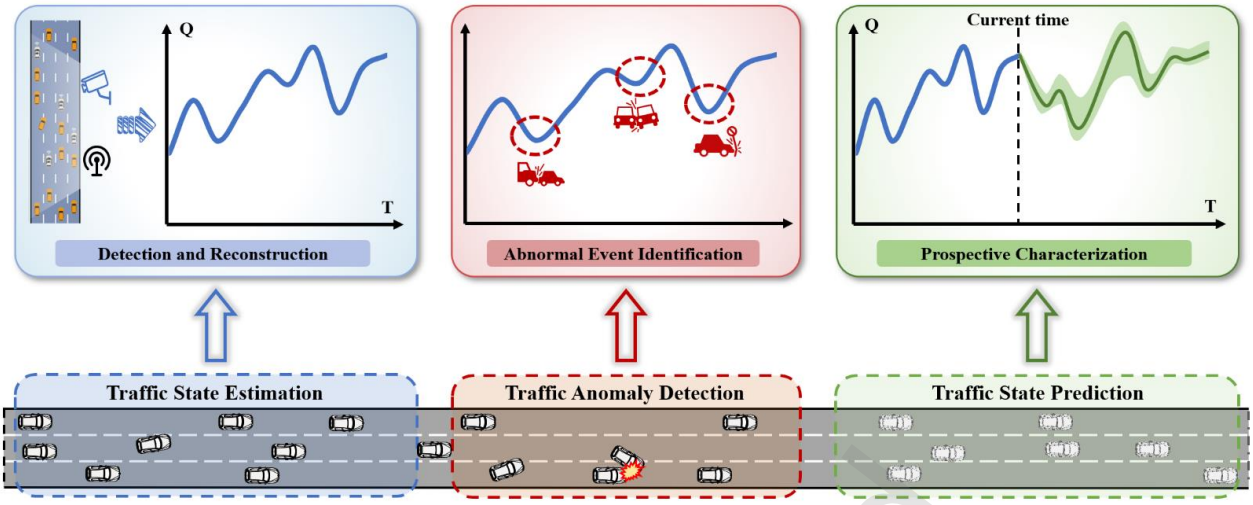


Fig. 7. Vehicle-trajectory-enabled traffic state analysis for freeway flow

Table 2. Typical studies on vehicle-trajectory-enabled traffic state analysis for freeway flow

Topic	Approach	Papers	VTD Use			Performance			
			Calib.	Infer.	Recon.	L.P.A.	N.D.R.	S.S.A.	U.Q.
TSE	M.D.	(Zheng et al., 2018)			√	√			
		(Wu et al., 2024a)			√	√			√
		(Han et al., 2022c)		√	√	√			
		(Wang et al., 2022b)	√	√					
		(Han and Ahn, 2021a)		√		√			
	D.D.	(Nie et al., 2022)		√			√		
		(Aljuaydi et al., 2023)		√			√		
	Hyb.	(Usama et al., 2022)		√	√	√	√		
		(Zhang et al., 2024b)		√		√			
TSP	M.D.	(Wang et al., 2018)	√	√					
		(Emami et al., 2019)		√		√			
		(Heshami and Kattan, 2024)	√	√					
		(Wu et al., 2025)		√					√
	D.D.	(Jeong et al., 2021)		√			√		
		(Zhou et al., 2024)		√					
	Hyb.	(Ji et al., 2022)		√			√		
		(Deshpande et al., 2025)	√	√					√
TAD	M.D.	(Asakura et al., 2017)				√			
		(He et al., 2024a)			√	√			
		(Khoda Bakhshi and Ahmed, 2022)		√					
		(Chakraborty et al., 2019)		√			√		
		(Xu et al., 2019)		√			√		
	D.D.	(Zhang and Abdel-Aty, 2022b)		√			√		
		(Lin et al., 2020)		√			√	√	
		(Liu et al., 2022b)		√				√	√
		(Parsa et al., 2020)		√				√	

Note: M.D. – Model-Driven; D.D. – Data-Driven; Hyb. – Hybrid Model-Data Driven; Calib. – Data Calibration; Infer. – State Inference; Recon. – Full-Field Reconstruction; L.P.A.– Low Penetration Adaptability; N.D.R. – Noisy Data Robustness; S.S.A. – Small Sample Adaptability; U.Q. – Uncertainty Quantification.

3.1.1 TSE based on traffic flow theory

Traffic-flow-theory-based TSE methods address partial observability by exploiting conservation laws, fundamental diagrams, traffic-wave propagation, or traffic-state evolution dynamics to infer unobserved traffic states from sampled VTD. These methods generally assume that the adopted traffic-flow relationships adequately describe the prevailing traffic regime, while many formulations further require sampled CV trajectories to be sufficiently representative of the overall traffic stream or auxiliary information to compensate for unobserved vehicles. Depending on how VTD is incorporated, existing studies can be broadly divided into indirect estimation based on intermediate traffic variables and direct estimation based on explicit traffic-flow models.

Indirect methods first extract or infer intermediate traffic variables,

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such as average speed, travel time, vehicle count, or queue-related information, from sampled VTD and subsequently derive macroscopic states through analytical traffic-flow relationships. For example, Grumert et al. (Grumert and Tapani, 2018) assumed that CVs and conventional vehicles share the same speed distribution. They used VTD to estimate segment-level average speed, combined it with fixed-detector data to infer CV penetration and total vehicle counts, and subsequently derived traffic states such as flow and density through fundamental-diagram relationships. Han et al. (Han et al., 2022c) used timestamp, position, and speed information from probe trajectories to infer the number of unobserved vehicles between probe vehicles and reconstruct segment-level traffic states based on traffic-wave theory. These approaches can reduce the amount of trajectory information required for state estimation by linking sparse vehicle observations with aggregate traffic states. However, their reliability depends strongly on the accuracy of intermediate variables and the validity of the underlying assumptions. Estimation errors may accumulate through successive inference steps, while biased CV sampling may further reduce estimation reliability under heterogeneous traffic conditions.

Direct model-based methods assimilate VTD into explicit traffic-flow models for parameter calibration, boundary-condition specification, or dynamic state updating. Traffic conservation and state-evolution dynamics provide additional constraints on unobserved regions, making these methods attractive when trajectory observations are incomplete. For example, Zheng et al. (Zheng et al., 2018) developed a stochastic Lagrangian framework that represents driver heterogeneity through vehicle-specific speed–spacing relationships and performs traffic-state estimation through recursive data assimilation. Wang et al. (Wang et al., 2022b) investigated joint traffic-state and model-parameter estimation by integrating fixed-sensor measurements with CV data. Similar model-based frameworks have shown that conservation relationships and CV position/speed information can support traffic-state reconstruction at relatively low penetration rates (Bekiaris-Liberis et al., 2017).

The main limitation of traffic-flow-theory-based TSE methods lies in their dependence on model specification, parameter calibration, and system observability. When the adopted fundamental diagram, car-following relationships, or state-evolution dynamics fail to represent prevailing traffic conditions, model misspecification may introduce systematic estimation errors, particularly under heterogeneous or rapidly changing traffic regimes. Accordingly, these approaches are most applicable when traffic dynamics can be reasonably represented by the adopted model and sparse VTD can be supplemented by reliable boundary information, fixed-sensor observations, or well-calibrated model parameters.

3.1.2 TSE based on statistical models

Statistical-model-based TSE methods address partial observability by establishing statistical or probabilistic relationships between sampled VTD and underlying traffic states. Rather than relying primarily on explicit traffic-flow dynamics, these approaches infer unobserved states from incomplete and potentially noisy observations. In many formulations, traffic states are treated as latent variables and estimated through probabilistic inference. Their effectiveness generally depends on whether the available VTD is sufficiently informative and representative of the unobserved traffic population and whether the assumed statistical relationships or probabilistic structures remain valid under prevailing traffic conditions. Within this framework, historical observations, prior knowledge, and real-time VTD can be jointly incorporated to update the posterior distribution of traffic states. Bayesian inference and Gaussian-process-based reconstruction are representative approaches. For example, Han and Ahn (Han and Ahn, 2021a) employed Bayesian inference to estimate traffic flow rates from headway information extracted from CV trajectories, where historical information is incorporated as prior knowledge to compensate for limited real-time observations. Wu et al. (Wu et al., 2024a) developed an anisotropic Gaussian-process framework to reconstruct continuous traffic-state fields from sparse VTD while simultaneously quantifying estimation uncertainty. These studies illustrate the key advantage of statistical approaches: prior knowledge and probabilistic correlations can compensate for incomplete observations while explicitly accounting for estimation uncertainty.

However, the reliability of such approaches depends strongly on the validity of the assumed statistical relationships. At low penetration rates, limited samples may inadequately represent the underlying traffic population, while non-random CV sampling can introduce systematic bias. Moreover, changes in traffic demand, congestion regimes, vehicle composition, or sensing quality may cause the observation distribution to deviate from historical priors, leading to biased or overconfident estimates. Therefore, statistical approaches are most applicable when observation uncertainty can be reasonably characterized and the probabilistic relationship between sampled trajectories and traffic states remains sufficiently stable. Improving robustness to distribution shifts, sampling bias, and dynamically varying data quality remains an important challenge for practical deployment.

3.1.3 TSE based on ML

ML-based TSE methods aim to learn nonlinear mappings from incomplete vehicle observations to traffic-state variables, such as speed, flow, and density, without explicitly specifying traffic-flow relationships. Their performance generally relies on the assumption that historical training data are sufficiently representative of the traffic conditions encountered during application. Traditional ML approaches mainly use manually constructed trajectory features as inputs and learn statistical mappings through models such as random forests (Zhang and Yang, 2020) and XGBoost (Mussah and Adu-Gyamfi, 2022). These methods are relatively simple and computationally efficient, but their performance depends strongly on feature quality and they have limited capability to capture complex spatiotemporal dependencies.

DL methods reduce the reliance on manual feature engineering by automatically extracting high-dimensional representations from VTD. Representative architectures include CNN, RNN, LSTM, and GRU (Ding et al., 2022; Nie et al., 2022; Rempe et al., 2022; Yang et al., 2022). Hybrid architectures further combine spatial and temporal modeling capabilities; for example, CNN–LSTM models have been applied to capture traffic-state variations under complex disturbances such as incidents and rainfall (Aljuaydi et al., 2023). These approaches are particularly effective when sufficient high-quality trajectory data are available, but their accuracy may deteriorate when observations are sparse, noisy, or substantially different from the training data. Their limited interpretability also makes it difficult to assess whether learned relationships remain valid under changing traffic conditions.

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From the perspective of scalability and practical deployment, ML-based TSE faces a trade-off between modeling capability and computational requirements. Large-scale DL models demand considerable computational resources, while real-time applications require efficient processing of continuously updated trajectory streams. Moreover, models trained under specific penetration rates, traffic regimes, or sensing conditions may not generalize reliably to different environments. Therefore, improving data efficiency, cross-scenario generalization, computational scalability, and interpretability remains critical for practical deployment.

3.1.4 TSE based on physics-guided and hybrid learning

Physics-guided and hybrid learning methods aim to reduce the dependence of purely data-driven TSE on large-scale, high-quality training data by incorporating traffic-flow knowledge into the learning process. Their basic idea is to use conservation laws, wave-propagation mechanisms, or traffic-state dynamics as physical priors, while learning components capture patterns or disturbances that cannot be fully represented by analytical models. These approaches generally assume that the embedded traffic-flow relationships remain sufficiently valid to provide meaningful guidance, making them particularly useful under sparse or incomplete VTD conditions.

One major direction embeds physical constraints directly into learning models. Physics-Informed Neural Networks (PINNs) incorporate governing traffic-flow equations into the training objective to improve the physical consistency of state reconstruction (Raissi et al., 2019; Usama et al., 2022). Zhang et al. (Zhang et al., 2024b) further embedded traffic-flow models into neural-network training and used computational graphs to jointly identify fundamental-diagram parameters and traffic states under sparse observations. Another direction couples learning with model-based state evolution or correction. Deshpande and Park (Deshpande et al., 2025) integrated physics-informed learning with a Kalman-filter mixture model, while gray-box frameworks use traffic-flow models to describe the main state evolution and learning models to capture systematic model errors and heterogeneous disturbances (Jin et al., 2021; Pan et al., 2022).

The effectiveness of these approaches depends strongly on the compatibility between the embedded physical model and actual traffic dynamics. Overly restrictive physical assumptions may introduce systematic bias, whereas weak physical constraints provide limited advantages over purely data-driven methods. From the perspective of scalability and deployment, jointly optimizing physical and learning components may increase computational burden, while transferability can deteriorate when traffic regimes, vehicle compositions, or model parameters vary across locations. Therefore, improving computational efficiency, adaptive integration of physical knowledge, and cross-scenario robustness remains important for large-scale deployment.

3.1.5 Method comparison

The four TSE paradigms exhibit distinct trade-offs in data requirements, methodology, and practicality, as summarized in Table 3. In terms of data requirements, the main differences concern VTD penetration and data quality. Traffic-flow-theory-based methods generally have lower requirements for VTD penetration and data quality because traffic-flow relationships provide additional constraints for reconstructing unobserved states. Statistical-model-based methods have moderate data requirements, but their performance depends on whether the sampled trajectories are representative of the overall traffic stream. ML-based methods generally require higher VTD penetration and higher-quality data because their performance relies strongly on abundant and representative observations. Physics-guided and hybrid methods reduce part of this data dependence by incorporating physical knowledge into data-driven estimation.

Table 3. Comparison of TSE paradigms under partially connected conditions

Method	Data requirements		Main strength	Main limitation	Practicality	
	VTD penetration	Data quality			Computation burden	Transferability
Traffic-flow-theory-based	Low–moderate	Low	Physical interpretability	Limited generalizability	Low–moderate	Moderate
Statistical-model-based	Moderate	Moderate	Uncertainty quantification	Sensitive to sampling bias	Moderate	Moderate
ML-based	High	High	Nonlinear representation	Limited interpretability	High	Low
Physics-guided / hybrid	Moderate	Moderate	Physical consistency and data efficiency	Training difficulty	Moderate–high	Moderate–high

The four paradigms also differ in their main strengths and limitations. Traffic-flow-theory-based methods provide strong physical interpretability, but their generalizability is limited when the assumed traffic-flow relationships or calibrated parameters do not remain valid. Statistical-model-based methods provide uncertainty quantification through probabilistic inference, but they are sensitive to sampling bias. ML-based methods have strong nonlinear representation capability, but their interpretability is limited. Physics-guided and hybrid methods combine physical consistency with data efficiency, but the integration of physical and learning components can increase training difficulty.

In terms of practicality, the main differences lie in computational burden and transferability. Traffic-flow-theory-based methods generally have a low-to-moderate computational burden and moderate transferability. Statistical-model-based methods have moderate computational requirements and moderate transferability. ML-based methods usually involve a high computational burden because of model training and inference, and their transferability can be limited by distribution shifts across traffic regimes, network conditions, or sensing

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environments. Physics-guided and hybrid methods generally have a moderate-to-high computational burden because physical constraints and learning components must be jointly handled. Their transferability can nevertheless be improved by incorporating physically meaningful information. Consequently, no single paradigm is uniformly preferable. Traffic-flow-theory-based methods are attractive when data are limited and interpretability is important. Statistical-model-based methods are useful when uncertainty quantification is required. ML-based methods are advantageous when abundant and high-quality VTD are available. Physics-guided and hybrid methods provide a compromise between physical consistency, data efficiency, and transferability.

3.1.6 Practical deployment

Practical deployment of VTD-enabled TSE is likely to follow an incremental hybrid-sensing pathway, with VTD supplementing existing roadside detectors as connectivity increases. Fixed sensors provide stable observations at predefined locations, while CVs extend spatial coverage through mobile measurements. Mixed-sensing studies have demonstrated the technical feasibility of such integration, although most evaluations remain based on experimental or trajectory datasets instead of sustained field operation (Wang et al., 2022b).

A central deployment requirement is maintaining reliable estimation while integrating VTD into existing traffic-management systems. CV pilots indicate that vehicle-generated data can be incorporated into established operational architectures; for example, the Wyoming CV Pilot integrated such data with the WYDOT Traffic Management Center for processing and distribution (Fok et al., 2019). For TSE, this requires accommodating time-varying penetration, uneven spatial sampling, missing observations, and heterogeneous data sources while remaining compatible with existing sensing and management platforms.

