Machine Intelligence Research
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20(5), October 2023, 614-639
DOI: 10.1007/s11633-022-1395-3

A Review and Outlook on Predictive Cruise Control of Vehicles and Typical Applications Under Cloud Control System

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Abstract: With the application of mobile communication technology in the automotive industry, intelligent connected vehicles equipped with communication and sensing devices have been rapidly promoted. The road and traffic information perceived by intelligent vehicles has important potential application value, especially for improving the energy-saving and safe-driving of vehicles as well as the efficient operation of traffic. Therefore, a type of vehicle control technology called predictive cruise control (PCC) has become a hot research topic. It fully taps the perceived or predicted environmental information to carry out predictive cruise control of vehicles and improves the comprehensive performance of the vehicle-road system. Most existing reviews focus on the economical driving of vehicles, but few scholars have conducted a comprehensive survey of PCC from theory to the status quo. In this paper, the methods and advances of PCC technologies are reviewed comprehensively by investigating the global literature, and typical applications under a cloud control system (CCS) are proposed. Firstly, the methodology of PCC is generally introduced. Then according to typical scenarios, the PCC-related research is deeply surveyed, including freeway and urban traffic scenarios involving traditional vehicles, new energy vehicles, intelligent vehicles, and multi-vehicle platoons. Finally, the general architecture and three typical applications of the cloud control system (CCS) on PCC are briefly introduced, and the prospect and future trends of PCC are proposed.

Keywords: Predictive cruise control (PCC), cloud control system (CCS), cooperative control, efficient operation, intelligent connected vehicle.

Citation: B. Gao, K. Wan, Q. Chen, Z. Wang, R. Li, Y. Jiang, R. Mei, Y. Luo, K. Li. A review and outlook on predictive cruise control of vehicles and typical applications under cloud control system. *Machine Intelligence Research*, vol.20, no.5, pp.614–639, 2023. http://doi.org/10.1007/s11633-022-1395-3

1 Introduction

The energy crisis, environmental pollution, and traffic safety are the main concerns in the automotive industry. Research on advanced vehicle control technologies is considered a potential measure to solve these problems. Predictive cruise control (PCC) is a type of intelligent control technology. In comparison with traditional constant speed cruise control (CC) and adaptive cruise control (ACC), the PCC technologies can help vehicles become safer and more economical, as well as improve traffic efficiency. The reason lies in their capacity to adjust economic speed adaptively and the fact that an additional degree of freedom is available to pass-through urban intersections more efficiently. The academic community generally refers to PCC as a type of lateral and longitudinal predictive planning and control, that is, through the control of vehicle driving states such as speed or lane-changing, to complete driving tasks in a more efficient and safe manner[1, 2]. Also, it is commonly acknowledged that improvements in fuel economy and traffic efficiency are closely dependent on the design of PCC strategies. Related research notes that the performance of PCC is closely related to many factors, e.g., static road information, dynamic traffic information, powertrain configurations, and prediction range[3–5]. However, the complexity and uncertainty of the traffic environment often compromise the performance of the established PCC. Therefore, how to study and optimize PCC technologies constitutes a significant research subject.

Review
Manuscript received on August 11, 2022; accepted on November 11, 2022; published online on March 9, 2023
Recommended by Associate Editor Long Cheng
Colored figures are available in the online version at https://link.springer.com/journal/11633

In recent years, with the rapid development of autonomous driving and vehicle-connected technologies, automobiles have seen great changes in intelligence and connection. Intelligent connected vehicles (ICV) technologies have emerged to catalyze energy-saving and safety for traditional and new energy vehicles[6]. ICV technologies provide novel ideas for the optimal design of PCC by integrating wide-area road traffic information and improving control architecture with the use of a cloud platform. With advanced sensors and communication equipment, vehicles can communicate with traffic participants via vehicle to everything (V2X) technologies and exchange and share massive data of current traffic states and vehicle operating data[7], which is greatly essential for researching PCC technologies.

PCC systems require numerous perceived information and real-time computational support. The vehicle-side platform suffers from weak computing power and incomplete sensed effect, which are notable reasons for hindering the industrial application of PCC. Recently, the emergence of an intelligent connected vehicle cloud control system (ICVCCS) provides a new solution to the above problems. As shown in Fig. 1, ICVCCS integrates vehicle-road