Operational scalability becomes increasingly important as VTD volume and system complexity grow. High-frequency vehicle data impose substantial communication, storage, and processing demands, motivating scalable data-management architectures such as distributed or edge processing (Thompson, 2018). Operational TSE should also remain functional under degraded VTD availability, quantify estimation reliability, and provide sufficiently timely outputs for downstream surveillance and control. Deployment readiness therefore depends on robust performance under changing sensing conditions, scalable data processing, and effective integration with existing freeway-management systems.

3.2 Traffic state prediction

Unlike TSE, which focuses on reconstructing current traffic conditions, Traffic State Prediction (TSP) aims to anticipate the future spatiotemporal evolution of traffic flow. For freeways, prediction is particularly concerned with how congestion, traffic waves, and bottleneck-induced disturbances propagate along continuous corridors and interact with ramp inflows and downstream traffic conditions. In partially connected environments, sparse and incomplete VTD may provide only a partial representation of current traffic conditions, and these uncertainties can further propagate over the prediction horizon. High-resolution VTD nevertheless provides continuous vehicle-level information that can support the modeling of traffic evolution and disturbance propagation. Existing TSP studies can be broadly classified into four categories: traffic-flow-model-based, statistical-model-based, spatiotemporal-learning-based, and physics-guided or hybrid approaches.

3.2.1 TSP based on the traffic flow models

Traffic-flow-model-based TSP methods predict future traffic states by propagating current observations through explicit traffic-flow dynamics. Their basic assumption is that the adopted macroscopic or microscopic models can adequately represent short-term traffic evolution and that model states and parameters can be reliably initialized or updated from available observations. Depending on the prediction scale, existing studies can be broadly divided into macroscopic traffic-state prediction and microscopic vehicle-state prediction.

Macroscopic approaches describe traffic evolution using aggregate variables such as density, flow, and average speed. VTD is mainly used for state initialization, parameter calibration, and online model updating, while traffic-flow dynamics are used to propagate the estimated state forward. For example, extended METANET-based frameworks have incorporated VTD into traffic-state estimation and parameter calibration for congested freeway corridors (Wang et al., 2018), while VTD has also been fused with fixed-detector data in second-order traffic-flow models for short-term prediction (Mannini et al., 2015). These approaches are physically interpretable and can compensate for incomplete observations through model constraints, but their prediction accuracy depends strongly on model calibration and the validity of the assumed traffic dynamics.

Microscopic approaches instead describe the evolution of individual vehicles through car-following, lane-changing, or trajectory-dynamics models. VTD provides vehicle states and interaction information for model initialization, calibration, and correction. For example, Heshami and Kattan (Heshami and Kattan, 2024) incorporated vehicle interactions into a microscopic traffic-flow model to predict short-term traffic variables such as speed, flow, and travel time. Compared with macroscopic approaches, microscopic models preserve finer vehicle-level dynamics but require more detailed and continuous trajectory observations and are more sensitive to errors in behavioral assumptions and vehicle-state measurements.

These differences also lead to distinct challenges in large-scale and real-time applications. Macroscopic models are more suitable for corridor- or network-level prediction because of their lower computational burden, but they may overlook heterogeneous vehicle interactions. Microscopic models provide finer behavioral representation, yet require more detailed observations and substantially higher computational costs. Therefore, the practical deployment of traffic-flow-model-based TSP requires a balance among model fidelity, data availability, computational efficiency, and real-time performance.

3.2.2 TSP based on statistical models

Statistical-model-based TSP methods predict future traffic states by exploiting temporal dependencies or probabilistic relationships in historical observations and VTD. Their effectiveness generally relies on the assumption that the statistical patterns learned from historical or recent observations remain sufficiently stable over the prediction horizon. Existing approaches can be broadly divided into time-series analysis, state-space and recursive estimation, and regression or probabilistic modeling methods.

Time-series methods exploit temporal autocorrelation and periodicity in traffic states using models such as ARIMA (Ahmed and

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Cook, 1979) and SARIMA. In CV environments, VTD can be aggregated or reconstructed into high-resolution traffic-state sequences for short-term forecasting. For example, Qian et al. (Qian et al., 2025) compared SARIMA and GRU models in freeway on-ramp and off-ramp scenarios, showing that statistical time-series models retain practical value because of their simple structure and interpretability. However, their reliance on relatively stable temporal patterns limits their ability to capture abrupt regime changes and complex spatial interactions.

State-space and recursive estimation methods formulate TSP as a dynamic state-transition problem, in which traffic states are continuously updated through state and observation equations. VTD can be incorporated as real-time observations to correct the estimated state under partial observability. Emami et al. (Emami et al., 2019), for example, developed a Kalman-filter-based framework integrating VTD for short-term traffic-flow prediction. These methods are well suited to sequential updating, but their performance depends on the specification of state-transition and observation models and may deteriorate when traffic dynamics deviate substantially from these assumptions.

Regression and probabilistic approaches predict future states by modeling statistical relationships between traffic conditions and their influencing factors. Song et al. (Song et al., 2025) combined VTD with automatic vehicle identification data in a Bayesian prediction framework, while Wu et al. (Wu et al., 2025) jointly modeled traffic-state evolution and variability through Bayesian learning. Such approaches can explicitly represent prediction uncertainty, but their reliability remains dependent on the stability of the underlying statistical relationships and the representativeness of available observations.

These characteristics make statistical TSP attractive for short-term and real-time applications because of its relatively simple structure and moderate computational requirements. However, its scalability to large and heterogeneous networks is constrained by limited capability to represent nonlinear dynamics and complex spatial dependencies. Practical deployment therefore requires a balance between model simplicity, adaptability to changing traffic regimes, and prediction accuracy.

3.2.3 TSP based on spatiotemporal learning

Spatiotemporal-learning-based TSP methods predict future traffic states by learning nonlinear temporal and spatial dependencies directly from historical VTD or reconstructed traffic-state sequences. Their performance generally relies on the assumption that the spatiotemporal patterns contained in training data remain sufficiently representative of future traffic evolution. Depending on how spatial and temporal dependencies are modeled, existing approaches can be broadly divided into temporal dependency modeling, local spatiotemporal joint modeling, and graph-based spatiotemporal modeling.

Temporal dependency modeling methods mainly use RNN, GRU, or LSTM architectures to capture sequential patterns in traffic states. For example, Jeong et al. (Jeong et al., 2021) employed a GRU model for freeway speed prediction, while Bharti et al. (Bharti et al., 2023) applied a Bidirectional LSTM model for short-term traffic-flow prediction. These methods are effective in capturing temporal evolution, but their lack of explicit spatial representation limits their ability to model traffic propagation across interconnected road segments.

Local spatiotemporal joint modeling methods further incorporate interactions among adjacent road segments by transforming VTD into structured inputs such as spatiotemporal matrices or grids. Architectures such as CNN (Ma et al., 2017), CNN – LSTM, and ConvLSTM (Yang et al., 2018) jointly capture local spatial patterns and temporal dynamics. However, their dependence on predefined neighborhoods or regular grid structures limits their ability to represent irregular and non-Euclidean relationships in transportation networks.

Graph-based spatiotemporal modeling methods address this limitation by representing road segments or traffic entities as graph nodes and their topological or interaction relationships as edges. GNN, GCN, GAT, and STGNN architectures can therefore capture more flexible spatial dependencies and long-range network interactions. For example, Li et al. (Li et al., 2021) proposed a Trajectory-based Graph Neural Network (TrGNN) that constructs graph structures from trajectory transition patterns, while Zhou et al. (Zhou et al., 2024) developed a KR-STGNN model to jointly capture spatial and temporal dependencies in complex traffic scenarios.

Despite their strong representation capability, these methods remain highly dependent on data quality and training-distribution consistency. Prediction performance may deteriorate under sparse VTD, changing penetration rates, or traffic regimes that differ substantially from the training data. Graph-based models further introduce higher computational and memory requirements as network scale increases. Therefore, improving data efficiency, cross-scenario generalization, and computational scalability remains important for practical deployment.

3.2.4 TSP based on physics-guided and hybrid learning

Physics-guided and hybrid learning methods aim to improve the robustness and interpretability of data-driven TSP by incorporating traffic-flow knowledge into the prediction process. Their basic idea is to embed conservation laws, wave-propagation mechanisms, or traffic-state dynamics into learning frameworks, allowing physical constraints to guide future-state prediction while data-driven components capture complex nonlinear patterns. These approaches generally assume that the embedded traffic-flow mechanisms remain sufficiently valid to provide meaningful guidance under the predicted traffic conditions.

One major direction embeds physical dynamics directly into learning models. For example, Ji et al. (Ji et al., 2022) proposed a physics-guided DL framework, STDEN, which incorporates traffic-flow dynamics represented by differential equations into deep neural networks for network-level traffic-flow prediction. Another direction combines learning models with model-based state correction. Deshpande and Park (Deshpande et al., 2025) integrated DL with a Kalman-filter mixture under LWR model constraints, combining mechanistic information with online state updating to improve prediction under incomplete observations and high uncertainty.

The effectiveness of these approaches depends on the compatibility between the embedded physical model and actual traffic evolution. Inaccurate or overly restrictive physical assumptions may limit prediction performance, whereas weak physical constraints provide limited advantages over purely data-driven methods. In addition, jointly combining physical models, learning components, and online correction may increase computational complexity. Improving adaptive integration of physical knowledge, computational efficiency, and robustness across changing traffic regimes therefore remains important for practical deployment.

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3.2.5 Method comparison

The four TSP paradigms exhibit distinct trade-offs in data requirements, methodology, and practicality, as summarized in Table 4. In terms of data requirements, the main differences concern VTD penetration and data quality. Traffic-flow-model-based methods generally require relatively low VTD penetration and can operate with lower-quality data because explicit traffic-flow relationships provide additional information for prediction. Statistical-model-based methods have moderate requirements for both VTD penetration and data quality. Spatiotemporal learning methods have the highest data requirements because their performance depends strongly on dense and high-quality observations. Physics-guided and hybrid methods have moderate data requirements because physical knowledge can partially compensate for limited data.

The four paradigms also differ in their main strengths and limitations. Traffic-flow-model-based methods provide explicit traffic propagation, which supports physically meaningful prediction of traffic evolution. Their main limitation is long-horizon error accumulation, as state and parameter errors can propagate over successive prediction steps. Statistical-model-based methods are effective for temporal dependency modeling, but their ability to represent complex spatial relationships is limited. Spatiotemporal learning methods are well suited to spatiotemporal dependency learning, but they are sensitive to sampling bias when future traffic conditions differ from the training data. Physics-guided and hybrid methods improve physical consistency and data efficiency by incorporating physical knowledge into learning-based prediction. However, combining physical constraints with data-driven models can increase training difficulty.

In terms of practicality, the main differences lie in computational burden and transferability. Traffic-flow-model-based methods generally have a moderate computational burden and moderate transferability. Statistical-model-based methods have a relatively low-to-moderate computational burden and moderate transferability. Spatiotemporal learning methods usually involve a high computational burden because of model training and inference, and their transferability is relatively low under changing traffic regimes, network structures, or sensing conditions. Physics-guided and hybrid methods generally have a moderate-to-high computational burden because physical and learning components must be jointly handled. Their transferability is relatively high because physical constraints can reduce dependence on a specific training distribution. Consequently, no single paradigm is uniformly preferable. Traffic-flow-model-based methods are attractive when explicit traffic dynamics are important, statistical-model-based methods are suitable when temporal regularity dominates, spatiotemporal learning methods are advantageous when abundant high-quality VTD are available, and physics-guided or hybrid methods provide a compromise between physical consistency, data efficiency, and transferability.

Table 4. Comparison of TSP paradigms under partially connected conditions

Method	Data requirements		Main strength	Main limitation	Practicality	
	VTD penetration	Data quality			Computation burden	Transferability
Traffic-flow-model-based	Low–moderate	Low	Explicit traffic propagation	Long-horizon error accumulation	Moderate	Moderate
Statistical-model-based	Moderate	Moderate	Temporal dependency modeling	Limited spatial modeling	Low–moderate	Moderate
Spatiotemporal-learning-based	High	High	Spatiotemporal dependency learning	Sensitive to sampling bias	High	Low
Physics-guided / hybrid	Moderate	Moderate	Physical consistency and data efficiency	Training difficulty	Moderate–high	Moderate–high

3.2.6 Practical deployment

Practical deployment of VTD-enabled TSP requires a continuously updated prediction framework that can maintain reliable forecasts as traffic conditions and VTD availability change. Because uncertainty in the current traffic state can propagate over the prediction horizon, operational systems should support frequent state updating and integration of complementary observations. Combining VTD with fixed detectors and other operational data can improve prediction continuity under sparse or uneven vehicle sampling, while sequential estimation frameworks provide a practical basis for incorporating newly available information (Emami et al., 2019; Wu et al., 2025).

A second requirement is integration with existing predictive traffic-management systems. Emerging deployments indicate that vehicle-generated data can be incorporated into operational platforms together with roadside sensing and other data sources. For example, the I-270 Predictive Layered Operations Initiative integrated connected-vehicle and infrastructure data to support crash-risk prediction and incident identification (WSP USA, 2024). Although not designed for continuous traffic-state prediction, it demonstrates a feasible pathway for incorporating VTD into real-time predictive operations. For TSP, such integration is valuable only when forecasts can be delivered with sufficient timeliness to support subsequent traffic-management decisions.

Operational scalability further constrains model complexity. Rich spatiotemporal models can capture broader traffic interactions but increase computational and memory requirements as network scale and prediction resolution grow (Zhou et al., 2024). Physics-guided and hybrid approaches may improve physical consistency but introduce additional implementation costs (Deshpande et al., 2025). Practical systems must therefore balance prediction accuracy and horizon with

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computational cost and update frequency. Deployment readiness ultimately depends on providing reliable forecasts within the time and resource constraints of operational traffic management.

3.3 Traffic anomaly detection

Traffic Anomaly Detection (TAD) aims to identify abnormal traffic conditions that deviate from recurrent traffic patterns, such as incidents or sudden disturbances. In partially connected environments, this task is challenging because anomalous events are often localized and transient, while VTD provides only partial and potentially uneven observations of network conditions. Continuous vehicle-level trajectories nevertheless offer richer spatiotemporal information than fixed sensors, enabling abnormal traffic patterns to be identified from changes in vehicle movements and traffic states (Zheng et al., 2025a). Existing TAD methods can be broadly classified into analytical approaches, including threshold-based, statistical, and tensor-decomposition methods, and data-driven approaches.

3.3.1 TAD based on empirical thresholds

Empirical threshold–based TAD methods identify anomalous traffic conditions by comparing trajectory-derived kinematic features, such as abrupt speed drops or heading changes, against predefined decision thresholds. Their effectiveness generally relies on the assumption that abnormal events produce sufficiently distinct deviations from normal driving behavior and that suitable thresholds can be specified from traffic-flow knowledge or prior experience. For example, Houbraken et al. (Houbraken et al., 2017) developed a virtual-sensor architecture using floating car data on Dutch freeways and applied piecewise thresholds that account for probe-vehicle dynamics, reducing false alarms compared with conventional static thresholds. Asakura et al. (Asakura et al., 2017) proposed a three-stage threshold-based detection algorithm that maintained stable performance even at probe-vehicle penetration rates below 5%.

These methods are computationally efficient and physically interpretable, making them suitable for real-time anomaly screening. However, their performance is highly sensitive to threshold selection. Normal traffic fluctuations, such as routine deceleration or lane-changing behavior, may resemble incident-induced disturbances, leading to false alarms, while fixed thresholds may fail to adapt to changing traffic regimes. Consequently, threshold-based methods are increasingly used as preliminary filtering modules that remove clearly normal trajectories before more sophisticated detection procedures (ElSahly and Abdelfatah, 2022).

3.3.2 TAD based on statistical models

Statistical-model-based TAD methods identify anomalies by characterizing the distribution of normal traffic behavior and detecting observations that significantly deviate from expected statistical ranges. Their effectiveness generally relies on the assumption that normal traffic features follow sufficiently stable statistical patterns and that available VTD is adequate for estimating these distributions. For example, Khoda Bakhshi and Ahmed (Khoda Bakhshi and Ahmed, 2022) combined Bayesian inference with extreme value theory to fit a Generalized Extreme Value (GEV) distribution and identify accident-prone states from microscopic driving indicators. To improve robustness to outliers and masking effects, Chakraborty et al. (Chakraborty et al., 2019) introduced Median Absolute Deviation (MAD) and Interquartile Range (IQR) based methods. Luan et al. (Luan et al., 2021) developed an iterative GESD test, while Gokasar et al. (Gokasar et al., 2023) further improved detection robustness through multi-parameter integration.

Statistical approaches are mathematically interpretable and effective when traffic-feature distributions remain relatively stable. However, their performance depends strongly on sample adequacy and the validity of distributional assumptions. Sparse or biased VTD, particularly at low penetration rates, can lead to unreliable statistical boundaries, while changes in traffic regimes may cause distribution shifts and increase false alarms or missed detections. Practical deployment therefore requires statistical thresholds to be updated adaptively without imposing excessive computational overhead.

3.3.3 TAD based on tensor decomposition

Tensor-decomposition-based TAD methods exploit the multi-dimensional spatiotemporal structure of VTD by organizing trajectory observations into matrices or high-order tensors. Their basic assumption is that normal traffic patterns exhibit relatively stable low-rank structures, whereas anomalies appear as sparse deviations from this background. Based on this idea, tensor decomposition, matrix completion, and low-rank reconstruction are used to separate normal traffic components from anomaly-related disturbances. For example, Xu et al. (Xu et al., 2019) proposed a Sliding Window Tensor Factorization (SWTF) algorithm for real-time anomaly detection from streaming trajectory data. He et al. (He et al., 2024a) incorporated traffic-wave propagation priors into an oblique-grid traffic-state matrix and achieved reliable detection under probe-vehicle penetration rates as low as 2%. Later studies, including low-rank tensor autoregressive models (Wang and Sun, 2021a) and the GLOSS framework (Sofuoglu and Aviyente, 2022), further enhanced spatiotemporal representation for more complex traffic scenarios.

These methods are well suited to sparse, noisy, and large-scale trajectory data because they can exploit structural redundancy across time, space, and vehicles. However, their performance depends on whether the assumed low-rank background and sparse-anomaly structure remain valid under changing traffic regimes. In addition, high-dimensional tensor construction and decomposition can introduce substantial computational and storage costs, which may limit real-time deployment at large network scales. Improving computational efficiency and adaptability to evolving traffic patterns therefore remains important for practical application.

3.3.4 TAD based on ML

ML-based TAD methods identify anomalous traffic patterns by learning nonlinear relationships and decision boundaries directly from VTD. Their effectiveness generally relies on the assumption that available training data adequately represent both normal and anomalous traffic conditions and that the learned patterns remain valid during deployment. Existing studies can be broadly grouped into ensemble learning, DL, and learning frameworks designed to address data scarcity and uncertainty.

Ensemble learning methods mainly combine multiple classifiers or weighted learning strategies to improve robustness under imbalanced anomaly samples. For example, Parsa et al. (Parsa et al., 2020) and Jiang et al. (Jiang and Deng, 2020) employed XGBoost and weighted random forests to mitigate class imbalance caused by scarce accident samples and improve detection stability. DL methods further learn complex

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spatiotemporal representations directly from trajectory data. Yang et al. (Yang et al., 2021) used deep convolutional networks for traffic-accident classification, Ji et al. (Ji et al., 2020) employed RNNs to model anomalies in variable-length trajectories, and Zhang et al. (Zhang and Abdel-Aty, 2022b) combined BiLSTM and CNN to capture spatiotemporal patterns for real-time collision-risk prediction.

Recent studies have further addressed limited data quality, sample scarcity, and prediction uncertainty. Roy et al. (Roy and Hasan, 2026) transformed non-uniform and low-quality VTD into virtual detector sequences, while Lin et al. (Lin et al., 2020) and Li et al. (Li et al., 2021) used GANs to generate additional accident samples. Liu et al. (Liu et al., 2022b) introduced Bayesian DL for uncertainty quantification, and hierarchical federated learning has been explored to improve privacy preservation and cross-regional generalization (Wang et al., 2023).

Despite their strong capability to model nonlinear and heterogeneous traffic patterns, ML-based TAD remains sensitive to class imbalance, data quality, and distribution shifts. Limited interpretability and the computational requirements of complex DL models also constrain large-scale real-time deployment.

3.3.5 Method comparison

The four TAD paradigms exhibit distinct trade-offs in data requirements, methodology, and practicality, as summarized in Table 5. In terms of data requirements, the main differences concern VTD penetration and data quality. Empirical threshold-based methods generally require low VTD penetration because pronounced anomalies can be detected from relatively limited trajectory observations. However, reliable detection still requires sufficient data quality to capture abrupt changes in vehicle behavior. Statistical-model-based methods have moderate requirements for both VTD penetration and data quality because reliable statistical boundaries depend on representative observations. Tensor-based methods can operate under relatively low VTD penetration and lower data quality by exploiting redundancy in the spatiotemporal structure of VTD. ML-based methods have the highest data requirements because their performance depends strongly on abundant and high-quality training data that adequately represent both normal and anomalous traffic conditions.

The four paradigms also differ in their main strengths and limitations. Empirical threshold-based methods offer simple implementation, but their performance is sensitive to threshold selection. Statistical-model-based methods can support uncertainty quantification through probabilistic and statistical inference, but they are sensitive to sampling bias when observed trajectories are not representative of the overall traffic stream. Tensor-based methods provide effective spatiotemporal representation by exploiting recurrent structures in trajectory data. Their main limitation is the low-rank assumption, which may not remain valid under complex or rapidly changing traffic conditions. ML-based methods provide strong nonlinear representation capability for complex anomaly patterns, but their interpretability is limited. These limitations become particularly important when anomaly samples are scarce or traffic conditions differ from those represented during model development.

In terms of practicality, the main differences lie in computational burden and transferability. Empirical threshold-based methods have a low computational burden and are suitable for lightweight online detection, but their transferability is limited because thresholds often require adjustment across traffic conditions or locations. Statistical-model-based methods have a moderate computational burden and moderate transferability. Tensor-based methods have a moderate-to-high computational burden because tensor construction and decomposition require additional computation and storage, while their transferability is moderate. ML-based methods have the highest computational burden because of model training and inference, and their transferability is relatively low when traffic regimes, sensing conditions, or data distributions differ from the training environment. Consequently, empirical threshold-based methods are attractive when simple and computationally efficient detection is required, statistical-model-based methods are useful when uncertainty characterization is important, tensor-based methods are suitable when exploitable spatiotemporal structure is present, and ML-based methods are advantageous when abundant high-quality VTD are available for modeling complex anomaly patterns.

Table 5. Comparison of TAD paradigms under partially connected conditions

Method	Data requirements		Main strength	Main limitation	Practicality	
	VTD penetration	Data quality			Computation burden	Transferability
Empirical threshold-based	Low	Moderate	Simple implementation	Sensitive to threshold selection	Low	Low
Statistical-model-based	Moderate	Moderate	Uncertainty quantification	Sensitive to sampling bias	Moderate	Moderate
Tensor-based	Low–moderate	Low	Spatiotemporal representation	Low-rank assumption	Moderate–high	Moderate
ML-based	High	High	Nonlinear representation	Limited interpretability	High	Low

3.3.6 Practical deployment

Practical deployment of VTD-enabled TAD requires timely and reliable anomaly detection within existing traffic-management workflows. Detection accuracy alone is insufficient for operational use because excessive delay or false alarms can reduce the value of anomaly information for incident verification and traffic response. Operational systems therefore need to balance detection sensitivity with latency and false-alarm control so that detected events can support subsequent management actions.

A practical deployment pathway is to integrate VTD-based TAD as

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a complementary layer to existing monitoring systems. Fixed detectors provide stable observations at predefined locations, while vehicle data extend spatial coverage beyond these locations. Field experience has demonstrated the feasibility of such integration. Houbraken et al. (2017), for example, implemented a live automated incident-detection system using real-time floating-car data on Dutch freeways and transmitted detection results directly to the highway operator (Houbraken et al., 2017). This indicates that VTD-based detection can be incorporated into established monitoring workflows while supplementing conventional detector-based AID.

Operational robustness further depends on maintaining useful detection performance when VTD availability and quality vary. Time-varying penetration, missing observations, and communication delays can affect both detection latency and confidence, making reliable data interfaces and quality assessment important for field operation. Practical systems should therefore provide confidence information or support operator verification when evidence is insufficient. Deployment readiness ultimately depends on whether VTD-enabled TAD can deliver timely, interpretable, and sufficiently reliable anomaly information without disrupting established traffic-management operations.

4. Vehicle-trajectory-enabled traffic control for freeway flow

The core idea of vehicle-trajectory-enabled traffic control for freeway flow is to use VTD together with control-area flow measurements to support adaptive flow-level control. VTD supplements conventional flow measurements with finer-grained vehicle information, thereby improving the responsiveness and adaptability of traffic regulation. The resulting decisions remain at the flow level and take the form of adaptive flow-level control strategies, such as VSL and RM, rather than vehicle guidance strategies. Depending on the specific control strategies, these methods can be broadly classified into two main categories: VSL and RM, as illustrated in Fig. 8. Table 6 summarizes the existing studies in the literature, with most of the reviewed papers published within the last decade.

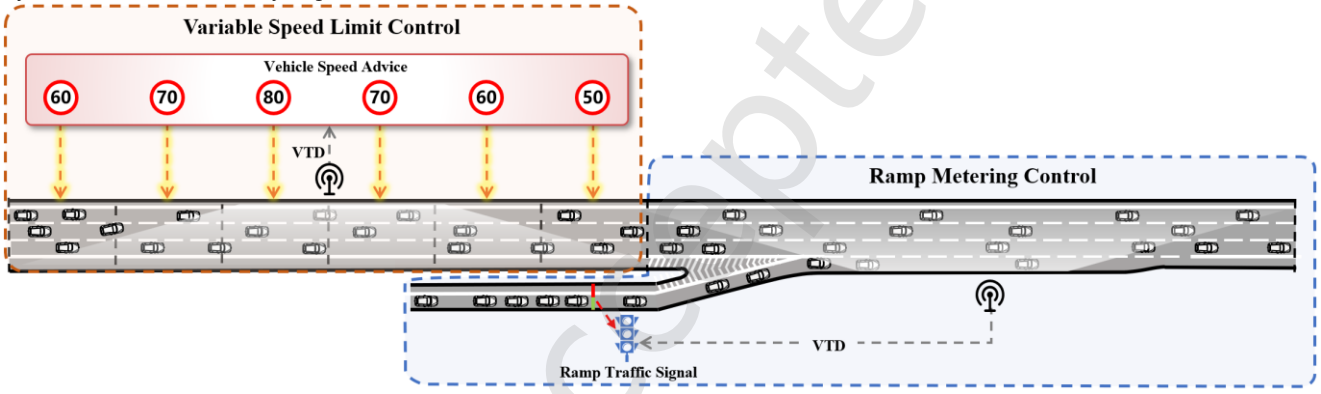


Fig. 8. Vehicle-trajectory-enabled traffic control for freeway flow

4.1 Variable speed limit control

VSL control aims to regulate vehicle speeds upstream of congested or unstable traffic regions to smooth traffic flow and reduce the propagation of disturbances. In partially connected environments, VTD provides continuous vehicle-level observations that enable traffic conditions to be identified at finer spatial and temporal resolutions, supporting more adaptive speed regulation than conventional detector-based approaches. According to control granularity, existing VSL strategies can be broadly classified into link-level and lane-level control.

4.1.1 Link-level VSL control

Link-level VSL control applies a uniform speed limit across all lanes within a road segment and is widely adopted because of its relatively simple control structure and implementation. Conventional approaches are primarily model-driven, using traffic-flow models to predict traffic evolution and optimize speed limits according to predefined objectives. Their effectiveness therefore depends on whether the adopted model and calibrated parameters can adequately represent prevailing traffic conditions. With the availability of VTD, vehicle-level information such as speed, position, and car-following behavior can be incorporated to improve state estimation, model calibration, and traffic representation (Kim et al., 2023). Wang et al. (Wang et al., 2021b), for example, improved the METANET model and developed an online VSL strategy for freeway mainline control.

Many model-driven VSL approaches formulate speed-limit control as an optimization problem subject to traffic-flow dynamics and operational constraints. Khondaker and Kattan (Khondaker and Kattan, 2015) developed a microscopic prediction and multi-objective optimization framework considering travel time, safety, and fuel consumption. MPC further enables repeated optimization as traffic conditions evolve. Han et al. (Han et al., 2017) proposed a fast MPC-based VSL method using a first-order traffic-flow model to mitigate congestion-wave propagation, while Perraki et al. (Perraki et al., 2018) evaluated MPC-based VSL under partial observation conditions. These approaches provide clear physical interpretation and explicit control constraints, but their performance remains sensitive to model accuracy and the computational cost of online optimization.

Learning-based approaches instead learn speed-control policies directly from traffic observations and control feedback. Early studies mainly adopted single-agent RL, treating the controlled freeway section as a centralized decision-making system. Zhu and Ukkusuri (Zhu and Ukkusuri, 2014) demonstrated the feasibility of RL for VSL control, while Han et al. (Han et al., 2022a) developed an RL-based strategy for mitigating freeway jam waves. For large-scale corridors and multiple bottlenecks, MARL has subsequently been introduced by assigning different road segments or control regions to multiple agents for distributed and coordinated control; Zhang et al. (Zhang et al., 2026) validated such an approach in real-world freeway scenarios. More recent studies have adopted DRL to handle the higher-dimensional traffic states provided by VTD. Gregurić et al. (Gregurić et al., 2022)

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combined DDPG with ConvLSTM to capture the spatial and temporal evolution of speed-control states, while Gao et al. (Gao et al., 2024) applied DRL in partially connected environments with coexisting CVs and HDVs.

4.1.2 Lane-level VSL control

Lane-level VSL control applies differentiated speed limits across lanes to regulate multi-lane traffic more precisely than uniform link-level control. Its effectiveness relies on sufficiently accurate lane-specific traffic information and on the ability to capture inter-lane interactions, particularly lane-changing behavior and flow redistribution. VTD provides vehicle-level information such as position, speed, lane occupancy, and interaction patterns, thereby supporting high-resolution estimation of lane-specific traffic states and control decisions.

Model-driven approaches typically employ multi-lane traffic-flow models that explicitly represent inter-lane interactions. Jin et al. (Jin et al., 2024), for example, developed a lane-level VSL strategy based on an extended multi-lane CTM and used iterative optimization to determine lane-specific speed limits upstream of bottlenecks. Chen et al. (Chen et al., 2025) further formulated lane-level VSL as a coordinated optimization problem for freeway merging areas, jointly considering traffic efficiency and collision risk under multi-lane traffic-flow constraints. These approaches provide explicit physical interpretation and control constraints, but their performance depends strongly on the accuracy of lane-level traffic-state estimation and the representation of lane-changing behavior.

Learning-based approaches are increasingly adopted because lane-level VSL involves higher-dimensional states and stronger interactions among lanes. Actor–critic DRL methods such as DDPG (Wu et al., 2020) and TD3 (Lu et al., 2023a) can directly generate differentiated speed limits in continuous action spaces, while value-based methods such as D3QN have also been used to learn lane-specific control policies (Song et al., 2025b). MARL further represents different lanes or lane segments as interacting agents to support coordinated decision-making. Han et al. (Han et al., 2024), for example, developed a centralized-training and decentralized-execution framework for coordinated multi-lane VSL control.

Lane-level VSL provides greater control flexibility than link-level strategies, but this finer granularity also increases sensing, modeling, and computational requirements. Its performance is particularly sensitive to the quality of lane-specific VTD and the representation of inter-lane interactions, while learning-based methods further depend on the representativeness of training scenarios. Practical deployment therefore requires balancing control granularity with observation reliability, computational efficiency, and coordination complexity.

Table 6. Typical studies on vehicle-trajectory-enabled traffic control for freeway flow

Topic	Subcategory	Papers	VTD Empower			Engineering Adapt			
			M.C.	P.E.	D.O.	M.N.C.	F.G.C.	H.T.A.	Interp.
VSL	Link-Level	(Wang et al., 2021b)	√						√
		(Han et al., 2017)	√		√				√
		(Han et al., 2022a)		√					
		(Zhang et al., 2026)				√			
	Lane-Level	(Gao et al., 2024)					√	√	
		(Jin et al., 2024)		√	√	√			√
		(Chen et al., 2025)		√	√	√	√	√	√
		(Song et al., 2025b)		√			√		
		(Han et al., 2024)		√		√	√		
RM	Local	(Shang et al., 2023)	√	√				√	√
		(Heshami and Kattan, 2021)		√			√	√	√
		(Cheng et al., 2024)		√					
		(Zheng et al., 2024b)		√					
		(Han et al., 2022b)		√					√
	Coordinated	(Han et al., 2020)	√		√	√			√
		(Han et al., 2025)		√		√		√	
		(Yu et al., 2024)		√		√			
		(Hu and Ma, 2024b)		√		√			√

Note: M.C. – Model Calibration; P.E. – Perception Enhancement; D.O. – Decision Optimization; M.N.C. – Multi-Node Coordination; F.G.C. – Fine-Grained Control; H.T.A. – Heterogeneous Traffic Adaptability; Interp. – Interpretability.

4.1.3 Method comparison

VSL methods exhibit distinct trade-offs in data requirements, communication robustness, driver compliance sensitivity, and practicality under partially connected conditions, as summarized in Table 7. In terms of data requirements, link-level model-driven methods have the lowest requirements for both VTD penetration and data quality because they can operate on aggregated traffic states and predefined traffic-flow relationships. Link-level learning-based methods have moderate data requirements because representative observations are needed for policy training. Lane-level VSL requires much denser trajectory coverage to identify lane-specific traffic conditions, leading to high VTD penetration requirements. This dependence is strongest for lane-level learning-based methods, which also require relatively high-quality VTD to represent lane-specific states and inter-lane interactions reliably.

Communication robustness generally decreases as control becomes more fine-grained and data-driven. Link-level model-driven methods are the most robust because aggregated states vary relatively smoothly and can be supported by conventional roadside measurements when VTD is temporarily unavailable. Link-level learning-based and lane-

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level model-driven methods have moderate robustness because their decisions depend more strongly on timely vehicle information. Lane-level learning-based methods are the most sensitive to communication imperfections because delayed or missing observations can directly affect lane-specific state representation and coordinated control decisions.

Driver compliance sensitivity is influenced mainly by control granularity. Link-level VSL has moderate sensitivity because the same or similar speed regulation is applied across lanes, reducing the effect of heterogeneous vehicle responses on lane-level traffic redistribution. In contrast, lane-level VSL has high sensitivity to driver compliance because differentiated speed limits rely on consistent responses across lanes. Non-compliance, delayed response, or induced lane changes can therefore weaken the intended control effect. This sensitivity applies to both model-driven and learning-based lane-level methods, although the way driver responses are represented differs between predefined behavioral models and training-based policies.

In terms of practicality, the main differences lie in computational burden and transferability. Link-level model-driven methods have a relatively low computational burden and moderate transferability, making them suitable for conventional real-time VSL operation. Link-level learning-based methods shift much of the computational burden to policy training and therefore have high computational requirements, while their transferability is relatively low when traffic conditions differ from the training environment. Lane-level model-driven methods require more detailed state estimation and more decision variables, leading to a moderate-to-high computational burden and lower transferability. Lane-level learning-based methods have the highest computational burden and the lowest transferability because their policies depend strongly on lane-specific traffic patterns, VTD conditions, communication quality, and training scenarios. Overall, link-level model-driven VSL is more suitable when sensing and communication resources are limited, whereas lane-level and learning-based methods become more attractive when reliable VTD, communication support, and representative training conditions are available.

Table 7. Comparison of VSL methods under partially connected conditions

Method	Data requirements		Communication robustness	Driver compliance sensitivity	Practicality	
	VTD penetration	Data quality			Computational burden	Transferability
Link-level, model-driven	Low–moderate	Low	High	Moderate	Low–moderate	Moderate
Link-level, learning-based	Moderate	Moderate	Moderate	Moderate	High	Low
Lane-level, model-driven	High	Moderate	Moderate	High	Moderate–high	Low–moderate
Lane-level, learning-based	High	Moderate-high	Low–moderate	High	High	Low

4.1.4 Practical deployment

Practical deployment of advanced VSL is likely to follow an incremental integration pathway, in which VTD and advanced control algorithms supplement existing roadside sensing and freeway-management infrastructure. Such integration allows richer spatial traffic information and more adaptive control to be introduced while retaining conventional detectors and supervisory functions when vehicle observations are insufficient.

Closed-loop operation requires strong safety and supervisory safeguards. The I-24 corridor near Nashville provides a representative example, where a MARL-based VSL controller progressed from simulation and open-loop testing to closed-loop field operation within an existing 17-mile VSL corridor. Independent safety mechanisms constrained generated speed limits to satisfy operational and regulatory requirements (Zhang et al., 2026). Similarly, dynamic speed advisories on I-35W in Minneapolis operate within a broader active traffic-management system that also includes ramp metering and other corridor functions (Neudorff and McCabe, 2015). These deployments show that advanced VSL can be introduced within established operational architectures while preserving supervisory control.

Infrastructure reuse and regulatory compatibility largely determine deployment feasibility. Costs depend strongly on existing communication, sensing, gantry, and control infrastructure; FHWA reported approximately $16 million for the I-35W VSL system and $39 million for I-66, with the latter requiring more extensive infrastructure investment (Katz et al., 2017). VTD-enabled VSL must therefore provide sufficient incremental benefit to justify additional communication, computation, integration, and maintenance costs. Dynamically generated speed commands must also comply with local operating authority and enforcement rules, as illustrated by advisory operation on I-35W and the transition of the former I-270 system in Missouri from regulatory to advisory control (Neudorff and McCabe, 2015). Since most field deployments still rely primarily on roadside sensing, they demonstrate the operational maturity of VSL systems more clearly than the large-scale readiness of VTD-enabled VSL.

4.2 Ramp metering control

RM control regulates on-ramp inflow to balance ramp demand with mainline traffic conditions, thereby reducing congestion near merging areas and improving freeway efficiency. In partially connected environments, VTD provides continuous vehicle-level observations of mainline, ramp, and merging traffic, enabling more timely and adaptive control than conventional detector-based approaches. According to the control scope, existing RM strategies can be broadly classified into local RM and coordinated RM.

4.2.1 Local RM control

Local RM regulates the inflow of a single on-ramp according to nearby mainline traffic conditions, with the aim of maintaining traffic

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operation near critical conditions and delaying congestion formation. Its effectiveness depends on sufficiently accurate perception of local mainline and ramp states. VTD provides high-resolution information on vehicle speed, position, and travel time, enabling more detailed characterization of merging-area traffic than conventional detector-based observations.

Model-driven approaches typically use traffic-flow models such as CTM or METANET to represent mainline density evolution, ramp demand, and merging constraints, and determine metering rates through feedback or predictive optimization. Shang et al. (Shang et al., 2023), for example, modified conventional RM within a CTM framework by accounting for changes in the fundamental diagram under partial connectivity. Heshami and Kattan (Heshami and Kattan, 2021) further developed a prediction-driven RM method that integrates VTD and fixed-detector data through adaptive Kalman filtering to support multi-step traffic-state prediction and dynamic metering adjustment. These approaches provide clear physical interpretation, but their performance remains sensitive to model calibration and prediction accuracy.

Learning-based approaches, particularly RL-based methods, learn adaptive RM policies from interactions among traffic states, control actions, and system feedback. RL-based RM is commonly formulated as a Markov Decision Process, allowing control policies to be optimized through repeated interaction with the traffic environment. Cheng et al. (Cheng et al., 2024) proposed a DQN-based method with a multi-objective reward function for adaptive ramp control, while Zheng et al. (Zheng et al., 2024b) introduced curriculum learning with an extended CTM to improve RL training efficiency under complex bottleneck conditions. Such methods are more flexible in handling nonlinear and time-varying traffic dynamics, but they remain constrained by sample efficiency, training stability, and policy interpretability.

Hybrid model–learning approaches have therefore been explored to incorporate traffic-flow knowledge into RL and improve learning reliability. Han et al. (Han et al., 2022b), for example, proposed a physics-informed RL framework trained using both model-generated and historical data to improve robustness and learning efficiency. Overall, local RM is relatively easy to implement because it relies mainly on nearby traffic information, but its effectiveness may deteriorate when congestion interactions extend beyond a single ramp or bottleneck. Practical deployment therefore requires reliable local observations, efficient online decision-making, and adequate coordination with surrounding traffic conditions.

4.2.2 Coordinated RM control

Coordinated RM jointly regulates multiple on-ramps to improve traffic performance over a corridor or network scale. Compared with local RM, its key challenge is to account for interactions among ramps and the mainline, since independent local control may lead to uneven queue distribution or shift congestion from one bottleneck to another (Zhang et al., 2023). VTD collected from multiple ramp locations provides detailed information on mainline states, ramp demand, and merging conditions, supporting system-level modeling and coordinated decision-making.

Model-driven approaches typically construct multi-ramp traffic-flow models and optimize metering rates jointly under system dynamics and operational constraints. Han et al. (Han et al., 2020), for example, developed an aggregated traffic-flow model for freeway networks with multiple on-ramps to represent traffic evolution on both the mainline and ramps at different spatial scales. Combined with MPC, the framework enables coordinated adjustment of ramp flows over time. These approaches provide explicit system dynamics and control constraints, but their performance depends on model accuracy and the computational efficiency of large-scale online optimization.

Learning-based approaches have increasingly adopted DRL and MARL to handle the higher-dimensional states and interactions involved in multi-ramp control. In MARL frameworks, individual ramps are typically modeled as agents that learn coordinated policies through shared information or cooperative objectives. Han et al. (Han et al., 2025) proposed an enhanced multi-agent DRL framework for freeway corridors with multiple ramp bottlenecks, while Yu et al. (Yu et al., 2024) employed QMIX to coordinate metering decisions across multiple ramps and address dimensionality and non-stationarity issues. Model-based or demonstration-guided mechanisms have also been introduced to improve training efficiency. Hu and Ma (Hu and Ma, 2024b), for example, incorporated demonstration policies generated by conventional feedback controllers into DRL training to accelerate convergence.

Coordinated RM offers greater system-level benefits than isolated local control, but its complexity increases rapidly with the number of ramps, traffic-state dimensions, and communication requirements. Model-driven methods may face increasing computational burdens, while MARL approaches remain sensitive to training stability, inter-agent coordination, and changing traffic conditions. Practical deployment therefore requires scalable decision architectures, reliable multi-location observations, and efficient information exchange among ramp controllers.

4.2.3 Method comparison

RM strategies exhibit distinct trade-offs in data requirements, communication robustness, and practicality under partially connected conditions, as summarized in Table 8. In terms of data requirements, the main differences concern VTD penetration and data quality. Local model-driven RM has the lowest requirements because it primarily relies on traffic states near a single ramp and can partly compensate for limited VTD through traffic-flow models and auxiliary detector data. Local learning-based RM has moderate requirements because representative observations are needed for policy training. Coordinated RM requires observations from multiple ramps and mainline segments to capture queue propagation and bottleneck interactions, and therefore requires higher VTD penetration. Coordinated learning-based RM also places relatively high demands on data quality because its performance depends on representative observations across different traffic states, penetration levels, and coordination scenarios.

Communication robustness is mainly determined by the spatial scope of control. Local RM involves limited information exchange beyond the controlled ramp and can operate primarily from local measurements. Both local model-driven and learning-based methods are therefore relatively robust to communication imperfections. Coordinated RM relies on timely information from multiple ramps and mainline locations, making it more vulnerable to communication delays, packet loss, and asynchronous observations. This dependence becomes particularly important for coordinated learning-based control when shared states or inter-agent information are used to support metering

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decisions. Consequently, coordinated methods generally exhibit lower communication robustness than local methods.

In terms of practicality, the main differences lie in computational burden and transferability. Local model-driven RM has a relatively low computational burden and moderate transferability, making it suitable for real-time control with limited computational resources. Local learning-based RM has a high computational burden because of policy training, while its transferability is relatively low when traffic conditions differ from the training environment. Coordinated model-driven RM has a moderate-to-high computational burden because more ramps, traffic states, and decision variables must be considered jointly. Its transferability remains moderate because the underlying traffic-flow models can be recalibrated for different networks and operating conditions. Coordinated learning-based RM also has a high computational burden and relatively low transferability because learned policies may degrade when traffic demand, CV penetration, network configuration, or observation conditions differ from those represented during training. These differences make local RM more suitable for relatively isolated bottlenecks with limited sensing, communication, and computational resources, whereas coordinated RM is more appropriate when congestion interactions extend across multiple ramps and reliable multi-location observations, communication, and scalable computation are available.

Table 8. Comparison of RM methods under partially connected conditions

Method	Data requirements		Communication robustness	Practicality	
	VTD penetration	Data quality		Computational burden	Transferability
Local RM, model-driven	Low–moderate	Low	High	Low–moderate	Moderate
Local RM, learning-based	Moderate	Moderate	High	High	Low
Coordinated RM, model-driven	High	Moderate	Low–moderate	Moderate–high	Moderate
Coordinated RM, learning-based	High	Moderate-high	Low–moderate	High	Low

4.2.4 Practical deployment

Practical deployment of RM requires balancing freeway-level traffic improvement with acceptable ramp operation. More aggressive metering can protect mainline capacity but may increase ramp delay, queue growth, and spillback, making queue management an integral part of operational control. The HERO system on the Monash Freeway coordinates local ALINEA controllers across multiple consecutive on-ramps to improve corridor performance (Papamichail et al., 2010), while the Twin Cities experience showed that mainline benefits must be considered together with ramp delay and queue impacts in large-scale operation (Cambridge Systematics, 2001).

Advanced RM is likely to be deployed through incremental upgrading of existing ramp-metering systems. The I-880 system in California, for example, was upgraded to corridor-wide adaptive operation so that metering decisions could account for downstream freeway conditions (California Department of Transportation, 2022). VTD can extend this pathway by supplementing conventional detectors with additional information on ramp demand, queue evolution, and mainline–ramp interactions, supporting more adaptive and coordinated metering without extensive reconstruction of existing infrastructure.

Deployment feasibility ultimately depends on whether these additional capabilities provide sufficient operational value to justify their implementation costs. The Twin Cities evaluation reported an overall benefit–cost ratio of approximately 15:1 for ramp metering (Cambridge Systematics, 2001; Jacobson et al., 2006), but this value reflects the complete RM system and does not isolate the incremental contribution of VTD. Future VTD-enabled deployment should therefore evaluate whether improvements in traffic and queue management justify the additional sensing, communication, computation, and integration costs. Regulatory requirements for RM are comparatively well established and primarily concern ramp signals, signing, queue management, and agency operation; more complex issues associated with vehicle-specific guidance are addressed later in the context of vehicle-guidance and collaborative vehicle–flow control.

5. Vehicle-guidance-enabled traffic control for freeway flow

Vehicle-guidance-enabled traffic control for freeway flow uses control-area flow measurements and VTD to generate guidance for individual vehicles. In this category, CVs serve not only as mobile detectors but also as actuators through which vehicle guidance can be implemented. Unlike the adaptive flow-level control strategies reviewed in Section 4, the resulting decisions are vehicle guidance strategies, such as speed advisory and lane-changing guidance. These strategies influence traffic conditions by modifying individual vehicle behavior rather than directly regulating traffic flow at the aggregate level. Existing approaches can be broadly classified into two paradigms according to how vehicle-level actions influence traffic flow: trajectory-planning-based methods coordinate individual vehicle movements to resolve localized interactions and disturbances, particularly at freeway mainline bottlenecks and on-ramp merging areas, whereas moving bottleneck-based methods use controlled vehicles as mobile actuators to regulate surrounding traffic. These two paradigms are reviewed in Sections 5.1 and 5.2, respectively, as illustrated in Fig. 9. Table 9 summarizes the representative studies.

5.1 Vehicle trajectory planning

Vehicle Trajectory Planning regulates traffic at the microscopic level by directly coordinating longitudinal and lateral vehicle movements to

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mitigate disturbances and resolve vehicle conflicts. It is typically applied to individual CVs or groups of vehicles, such as platoons, and aims to optimize objectives including safety, efficiency, energy consumption, and emissions (Zheng et al., 2025b). To synthesize studies across diverse freeway geometries, this review abstracts their common vehicle-interaction mechanisms into two representative settings: mainline bottlenecks and on-ramp merging, instead of treating individual bottleneck geometries as separate categories. Mainline bottlenecks encompass localized disturbance- or capacity-reduction scenarios along the freeway mainline, with lane-drop bottlenecks representing an important class. Permanent lane drops and work-zone lane closures, for example, involve reduced lane availability that induces mandatory lane changing and lateral traffic redistribution (Phan et al., 2022). On-ramp merging represents inflow-induced conflicts, where entering vehicles are integrated into mainline traffic through gap selection or creation, merging sequence coordination, and trajectory adjustment (Chen et al., 2024a). Specific scenarios, such as lane-drop sections, work zones, and weaving areas, can therefore be mapped to these representative settings according to their dominant vehicle-interaction and trajectory-control mechanisms. The following review considers cooperative trajectory planning at freeway mainline bottlenecks and for freeway on-ramp merging.

5.1.1 Cooperative trajectory planning at freeway mainline bottlenecks

Cooperative trajectory planning at freeway mainline bottlenecks aims to regulate vehicle interactions by coordinating longitudinal and lateral behaviors, thereby mitigating disturbance propagation and capacity drop. Depending on the modeling paradigm, existing studies can be broadly divided into analytical model-driven approaches and RL-based approaches. The former derive vehicle guidance decisions from explicit traffic-flow or vehicle-dynamics models, whereas the latter learn control policies through interactions with the traffic environment.

Analytical model-driven approaches typically formulate vehicle guidance as an optimization problem subject to traffic-flow dynamics, vehicle-motion constraints, and safety requirements. Optimal control, hierarchical planning, or combinatorial optimization can then be used to determine target speeds, time headways, or lane-changing decisions (Jeon and Benekohal, 2025). Vehicle-level VSL represents a typical example, in which controlled vehicles receive individualized speed or car-following guidance rather than uniform segment- or lane-level limits. Wang et al. (Wang et al., 2025), for example, proposed a Lagrangian VSL hierarchical speed-planning framework for partially connected environments, where a high-level server-side controller generates target speeds and onboard controllers execute vehicle-specific guidance. These approaches provide explicit physical interpretation and allow safety and kinematic constraints to be directly incorporated, but their effectiveness depends on model accuracy and the tractability of real-time optimization.

RL-based approaches instead learn vehicle-guidance policies directly from traffic states, control actions, and system feedback. Their advantage lies in representing nonlinear vehicle interactions without requiring fully specified analytical control laws. Kreidieh et al. (Kreidieh et al., 2018) applied DRL to jointly regulate car-following and lane-changing behavior in partially connected environments, while Wang et al. (Wang et al., 2024b) developed a multi-agent DRL framework with collision avoidance for mandatory lane-changing bottlenecks, enabling coordinated longitudinal and lateral control of CVs.

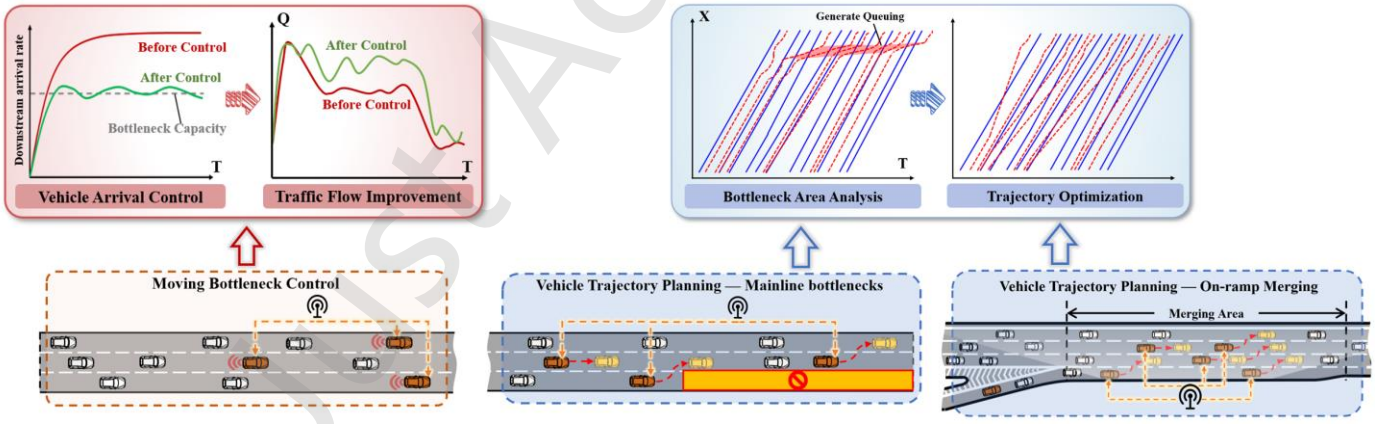


Fig. 9. Vehicle-guidance-enabled traffic control for freeway flow

RL-based trajectory planning offers greater adaptability to complex and uncertain bottleneck dynamics, but its performance depends strongly on the representativeness of training scenarios and the reliability of vehicle-level observations. Training stability, safety assurance, and real-time computation also remain important challenges. Therefore, practical deployment requires balancing the interpretability and constraint-handling capability of analytical methods with the adaptability of learning-based control.

5.1.2 Cooperative trajectory planning at freeway on-ramp merging

Freeway on-ramp merging involves intensive interactions between ramp and mainline vehicles within a limited spatiotemporal region. Cooperative trajectory planning addresses this problem by coordinating vehicle motions and, in some formulations, higher-level merging decisions such as merging order, target gaps, or merging positions. Depending on how high-level merging decisions and low-level vehicle motions are organized, existing studies can be broadly divided into direct trajectory optimization, hierarchical planning, and integrated optimization.

Direct trajectory optimization methods directly optimize vehicle trajectories under predefined or externally specified high-level merging relationships. Variables such as position, speed, and acceleration are optimized subject to vehicle-dynamics, safety, and comfort constraints. Depending on the specific formulation, these methods may be implemented through optimal control, mathematical programming, model predictive control, or other constrained optimization techniques.

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Zhou et al. (Zhou et al., 2018), for example, formulated the trajectories of ramp and cooperative mainline vehicles as interconnected optimal-control problems and jointly determined their speed and position profiles. These methods provide explicit vehicle-level control and are suitable for scenarios involving a limited number of interacting vehicles, but their computational burden can increase rapidly as traffic density and interaction complexity grow.

Hierarchical planning methods separate high-level merging coordination from low-level trajectory generation. Decisions such as merging sequence, target gaps, or candidate merging positions are first determined, after which feasible vehicle trajectories are generated and tracked. Han et al. (Han et al., 2023) proposed a two-layer framework combining merging coordination with trajectory optimization, while Wang et al. (Wang et al., 2024c) developed a bi-level framework that determines the merging sequence before optimizing vehicle motions. Such decomposition reduces the dimension of each decision stage and improves computational tractability, although performance may depend on the consistency between high-level decisions and subsequent trajectory execution.

Integrated optimization methods jointly optimize high-level merging decisions, such as merging sequence, target gaps, or lane-changing choices, together with vehicle trajectories within a unified framework. Chen et al. (Chen et al., 2024a) formulated cooperative merging of two traffic streams as a MINLP problem to jointly optimize passing order and vehicle trajectories. Mu et al. (Mu et al., 2025) further considered merging, yielding, lane-changing, and car-following behaviors in multi-lane mainline – ramp scenarios. By avoiding sequential decision decomposition, these methods can better account for interactions among multiple vehicles, but the enlarged decision space substantially increases optimization complexity.

Practical deployment therefore involves a trade-off between coordination capability and computational tractability. Direct methods are suitable for relatively small interaction groups, hierarchical frameworks improve scalability through decision decomposition, whereas integrated formulations provide stronger coordination at higher computational cost. Under partially connected conditions, their effectiveness also depends on reliable vehicle-state information and the ability to account for unobserved or uncontrolled vehicles.

Table 9. Typical studies on vehicle-guidance-enabled traffic control for freeway flow.

Topic	Subcategory	Papers	Control Paradigm		Control Capability				
			I.V.	M.C.O.	L.L.C.	M.V.C.	L.P.A.	H.T.A.	Interp.
Vehicle Trajectory Planning	Mainline Guidance	(Jeon and Benekohal, 2025)	√		√				√
		(Wang et al., 2025)	√					√	√
		(Kreidieh et al., 2018)	√		√			√	
	Merging Coordination	(Wang et al., 2024b)		√	√	√			
		(Han et al., 2023)		√	√	√			√
		(Wang et al., 2024c)		√	√	√			√
		(Chen et al., 2024a)		√	√	√			√
		(Mu et al., 2025)		√	√	√			√
Moving bottleneck control	Single Bottleneck	(Piacentini et al., 2018)	√				√	√	√
		(Daini et al., 2025)	√				√	√	√
		(Du et al., 2023a)	√				√	√	√
		(Wang et al., 2024a)	√				√	√	
	Multiple Bottlenecks	(Vinitsky et al., 2023)		√		√	√	√	
		(Lin et al., 2025)		√		√	√	√	

Note: I.V. – Individual Vehicle; M.C.O. – Multi-vehicle Cooperative Operation; L.L.C. – Longitudinal & Lateral Control; M.V.C. – Multi-Vehicle Coordination; L.P.A. – Low Penetration Adaptability; H.T.A. – Heterogeneous Traffic Adaptability; Interp. – Interpretability.

5.1.3 Method comparison

Vehicle trajectory planning methods exhibit distinct trade-offs in data requirements, communication robustness, driver compliance sensitivity, and practicality under partially connected conditions, as summarized in Table 10. In terms of data requirements, the main differences concern VTD penetration and data quality. VTD penetration is closely related to CV penetration: higher CV penetration not only increases the availability of vehicle-level observations, but also enlarges the set of vehicles that can receive guidance or participate in coordinated control. Mainline analytical methods have moderate requirements because vehicle guidance can be generated from local vehicle states together with broader traffic information, while explicit vehicle dynamics and safety constraints can partly compensate for incomplete observations. Mainline RL-based methods require higher VTD penetration and relatively high data quality because representative observations are needed for policy training. Cooperative merging places greater demands on vehicle-level information and generally benefits more from higher CV penetration because merging order, target gaps, and trajectories depend on accurate states and coordinated actions of multiple interacting vehicles. Direct and integrated optimization therefore require high VTD penetration and high data quality. Hierarchical planning has slightly lower requirements because high-level coordination and low-level trajectory generation are separated, reducing the amount of information that must be handled simultaneously.

Communication robustness decreases as vehicle coordination becomes more tightly coupled. Mainline analytical methods have relatively high robustness because guidance can be generated from local or periodically updated traffic states. Mainline RL-based methods have moderate robustness, as their performance depends more strongly on the observation conditions represented during training. Cooperative merging requires timely exchange of vehicle-state

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information to coordinate merging order, target gaps, and trajectories. Direct trajectory optimization is therefore more sensitive to communication delays or information loss, while integrated optimization has the lowest communication robustness because multiple vehicle decisions are coordinated within a tightly coupled framework. Hierarchical planning provides moderate robustness by separating strategic coordination from lower-level trajectory execution, although communication failures may still reduce consistency between the two levels.

Driver compliance sensitivity is also higher for tightly coordinated merging than for mainline guidance. Mainline analytical and RL-based methods have moderate sensitivity because deviations in individual vehicle responses can often be accommodated without immediately invalidating the overall guidance strategy. In cooperative merging, however, deviations from intended speeds, gaps, or merging sequences can affect several interacting vehicles and may compromise trajectory feasibility. Direct and integrated optimization are therefore highly sensitive to driver compliance. Hierarchical planning has moderate-to-high sensitivity because deviations during vehicle-level execution may weaken the consistency between high-level merging decisions and the realized trajectories. These issues are particularly relevant when guidance is provided to C-HDVs rather than directly controlled CAVs.

In terms of practicality, the main differences lie in computational burden and transferability. Mainline analytical methods have a moderate computational burden and moderate transferability because their optimization problems are relatively structured but still depend on model fidelity and vehicle-response assumptions. Mainline RL-based methods have a high computational burden due to policy training, while their transferability is low when traffic demand, CV penetration, communication conditions, or vehicle composition differ from the training environment. Direct trajectory optimization has a moderate-to-high computational burden because the optimization dimension grows with the number of interacting vehicles, and its transferability is relatively limited by model and interaction assumptions. Hierarchical planning reduces computational burden through decision decomposition and retains moderate transferability, although consistency between decision levels must be maintained. Integrated optimization has the highest computational burden because merging sequence, lane-changing decisions, and vehicle trajectories are optimized jointly, while its transferability remains limited by model fidelity, interaction complexity, and scenario scale. Simpler mainline or hierarchical formulations are therefore more suitable when sensing, communication, or computational resources are limited, whereas tightly coordinated merging methods become more attractive when reliable vehicle-level information, communication support, and controllability are available.

Table 10. Comparison of vehicle trajectory planning methods under partially connected conditions

Method	Data requirements		Communication robustness	Driver compliance sensitivity	Practicality	
	VTD penetration	Data quality			Computational burden	Transferability
Mainline Guidance, analytical	Moderate	Moderate	Moderate–high	Moderate	Moderate	Moderate
Mainline Guidance, RL-based	High	Moderate-high	Moderate	Moderate	High	Low
Merging Coordination, direct trajectory optimization	High	High	Low–moderate	High	Moderate–high	Low-moderate
Merging Coordination, hierarchical planning	Moderate–high	Moderate–high	Moderate	Moderate–high	Moderate	Moderate
Merging Coordination, integrated optimization	High	High	Low	High	High	Low-moderate

5.1.4 Practical deployment

Practical deployment of cooperative trajectory planning depends on whether coordinated decisions can be translated into safe and executable vehicle motions under changing traffic conditions. Deviations in speed, acceleration, gap acceptance, or lane-changing behavior can alter local interactions and invalidate planned maneuver sequences. Field operation therefore requires closed-loop coordination among trajectory planning, vehicle execution, and real-time adaptation, particularly in mixed traffic with uncontrolled vehicles.

A practical pathway is to integrate trajectory-guidance functions into existing vehicle and infrastructure systems. Field demonstrations have validated key elements of this pathway. The 2016 Grand Cooperative Driving Challenge employed a layered architecture for cooperative highway maneuvers (Ploeg et al., 2018), while FHWA tested cooperative merging, CACC, and speed harmonization on the I-95 Express Lanes under mixed traffic (Ma et al., 2021). Ji et al. (2023) further demonstrated roadside-perception-assisted speed guidance for on-ramp merging (Ji et al., 2023). These studies show that cooperative guidance can be incorporated into operational freeway environments, although large-scale validation of fully cooperative trajectory planning under heterogeneous traffic remains limited.

Deployment feasibility further depends on the infrastructure investment and control responsibility required for vehicle-level execution. Infrastructure-assisted approaches may require additional roadside sensing, communication, and computing resources, whose incremental benefits should justify the associated deployment and maintenance costs; FHWA-supported V2I benefit–cost tools provide one framework for such assessment (Badgley et al., 2025). Directly executed acceleration, braking, or lane-changing actions also impose stronger safety and regulatory requirements than advisory guidance. Practical systems should therefore retain vehicle-level safety constraints and fallback mechanisms while ensuring compliance with applicable vehicle-safety and traffic-operation regulations (National Highway Traffic Safety Administration, 2017).

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5.2 Moving bottleneck control

Moving bottleneck control uses one or more controlled vehicles as mobile traffic actuators whose motions are regulated to influence surrounding traffic and reshape traffic-flow evolution. A key advantage is that effective traffic regulation may be achieved with a relatively small number of controllable vehicles. While multi-vehicle trajectory coordination can effectively improve bottleneck operations, satisfactory performance often requires a relatively large proportion of controllable vehicles (e.g., around 30% (Gao et al., 2023)). Moving bottleneck approaches instead use a small number of CVs as active traffic regulators. By controlling their longitudinal and lateral behaviors, these vehicles influence surrounding traffic and reshape vehicle arrival patterns at downstream bottlenecks, thereby mitigating congestion. Existing studies can be broadly classified into single and multiple moving bottlenecks control.

5.2.1 Single moving bottleneck control

Single moving bottleneck control uses a controlled CV as a mobile actuator whose speed or longitudinal trajectory is regulated to influence surrounding traffic. By creating a moving constraint upstream of a bottleneck, the controlled vehicle can reshape local traffic states and downstream arrival patterns, thereby attenuating disturbance propagation and improving bottleneck operation. These approaches generally assume that the behavior of a single controlled vehicle can exert a sufficiently strong influence on surrounding traffic. Existing studies can be broadly divided into traffic-flow-model-based, vehicle-level optimization, and RL-based approaches.

Traffic-flow-model-based approaches characterize the interaction between the controlled vehicle and surrounding traffic from a macroscopic or multi-scale perspective. Representative formulations include coupled PDE–ODE models (Piacentini et al., 2018), hybrid fundamental-diagram models (Yang et al., 2019), multi-scale hybrid models (Daini et al., 2025), and CTM-based approaches (Cicic et al., 2018). These models provide physically interpretable descriptions of how a moving bottleneck affects traffic-flow evolution and can support control at low penetration rates. However, their effectiveness depends on whether the adopted traffic-flow dynamics adequately capture the response of heterogeneous surrounding vehicles to the controlled CV.

Vehicle-level optimization approaches formulate moving bottleneck control as a trajectory- or speed-guidance problem. System-level objectives are optimized subject to traffic rules, vehicle dynamics, and safety constraints (Larsson et al., 2021; Vishnoi et al., 2024), while heuristic methods can be used to reduce computational complexity (Liard et al., 2020; Wang et al., 2024e). For example, Du et al. (Du et al., 2023a) guided the speed of controlled vehicles to reshape upstream speed and density distributions and attenuate traffic fluctuations near bottlenecks. These approaches can explicitly incorporate operational and safety constraints, but their performance depends on accurate traffic-state information and tractable real-time optimization.

RL-based approaches learn adaptive moving-bottleneck policies directly from interactions between vehicle actions and traffic-system responses. Wang et al. (Wang et al., 2024a), for example, trained a controlled vehicle to dynamically regulate its speed and create localized low-density regions, thereby mitigating shockwave propagation. Such methods provide greater flexibility in nonlinear and uncertain traffic environments, but remain sensitive to training scenarios, reward design, and the transferability of learned policies to real traffic conditions.

Single moving bottleneck control is attractive for low-penetration environments because only a limited number of controllable vehicles are required. However, the spatial influence of a single controlled vehicle is inherently limited and may weaken under high demand, heterogeneous driver compliance, or multiple interacting bottlenecks. Its practical effectiveness therefore depends on reliable vehicle-state information, sufficient influence over surrounding traffic, and robust control under uncontrolled HDV behavior.

5.2.2 Multiple moving bottlenecks control

Multiple moving bottlenecks control extends the influence of individual controlled vehicles by coordinating several CVs to regulate traffic over a broader spatial range. This is particularly relevant in continuous-flow bottleneck scenarios, where disturbances may propagate from multiple locations and exceed the regulating capability of a single moving bottleneck. The key challenge is therefore to coordinate multiple controlled vehicles while accounting for their interactions with surrounding traffic and with each other.

Hierarchical model-based control provides one approach to coordinating multiple moving actuators. Han et al. (Han et al., 2021b) developed a Lagrangian MPC framework in which an upper-level controller determines target speeds for vehicle groups, while distributed CAVs act as microscopic actuators to regulate the following traffic through acceleration control. This hierarchical structure enables a small proportion of CAVs to collectively suppress freeway jam waves, demonstrating effective traffic regulation even at a CAV penetration rate as low as 5%. As the number of controlled vehicles increases, the state and action spaces expand rapidly, making centralized analytical or optimization-based control increasingly difficult to scale. RL-based approaches have therefore been widely explored, typically treating controlled vehicles as multiple agents that learn coordinated policies from traffic-system feedback. Vinitsky et al. (Vinitsky et al., 2023), for example, developed a distributed RL framework in which multiple controlled vehicles learn longitudinal control policies from local traffic states, while a shared system-level reward promotes implicit coordination. Lin et al. (Lin et al., 2025) further employed RL to coordinate longitudinal guidance among multiple moving bottlenecks and improve freeway traffic efficiency.

Existing studies have focused predominantly on longitudinal speed regulation, treating controlled vehicles primarily as mobile actuators that influence surrounding traffic through car-following interactions. Recent work has begun to extend this paradigm toward integrated longitudinal–lateral coordination. He et al. (He et al., 2026b), for example, developed a decentralized DRL-based VECT strategy for lane-drop bottlenecks, in which a limited number of CVs act as moving actuators and receive individualized speed and lane-changing advisories. An attention-based observation-sharing mechanism enables scalable decision-making across a varying number of CV actuators, and the strategy demonstrated effective traffic regulation even when fewer than 5% of vehicles acted as controllable actuators under a 75% driver compliance rate. Nevertheless, integrated longitudinal–lateral coordination among multiple moving actuators remains relatively underexplored, particularly in complex multi-lane and real-world mixed-traffic environments.

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5.2.3 Method comparison

Moving bottleneck strategies exhibit distinct trade-offs in data requirements, communication robustness, driver compliance sensitivity, and practicality under partially connected conditions, as summarized in Table 11. In terms of data requirements, the main differences concern VTD penetration and data quality. VTD penetration is closely related to CV penetration, while CV penetration additionally determines the availability and spatial distribution of vehicles that can serve as moving traffic actuators. Single moving bottleneck control generally requires fewer controllable vehicles and is therefore more applicable at relatively low CV penetration. Traffic-flow-model-based methods can further compensate for limited vehicle observations through explicit traffic-flow dynamics, whereas vehicle-level optimization requires reliable local traffic and vehicle states to generate feasible control actions. RL-based methods depend more strongly on representative observations across different traffic states and sensing conditions. Multiple moving bottlenecks control generally benefits from higher CV penetration because coordinated regulation requires several suitably distributed controllable vehicles together with consistent vehicle-level information. This increases the requirements for VTD penetration and data quality, particularly for learning-based approaches that rely on coordinated multi-vehicle observations during training and control.

Table 11. Comparison of moving bottleneck methods under partially connected conditions

Method		Data requirements		Communication robustness	Driver compliance sensitivity	Practicality	
		VTD penetration	Data quality			Computational burden	Transfer-ability
Single	Traffic-flow-model-based	Low–moderate	Low	High	Moderate	Low–moderate	Moderate
	Vehicle-level optimization	Moderate	Moderate	Moderate–high	Moderate	Moderate	Low–moderate
	RL-based	Moderate–high	Moderate–high	Moderate–high	Moderate	High	Low
Multiple	hierarchical model-based	High	Moderate	Moderate	High	Moderate–high	Low–moderate
	RL-based	High	Moderate–high	Low–moderate	High	High	Low

Communication robustness generally decreases as control shifts from a single actuator to coordinated multi-vehicle regulation. Single traffic-flow-model-based methods are comparatively robust because control decisions can rely partly on aggregate traffic dynamics and relatively limited information exchange. Vehicle-level optimization and single RL-based methods require more timely vehicle-state information, although their coordination scope remains local. Multiple moving bottlenecks rely on information exchange among spatially distributed actuators, making communication delays, packet loss, and asynchronous observations more consequential. Hierarchical model-based control can alleviate part of this burden by separating system-level target generation from distributed vehicle execution, whereas multiple RL-based methods may rely on shared or multi-vehicle observations to maintain coordinated policies. Communication requirements therefore increase with the number of controlled vehicles and the degree of interaction among them.

Driver compliance sensitivity also increases with the degree of multi-vehicle coordination. In single moving bottleneck control, imperfect execution mainly reduces the local regulating effect of the controlled vehicle, although heterogeneous responses from surrounding traffic can still weaken its influence. Multiple moving bottlenecks control is more sensitive because coordinated traffic regulation depends on several vehicles executing compatible speed, acceleration, or lane-changing actions. Deviations by individual vehicles may disturb the intended spatial distribution and collective effect of the moving actuators. This issue is particularly relevant when guidance is provided to C-HDVs, whose responses may be heterogeneous or incomplete, whereas directly controlled CAVs can execute prescribed actions more consistently. Existing multi-vehicle studies have also explicitly examined performance under imperfect compliance, highlighting its importance for coordinated moving bottleneck control.

In terms of practicality, the main differences lie in computational burden and transferability. Traffic-flow-model-based methods are relatively computationally efficient and provide physically interpretable descriptions of vehicle-to-flow effects, but their transferability depends on whether the adopted traffic-flow dynamics can represent heterogeneous vehicle responses under different conditions. Vehicle-level optimization can explicitly incorporate operational and safety constraints, although online computation becomes more demanding as the number of controlled vehicles and interactions increases. RL-based methods provide greater flexibility for nonlinear and uncertain traffic environments, but shift much of the computational burden to policy training and remain sensitive to differences between training and deployment conditions. These limitations become more pronounced for multiple moving bottlenecks because larger state and action spaces increase coordination and computational complexity. Hierarchical model-based control can improve tractability through decision decomposition, whereas multiple RL-based control still faces challenges in training stability, coordination, and transferability. These differences make single moving bottleneck strategies more suitable at relatively low CV penetration or when communication and computational resources are limited, whereas multiple moving bottlenecks strategies become more attractive at higher CV penetration when sufficient controllable vehicles are spatially available to support broader traffic regulation

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5.2.4 Practical deployment

Practical deployment of moving bottleneck control depends on whether a small and dynamically distributed set of controlled vehicles can exert sufficiently persistent influence on surrounding traffic under real-world mixed conditions. Closed-track experiments have provided an important proof of concept. In the Arizona ring experiment, a single automated vehicle among more than 20 vehicles was sufficient to dampen experimentally generated stop-and-go waves (Stern et al., 2018). This demonstrated the potential of sparse vehicles as mobile traffic actuators, although the controlled setting did not capture the full behavioral and operational uncertainty of open freeways.

Open-road deployment further requires this sparse control authority to be coordinated reliably across heterogeneous vehicles and changing traffic conditions. The CIRCLES MegaVanderTest on I-24 extended the concept to live freeway traffic by deploying 100 longitudinally controlled vehicles under a hierarchical architecture, in which a centralized Speed Planner generated traffic-level targets and decentralized vehicle controllers executed longitudinal actions (Lee et al., 2025). The heterogeneous fleet and real-world operating environment provide stronger evidence that mobile traffic control can be implemented through distributed vehicle-side actuation without relying on fixed roadside control points.

Large-scale deployment therefore hinges on the reliability and value of this mobile actuation architecture. Because control authority is sparse and dynamically distributed, performance may deteriorate when controlled vehicles are unavailable or when heterogeneous HDV responses weaken their influence on surrounding traffic. Deployment also requires vehicle-side control interfaces, communication, and coordination resources, whose additional costs should be justified by measurable system-level benefits. Current field experiments primarily establish technical feasibility, while large-scale benefit–cost evidence remains limited; existing connected-vehicle and V2I assessment tools can provide a basis for evaluating such investments under different penetration levels (Badgley et al., 2025). Automatically executed speed or acceleration actions must also remain consistent with applicable vehicle-safety and traffic-operation requirements (National Highway Traffic Safety Administration, 2017). Deployment readiness ultimately depends on whether sparse mobile actuators can produce reliable traffic-level effects despite changing actuator availability and heterogeneous driver responses.

6. Collaborative vehicle-flow control for freeway flow

Collaborative vehicle – flow control integrates adaptive flow-level control strategies with vehicle guidance strategies to support coordinated decision-making at both the traffic-flow and individual-vehicle levels. It uses control-area flow measurements and VTD, with CVs serving as both mobile detectors and actuators. Unlike the approaches reviewed in Sections 4 and 5, which generate flow-level or vehicle-level control strategies, respectively, collaborative vehicle – flow control explicitly coordinates the two decision scales within the same framework. Adaptive flow-level strategies, such as VSL and RM, regulate aggregate traffic conditions, while vehicle guidance strategies, such as speed advisory, lane-changing guidance, and trajectory control, influence individual vehicle behavior. The fundamental challenge is therefore not simply to apply the two types of strategies simultaneously, but to coordinate their information, objectives, and control decisions across the traffic-system and individual-vehicle scales.

One representative paradigm is centralized-information coordination, in which traffic-level and vehicle-level information is collected and integrated at the roadside or system side. The shared information may include aggregate traffic states, traffic demand, queue conditions, and infrastructure-control states, together with vehicle positions, speeds, gaps, intentions, and other vehicle-level states. Based on this information, control decisions can be generated either by an integrated centralized controller that jointly determines flow-level regulation and vehicle-level actions, or by hierarchical/bi-level controllers that separately generate decisions at the two levels (Pan et al., 2021; Zhao and Yildirimoglu, 2024). In hierarchical implementations, macroscopic targets or constraints can be passed to vehicle-level controllers, while vehicle-level feasibility and realized responses provide feedback for subsequent system-level updates. Objective conflicts can also be handled within the same coordinated framework. Although system-level and vehicle-level control may share objective dimensions such as efficiency, stability, and safety, these objectives are evaluated at different scales. Integrated control can reconcile them through multi-objective or weighted optimization and explicit safety and feasibility constraints, whereas hierarchical control can adjust system-level targets according to vehicle-level execution feasibility.

A second paradigm is decentralized or distributed interactive coordination, in which roadside and vehicle-side controllers retain their own observations and decision authority rather than forming a strict superior – subordinate control structure. Instead of centralizing all raw information, the controllers exchange only the information required for coordination. The roadside side may provide traffic conditions, flow-control decisions, and operational constraints, while connected vehicles provide vehicle states, intentions, planned maneuvers, or expected responses (Liu et al., 2022a; Ma et al., 2022). Because the participating controllers make decisions separately, objective conflicts cannot be resolved solely by translating system-level targets into vehicle-level actions. Instead, local and system-level objectives must be aligned through mechanisms such as shared or hybrid reward functions, coordination constraints, incentive mechanisms, negotiation, or other distributed decision structures. This is particularly important in learning-based approaches, where poorly aligned local objectives may improve individual performance at the expense of system-level outcomes, motivating coordinated reward designs that account for multiple performance dimensions (Han et al., 2025).

The scenarios reviewed in this section are organized according to their common cross-scale control mechanisms rather than specific bottleneck geometries. Accordingly, collaborative vehicle–flow control can also be applied to lane-drop sections, work zones, weaving areas, and similar bottlenecks when flow-level traffic regulation is explicitly coordinated with vehicle-level speed guidance, gap selection, lane-changing, or trajectory control. Although existing studies remain concentrated on on-ramp merging, related cross-scale coordination has also been explored in other bottleneck scenarios. Ren et al. (Ren et al., 2020), for example, coordinated work-zone merging regulation with vehicle-level longitudinal control, while Wu et al. (Wu et al., 2023) jointly optimized ramp control and CAV distribution and lane-changing in a freeway weaving scenario. These studies indicate that the basic principle of collaborative vehicle–flow control can extend beyond on-ramp

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merging, although the literature for these bottleneck types remains relatively limited. Existing freeway studies are therefore reviewed below mainly through two representative coordination problems: VSL–RM coordination and RM–ramp vehicle control, as illustrated in Fig. 10 and summarized in Table 12.

6.1 Coordination between VSL and RM

Coordination between VSL and RM links vehicle-level speed regulation on the mainline with flow-level control of ramp inflow. Unlike conventional VSL–RM coordination, the VSL considered here is implemented through individualized guidance of CV speeds or driving behavior rather than uniform segment- or lane-level speed limits. In this framework, RM regulates the amount and timing of ramp inflow, while vehicle-based VSL shapes mainline vehicle movements and arrival patterns near bottlenecks. Their coordination therefore requires ramp-level flow regulation to be aligned with vehicle-level guidance so that mainline traffic conditions and merging demand can be jointly managed. Existing studies can be broadly classified into analytical model-driven and data-driven approaches.

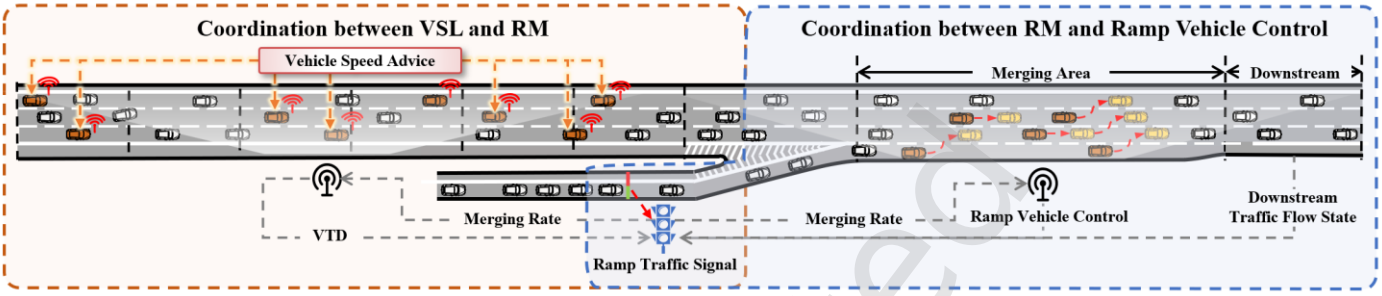


Fig. 10. Collaborative vehicle-flow control for freeway flow

Table 12. Typical studies on collaborative vehicle-flow control for freeway flow

Topic	Approach	Papers	Collaboration Mode			Collaboration Value			
			S.S.	I.F.	I.Fu.	G.T.R.	M.E.O.	H.T.A.	Interp.
VSL–RM coordination	M.D.	(Li et al., 2024a)		√		√			√
		(Yue et al., 2025)		√		√			√
		(Zhao and Yildirimoglu, 2024)			√	√	√	√	√
	D.D.	(Pan et al., 2021)			√	√	√	√	
		(Han et al., 2025)			√	√	√	√	
RM–vehicle control	M.D.	(Scarinci et al., 2017)	√				√		√
		(Fan et al., 2025)			√	√	√	√	√
		(Malekzadeh et al., 2025)	√				√		√
	D.D.	(Yang et al., 2025)	√				√	√	
		(Liu et al., 2026)	√				√	√	

Note: M.D. – Model-Driven; D.D. – Data-Driven; S.S. – Serial Superposition; I.F. – Interactive Feedback; I.Fu. – Integrated Fusion; G.T.R. – Global Traffic Regulation; M.E.O. – Merging Efficiency Optimization; H.T.A. – Heterogeneous Traffic Adaptability; Int. – Interpretability.

6.1.1 Analytical model-driven methods

Analytical model-driven methods coordinate flow-level regulation and vehicle-level guidance through explicit traffic-flow, vehicle-dynamics, and control models. From the information-coordination perspective introduced above, existing studies mainly adopt centralized-information architectures, while centralized – distributed implementations have also begun to emerge. These approaches generally assume that mainline – ramp traffic dynamics, vehicle responses, and driver compliance can be represented with sufficient fidelity to support consistent coordination between aggregate traffic regulation and microscopic vehicle actions.

Under centralized-information coordination, flow-level and vehicle-level information is integrated at the roadside or system side, while control decisions can be generated either jointly or through separate decision layers. Early studies mainly extended conventional VSL–RM optimization by incorporating mixed-traffic characteristics and vehicle-level behavior into a common control framework. He et al. (He et al., 2024b), for example, developed a mixed-traffic METANET model that accounts for heterogeneous responses of connected and regular vehicles and optimized VSL and RM according to vehicle-group safety and efficiency. Di et al. (Di et al., 2023) further integrated VSL and RM with active lane-changing control of CAVs, jointly optimizing mainline speed regulation, ramp inflow, and vehicle redistribution near merging bottlenecks. Such integrated formulations allow traffic-system objectives and vehicle-level behavioral requirements to be considered within the same model-based optimization framework.

Hierarchical or bi-level structures provide another form of centralized-information coordination by separating macroscopic regulation from microscopic execution. Zhao and Yildirimoglu (Zhao and Yildirimoglu, 2024), for example, proposed a macro–micro framework in which macroscopic control optimizes dynamic speed limits and ramp inflow, while microscopic trajectory planning and virtual platooning coordinate automated vehicles to realize the resulting traffic-flow targets. Aggregate traffic states and control targets are therefore translated into references or constraints for microscopic control, while vehicle states and execution feasibility can support subsequent system-level updates. This decomposition reduces the need to solve all flow- and vehicle-level decisions simultaneously, although its effectiveness depends on maintaining consistency between macroscopic targets and microscopic execution.

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Centralized–distributed implementations further reduce reliance on fully centralized computation by decomposing the control problem across system, subsystem, and vehicle levels. He et al. (He et al., 2026a) proposed a dynamic centralized – distributed vehicle – road – cloud architecture in which the freeway network is dynamically clustered according to traffic conditions, VSL and RM are jointly optimized at the subsystem level, and vehicle-level car-following control incorporates both local preceding-vehicle states and the optimal speed limits generated by the upper layer. This structure reduces communication and computational requirements while preserving coordination between flow-level regulation and vehicle-level execution. It also illustrates an intermediate architecture between fully centralized coordination and more decentralized vehicle-side decision-making, in which local vehicle information and control are retained without completely removing higher-level traffic regulation.

The main limitations of analytical model-driven approaches depend partly on how decision authority is organized. Integrated centralized formulations can become computationally demanding as network scale, microscopic detail, and the number of controlled vehicles increase. Hierarchical and centralized–distributed formulations can alleviate this burden through decision decomposition, but introduce additional consistency requirements across control layers or subsystems. System-level targets may also become infeasible or suboptimal at the vehicle level when driver compliance, vehicle interactions, or realized traffic conditions deviate from model assumptions. Across these architectures, performance remains dependent on accurate model calibration and reliable information exchange. Practical deployment therefore requires scalable optimization and robust coordination mechanisms that maintain consistency between traffic-system regulation and executable vehicle-level actions under uncertain traffic and communication conditions.

6.1.2 Data-driven methods

Data-driven methods learn coordination policies between flow-level regulation and vehicle-level guidance directly from interactions with the traffic environment. From the information-coordination perspective introduced above, these methods can support both centralized and decentralized/distributed decision architectures. Their basic idea is to represent heterogeneous traffic states, control actions, and cross-scale objectives within unified or multi-agent learning frameworks, allowing coordination to emerge through observations, rewards, and interactions with the traffic environment. Their effectiveness generally depends on whether the training environment adequately represents deployment conditions and whether the reward or constraint design can align objectives defined at the traffic-system and individual-vehicle scales.

In centralized or unified learning frameworks, flow-level and vehicle-level decisions are learned within a common decision process. Pan et al. (Pan et al., 2021), for example, developed an RL-based framework integrating RM, VSL, and CV-based vehicle guidance for on-ramp merging areas. Rather than optimizing each control measure independently, the framework learns their interactions from system feedback and coordinates macroscopic traffic regulation with microscopic vehicle behavior. Such unified formulations can directly account for interactions among multiple control components, but the resulting state and action spaces become increasingly complex as more traffic states, vehicles, and control variables are incorporated.

Decentralized or distributed learning frameworks decompose the coordination problem among multiple interacting agents while retaining information exchange or shared coordination mechanisms. Han et al. (Han et al., 2025), for example, modeled different controllers within bottleneck regions as interacting agents and introduced a ranking-based prioritized experience replay mechanism into a MATD3 framework to support coordinated decision-making under partially connected conditions. In such multi-agent formulations, coordination can be achieved through shared observations, reward structures, or inter-agent information exchange rather than through a single joint decision process. This decomposition improves the flexibility of large-scale coordination but makes performance more dependent on information availability, reward alignment, and interactions among simultaneously learning or operating agents.

The main limitations of data-driven approaches therefore depend partly on how the learning architecture is organized. Unified learning can capture strongly coupled vehicle – flow interactions but faces rapidly increasing state–action dimensionality and training complexity. Multi-agent approaches distribute the decision process but introduce additional challenges associated with inter-agent coordination, non-stationarity, and incomplete or delayed information exchange. Across both architectures, poorly designed rewards may produce decisions that favor performance at one scale at the expense of another, while insufficient representation of heterogeneous driver responses, CV penetration, communication uncertainty, and traffic conditions during training can reduce deployment robustness. Practical application therefore requires scalable learning architectures, reliable coordination mechanisms, and improved sample efficiency, training stability, interpretability, and transferability to real traffic environments.

6.1.3 Method comparison

VSL – RM coordination methods exhibit distinct trade-offs in data requirements, communication robustness, driver compliance sensitivity, and practicality under partially connected conditions, as summarized in Table 13. In terms of data requirements, the main differences concern VTD penetration and data quality. Analytical model-driven approaches have moderate requirements for VTD penetration because predefined traffic-flow and vehicle-response models can partly compensate for sparse or incomplete observations. They are also relatively tolerant of imperfect data quality, although reliable traffic states and vehicle responses are still required for coordinated control. Data-driven approaches require higher VTD penetration and higher-quality data because learned policies depend more strongly on representative observations across different traffic demands, penetration levels, vehicle compositions, and control responses. Sampling bias, missing vehicle-level information, and noisy observations can therefore have a greater influence on their performance.

Communication robustness depends on how information is organized across the coordination architecture. Analytical model-driven approaches have moderate robustness because explicit traffic-flow and vehicle-response models can preserve part of the control structure when information is temporarily incomplete. Nevertheless, integrated, hierarchical, and centralized – distributed implementations all require reliable exchange of relevant traffic states, control decisions, or vehicle responses, and delayed or missing information can create inconsistencies across control components. Data-driven approaches

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have lower communication robustness because unified or multi-agent policies may rely more strongly on timely observations, shared information, or inter-agent communication. Their performance can therefore deteriorate when communication delays, packet loss, or incomplete information exchange differ from the conditions represented during training.

Table 13. Comparison of VSL–RM coordination methods under partially connected conditions

Method	Data requirements		Communication robustness	Driver compliance sensitivity	Practicality	
	VTD penetration	Data quality			Computational burden	Transferability
Analytical model-driven	Moderate	Low–moderate	Moderate	Moderate–high	Moderate–high	Moderate
Data-driven	High	Moderate–high	Low–moderate	Moderate	High	Low

Driver compliance sensitivity also differs between the two method families. Analytical model-driven approaches have moderate-to-high sensitivity because vehicle-response relationships are explicitly embedded in the control models, and deviations from assumed compliance can weaken the expected vehicle-to-flow effect. This is particularly important when individualized speed guidance is provided to C-HDVs, whose responses may be heterogeneous or incomplete. Data-driven approaches have moderate sensitivity because heterogeneous behavioral responses can be incorporated during training when sufficient variation is represented in the data. Their effectiveness nevertheless depends on whether realistic compliance patterns and vehicle behaviors are adequately covered during training.

In terms of practicality, the main differences lie in computational burden and transferability. Analytical model-driven approaches have a moderate-to-high computational burden because coordination may involve joint optimization across flow- and vehicle-level decisions or decomposition across multiple control layers and subsystems. Computational effort generally increases with network scale, microscopic detail, and the number of controlled vehicles and decision variables. Their transferability is moderate because traffic-flow and vehicle-response models can be recalibrated for different conditions, although model validity remains important. Data-driven approaches have a high computational burden because policy training becomes increasingly demanding as the state‑action space and coordination complexity grow. Their transferability is relatively low because learned policies may degrade when CV penetration, traffic demand, communication reliability, vehicle composition, or driver compliance differs from the training environment. These differences favor analytical model-driven coordination when explicit physical relationships, constraints, and interpretable control structures are important, whereas data-driven approaches are more attractive when representative training data are available for learning complex nonlinear vehicle‑flow interactions.

6.1.4 Practical deployment

Practical deployment of VSL–RM collaborative control depends on whether flow-level coordination can be extended to vehicle-level execution within existing freeway-management systems. Conventional VSL–RM deployments provide an important operational foundation. For example, the combined CRM–VSA experiment on SR-99 in California integrated coordinated ramp metering and variable speed advisory algorithms, hardware, and software under real freeway conditions (Lu et al., 2023b). Because speed regulation was delivered through roadside advisory signs, however, this deployment primarily demonstrates the feasibility of coordinated flow-level operation and represents an intermediate step toward vehicle–flow collaborative control.

Extending this foundation requires a reliable cross-layer interface between traffic-management decisions and connected-vehicle actions. The CARMA Integrated Highway Prototype 2 provides a relevant engineering example by combining traffic-management functions, including speed, gap, lane, and queue management, with vehicle–infrastructure exchange of state, intent, and coordinated-plan information (Ma et al., 2022). Although still a prototype architecture, it illustrates how system-level objectives can be translated into cooperative vehicle actions and how vehicle responses can be incorporated into the coordination process. Large-scale deployment will therefore depend on whether such bidirectional interaction can operate reliably across heterogeneous vehicles, communication conditions, and existing traffic-management platforms.

Deployment feasibility further depends on whether the additional vehicle-level layer provides sufficient value and can be accommodated within existing operational responsibilities. Connected-vehicle functions may introduce additional costs for roadside communication, onboard equipment, application development, system integration, and back-office operation (Federal Highway Administration, 2016). Their benefits should therefore be evaluated as the incremental contribution of cross-layer coordination beyond that already provided by conventional VSL and RM. At the same time, vehicle-specific speed or maneuver actions introduce stronger safety and regulatory requirements than infrastructure-level control alone. Practical systems must maintain consistency among traffic-management authority, vehicle-level execution, and regulatory responsibility, in line with automated-vehicle policy frameworks that extend responsibilities across vehicle systems, infrastructure operators, and public authorities (U.S. Department of Transportation, 2018).

6.2 Coordination between RM and ramp vehicle control

Coordination between RM and ramp vehicle control links flow-level regulation of ramp inflow with vehicle-level management of the merging process. RM determines when and how much ramp traffic is released according to mainline and ramp conditions, whereas vehicle-level control determines how individual ramp vehicles merge through decisions on merging sequence, target gaps, speed trajectories, or lane-changing behavior. The key challenge is therefore to align ramp-release decisions with the feasibility and efficiency of subsequent vehicle merging, so that system-level traffic regulation can be translated into safe and executable vehicle actions. This requires information on

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mainline traffic states and ramp demand to guide release decisions, while vehicle-level merging states and execution feasibility provide feedback for subsequent control adjustments. Existing studies can be broadly classified into analytical model-driven and data-driven approaches.

6.2.1 Analytical model-driven methods

Analytical model-driven approaches coordinate ramp inflow regulation with vehicle-level merging control through explicit traffic-flow, vehicle-motion, and interaction models. From the information-coordination perspective introduced above, existing studies predominantly follow centralized-information coordination, in which ramp-level and vehicle-level information is integrated to support joint or hierarchical decision-making. These approaches generally assume that mainline–ramp traffic dynamics, vehicle interactions, and driver responses can be modeled with sufficient fidelity to coordinate ramp-release decisions with subsequent vehicle-level merging execution.

Within centralized-information coordination, early studies mainly linked ramp metering with microscopic merging assistance. Scarinci et al. (Scarinci et al., 2017), for example, coordinated mainline vehicle movements to create suitable gaps for vehicles released by RM, thereby connecting ramp inflow regulation with vehicle-level merging behavior. More recent studies have developed more tightly integrated macro–micro formulations. Fan et al. (Fan et al., 2025) combined RM with cooperative trajectory planning, in which ramp inflow is regulated at the flow level while vehicle trajectories are optimized at the microscopic level to coordinate the subsequent merging process. Such formulations allow vehicle-level merging feasibility to be incorporated into ramp-control decisions and provide a direct mechanism for translating aggregate release regulation into executable vehicle actions.

A related direction shifts part of the metering actuation from roadside signals to individual vehicles. Malekzadeh et al. (Malekzadeh et al., 2025), for example, implemented microscopic metering through direct speed regulation of ramp vehicles rather than conventional signal-based release, enabling more continuous regulation of the merging process. However, vehicle-side actuation does not necessarily imply decentralized decision-making, because the control actions may still be generated from centrally available traffic and vehicle information. As the metering function becomes increasingly embedded in vehicle-level control, the boundary between collaborative RM–vehicle control and purely vehicle-level merging guidance also becomes less distinct.

By contrast, decentralized or distributed interactive coordination remains less represented in the analytical RM – vehicle literature reviewed here. Existing model-driven formulations generally rely on a common controller or a predefined cross-level structure to coordinate ramp-release decisions and vehicle-level merging actions. A more distributed architecture would allow ramp-side and vehicle-side controllers to retain greater decision autonomy and exchange only coordination-relevant information. Such an architecture could reduce dependence on fully centralized computation and improve modularity, but it would also require mechanisms to maintain consistency among independently generated ramp-release, gap-selection, and trajectory decisions under limited or delayed information exchange. Developing scalable distributed RM – vehicle coordination therefore remains an important direction for further research.

The main limitations of analytical model-driven approaches arise from model dependence, computational scalability, and cross-scale consistency. Jointly optimizing ramp-release decisions and multiple vehicle trajectories can become computationally demanding as traffic density, interaction complexity, and network scale increase. In hierarchical or decomposed formulations, system-level targets may become infeasible or suboptimal at the vehicle level when vehicle interactions, driver compliance, or local traffic conditions deviate from model assumptions. Performance also depends on reliable vehicle-state information and accurate calibration of traffic-flow and vehicle-response models. Practical deployment therefore requires scalable optimization and robust coordination mechanisms that can accommodate model uncertainty, heterogeneous vehicle behavior, and limited connectivity.

6.2.2 Data-driven methods

Data-driven approaches coordinate ramp-level regulation and vehicle-level merging decisions by learning control policies directly from interactions with the traffic environment. From the information-coordination perspective introduced above, these approaches can be implemented through centralized or hierarchical learning as well as more distributed interactive structures. Their effectiveness generally depends on whether the training environment adequately represents partially connected traffic conditions and whether reward or constraint design can reconcile objectives defined at the traffic-system and individual-vehicle scales.

Under centralized-information or hierarchical learning, traffic and vehicle information is jointly available while different decision components may be generated within a unified or layered learning framework. Liu et al. (Liu et al., 2026), for example, formulated the upper-level merging decision as an MDP and used DQN to determine target merging positions, while lower-level real-time control and energy-aware optimization generated safe and smooth vehicle trajectories. Such hierarchical structures separate strategic decisions from microscopic execution and allow vehicle-level feasibility to be incorporated into the learning and control process.

More distributed or interactive learning structures decompose the merging-control problem among multiple decision modules or agents. Yang et al. (Yang et al., 2025), or example, developed two interacting PPO-based modules: a merging-control module that coordinates ramp and mainline vehicles and a lane-changing module that guides mainline CAV decisions. Distinct agents operate within these modules and coordinate their actions to improve traffic efficiency and safety under heterogeneous traffic conditions. Rather than relying on a single joint policy, such architectures distribute decision-making across interacting components, although they do not necessarily constitute fully decentralized roadside–vehicle control.

The main limitations of data-driven approaches depend partly on how the learning architecture is organized. Hierarchical methods require consistency between strategic decisions and subsequent vehicle-level execution, whereas distributed or interactive methods introduce additional challenges in information sharing, reward alignment, and coordination among agents. Across both structures, partial observability, stochastic HDV behavior, and communication imperfections can weaken learned policies, while increasing numbers of controlled vehicles and interacting decisions enlarge the state–action space and may destabilize training. Practical deployment therefore requires scalable learning architectures, robust coordination and

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reward mechanisms, and policies that generalize across CV penetration rates, traffic demands, communication conditions, and heterogeneous driver behaviors.

6.2.3 Method comparison

RM – vehicle control methods exhibit distinct trade-offs in data requirements, communication robustness, driver compliance sensitivity, and practicality under partially connected conditions, as summarized in Table 14. In terms of data requirements, the main differences concern VTD penetration and data quality. Analytical model-driven approaches have moderate requirements because traffic-flow and vehicle-motion models can partly compensate for sparse observations, although reliable vehicle-state information remains important for evaluating gap availability and merging feasibility. Data-driven approaches require higher VTD penetration and relatively high-quality data because learned coordination policies depend more strongly on representative observations of traffic states, vehicle interactions, and merging responses. Sparse sampling, biased observations, or missing vehicle-level information can therefore have a greater influence on their performance.

Communication robustness depends on both the methodological basis and the coordination architecture. Analytical model-driven approaches have moderate robustness because explicit traffic and vehicle models can support short-term state propagation when information is temporarily incomplete. However, centralized and hierarchical implementations still require reliable exchange between ramp-level regulation and vehicle-level execution, while more distributed implementations additionally require consistency among independently operating decision modules. Delayed or outdated information can therefore distort estimates of merging feasibility or create inconsistencies among coordinated decisions. Data-driven approaches have lower communication robustness because unified, hierarchical, or distributed learning structures may rely strongly on timely observations, shared information, or inter-agent communication. Their performance can deteriorate when communication delays, packet loss, or incomplete information exchange differ from the conditions represented during training.

Table 14. Comparison of RM–vehicle control methods under partially connected conditions

Method	Data requirements		Communication robustness	Driver compliance sensitivity	Practicality	
	VTD penetration	Data quality			Computational burden	Transferability
Analytical model-driven	Moderate	Moderate	Moderate	High	High	Low-moderate
Data-driven	High	Moderate–high	Low-moderate	Moderate–high	High	Low

Driver compliance sensitivity is particularly important because RM – vehicle coordination directly couples ramp regulation with microscopic merging behavior. Analytical model-driven approaches are highly sensitive to discrepancies between assumed and realized vehicle responses because such deviations can invalidate predicted gaps, trajectories, or expected ramp discharge. Data-driven approaches have somewhat lower sensitivity because heterogeneous behavioral responses can be represented during training, although their effectiveness still depends on whether realistic variation is sufficiently covered. Direct control of CAVs reduces this uncertainty for both method families, whereas incomplete or heterogeneous compliance by C-HDVs remains a major challenge for reliable merging execution.

In terms of practicality, both method families involve substantial computational demands, but the burden is distributed differently. Analytical model-driven approaches avoid extensive policy training but may require increasingly expensive online optimization as ramp-level and vehicle-level decisions become more tightly coupled. Hierarchical or decomposed formulations can improve scalability, although they introduce additional coordination requirements across decision layers or modules. Data-driven approaches shift much of the burden to policy training, where large state–action spaces, training stability, and cross-level or inter-agent credit assignment remain important challenges, while online inference can be comparatively efficient. Transferability is also limited in different ways: analytical approaches depend on model validity and recalibration when traffic conditions, vehicle interactions, or merging geometries change, whereas learned policies are more sensitive to sampling bias in traffic demand, CV penetration, communication reliability, network configuration, and driver behavior. These differences favor model-driven coordination when traffic and vehicle dynamics can be represented reliably, whereas data-driven approaches become more attractive when representative training environments are available for learning complex and uncertain interactions.

6.2.4 Practical deployment

Practical deployment of RM – vehicle collaborative control involves integrating two control layers with different levels of technological maturity. Conventional RM is already widely deployed, whereas cooperative vehicle-level merging remains largely at the prototype and field-testing stage. Physical experiments nevertheless show that infrastructure-generated coordination can be translated into executable vehicle actions. For example, the FHWA CARMA2 program tested cooperative on-ramp merging with automated longitudinal control using five equipped vehicles at the Aberdeen Test Center (Tiernan et al., 2019). Although this experiment did not implement a complete RM–vehicle collaborative controller, it demonstrated a key component required for cross-layer deployment.

A realistic near-term pathway is to extend existing RM with vehicle-level coordination while retaining ramp metering as the baseline control mechanism. Ramp signals can continue to regulate vehicle release for the overall traffic stream, while equipped vehicles receive speed, gap, or trajectory guidance to facilitate subsequent merging. This architecture is well suited to partial connectivity because conventional RM can remain operational when connected-vehicle availability or communication quality deteriorates. Existing integration of RM with freeway-management and traffic-management-center operations provides a practical basis for this extension (Jacobson et al., 2006).

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Deployment feasibility ultimately depends on whether vehicle-level coordination provides sufficient incremental value while remaining compatible with existing control authority and safety requirements. Cross-layer operation may require V2I communication, onboard control interfaces, additional computation, and system integration; existing V2I benefit–cost frameworks provide a basis for evaluating these investments under different technology-penetration levels (Badgley et al., 2025). Vehicle-level guidance may also range from driver advisories to automatically executed speed or merging actions, which must remain consistent with ramp-control indications and applicable vehicle-safety and traffic-operation requirements (National Highway Traffic Safety Administration, 2017). Deployment readiness therefore depends on maintaining reliable coordination between ramp-release decisions and vehicle-level merging execution without compromising safe operation.

7. Challenges and promising research directions

Freeway VECT has emerged as an important research direction with considerable potential. Despite the growing body of work in this area, several key challenges remain. The following directions are organized as cross-cutting challenges spanning different stages of VECT, from data acquisition and information exchange to control execution and practical deployment. Their relevance also varies across the four VECT categories: data acquisition and reconstruction are particularly important for trajectory-enabled traffic state analysis and traffic control, communication and information-related challenges become increasingly critical for vehicle-level guidance and collaborative control, while partial-connectivity uncertainty can affect sensing, decision-making, and actuation across the overall VECT framework. Based on these relationships, a number of promising directions for future research are outlined below.

7.1 High-resolution VTD acquisition and reconstruction

VECT relies heavily on high-resolution VTD, yet acquiring such data at scale in real-world settings remains challenging. In practice, VTD is obtained from onboard sensors, roadside devices, and V2X systems, which vary in sampling frequency, accuracy, and spatial coverage, often resulting in inconsistent data quality. In many practical datasets, VTD is still recorded at temporal intervals of around 5 s with positional accuracy on the order of 10 m (e.g., data from AutoNavi), which is still insufficient for high-precision traffic control applications. Under partial connectivity, limited CV penetration and uneven vehicle sampling may further reduce the completeness and representativeness of available trajectories. Addressing these limitations therefore requires further attention to both data acquisition and reconstruction.

On the one hand, multi-source data fusion across onboard sensing, roadside infrastructure, and communication systems is needed to improve the spatiotemporal completeness and consistency of trajectory data (Chen et al., 2024b). Future studies should further investigate how heterogeneous sensing sources with different sampling rates, accuracy levels, and spatial coverage can be reliably integrated under dynamically changing traffic and connectivity conditions. On the other hand, more robust methods for trajectory completion, interpolation, and error correction are required to handle sparse sampling, low penetration rates, and noisy observations (Wang et al., 2024d). Physics-guided and hybrid model–learning approaches provide a promising direction because physical knowledge can constrain trajectory reconstruction under limited observations, while learning models can capture nonlinear traffic patterns and model discrepancies. Ji et al. (Ji et al., 2026) integrated car-following models with neural networks through physics-based computational graphs to reconstruct unobserved vehicle trajectories, combining the data efficiency and interpretability of physical models with the flexibility of data-driven learning. Future research should further consider reconstruction uncertainty, physical consistency, and robustness across different penetration rates and traffic conditions, so that reconstructed VTD can provide a reliable basis for downstream traffic-state analysis and control. Recent advances in multimodal foundation models may further enhance vehicle perception and scene understanding in complex driving environments (Zheng et al., 2026). Advance in these directions will provide a more reliable data foundation for accurate modeling and stable implementation of freeway VECT strategies.

7.2 Secure and privacy-preserving information sharing and control

Beyond data quality, the trustworthiness and privacy of exchanged information are critical to reliable VECT operation. Open communication environments expose VECT systems to threats such as data tampering, false data injection, jamming, and denial-of-service (DoS) attacks. Compromised vehicle states, traffic information, or control messages can distort traffic-state awareness, interfere with control decisions, and potentially introduce safety risks. Recent studies have begun to address these threats through attack detection, anomaly identification, and security protection in connected-vehicle environments, particularly for DoS attacks and false data injection (Biron et al., 2018; Zhao et al., 2022). Future VECT systems therefore need resilient sensing and control mechanisms that can identify unreliable information and maintain acceptable operation when part of the exchanged data is compromised.

Privacy represents a related but distinct challenge. VTD contains rich spatiotemporal information that can reveal individual travel behavior, routes, and mobility patterns, creating privacy and data-governance concerns when trajectories are collected, shared, or used for control. Existing studies have explored trajectory anonymization, differential privacy, and privacy-preserving traffic control to reduce the exposure of sensitive information (Arif et al., 2021; Tan and Yang, 2024). However, stronger privacy protection may also reduce the spatial or temporal detail available for traffic-state inference and control. Future research should therefore explicitly evaluate the trade-offs among privacy protection, information utility, computational overhead, and control performance.

Security and privacy should ultimately be incorporated into VECT system design from the outset. Promising directions include attack-aware state estimation and control, secure multi-source information fusion, privacy-aware trajectory aggregation, and resilient control under compromised information. These mechanisms should be evaluated not only for detection or privacy performance, but also for their impacts on estimation accuracy, control stability, safety, and operational efficiency. Such integrated security–privacy–control design will be essential for trustworthy large-scale VECT deployment.

7.3 Communication latency-aware and efficient control

VECT relies on low-latency and reliable communication to support real-time perception, decision-making, and actuation. Even when

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exchanged information is trustworthy, its timeliness and availability can directly affect closed-loop control performance. In practice, V2X networks are subject to communication delays, packet loss, asynchronous updates, and bandwidth fluctuations, particularly under high traffic demand or network congestion. These imperfections can degrade real-time state awareness, disrupt control commands, and weaken coordination among distributed vehicles and traffic controllers.

Recent studies have begun to explicitly incorporate communication constraints into VECT design. Existing efforts include delay compensation, robust control, and control strategies under communication failures or limited information exchange (Liu et al., 2023; Wu et al., 2024b; Zheng et al., 2024a). Another direction is to reduce communication load by selectively transmitting information that is most relevant to control decisions, such as key vehicle states or control variables, without continuously exchanging complete high-frequency trajectories (Hu et al., 2024a). These approaches highlight the need to balance communication efficiency, information availability, and control performance.

Future research should further explore communication–control co-design, in which communication requirements are jointly determined by the sensitivity and time scale of the corresponding control task. Different VECT modules may tolerate different levels of delay, packet loss, and update frequency, and these operating limits should be explicitly quantified under realistic network conditions. Adaptive communication strategies that adjust information content and update rates according to traffic and control conditions may further improve efficiency while maintaining stable control. Such advances will be essential for reliable large-scale deployment of VECT.

7.4 Practical deployment under uncertainty in partially connected environments

Many VECT methods require a certain penetration of CVs to receive and execute guidance instructions. In practice, however, CAV penetration is likely to remain limited in the near future, and partially connected environments characterized by the coexistence of CAVs, C-HDVs, and HDVs are expected to remain dominant. While CAVs can be observed and guided, C-HDVs may respond imperfectly to control instructions — delaying, only partially following, or even ignoring guidance such as speed advisories or gap recommendations. Meanwhile, HDVs remain difficult to observe, predict, and control, and are characterized by strong randomness and behavioral heterogeneity. Together, these factors increase the uncertainty of traffic dynamics and make accurate vehicle-level prediction and reliable guidance more challenging. These issues highlight the need to better address uncertainty when deploying control strategies in partially connected environments. One direction is to improve the modeling of driver response deviations, behavioral heterogeneity, and their evolution over time, so as to better capture the gap between control inputs and actual traffic responses (Xiao et al., 2025). Another is to develop more robust and adaptive control methods that can operate effectively under low CV penetration, strong stochastic disturbances, and limited observability and controllability (Li et al., 2024b). Advances in these areas will be essential for improving the stability, adaptability, and practical feasibility of VECT in real-world freeway traffic.

Author contributions

Yuehai Hu: Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing. **Wensu Li**: Investigation, Methodology, Validation, Visualization, Writing - original draft. **Chunhui Yu**: Writing - review & editing, Funding acquisition, Resources, Supervision. **Wanjing Ma**: Writing - review & editing, Funding acquisition, Supervision. **Kaidi Yang**: Writing - review & editing, Funding acquisition, Project administration, Supervision.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT for polishing and paper organization. After utilizing this tool/service, the author(s) thoroughly reviewed and edited the content as necessary and take full responsibility for the final content of the published article.

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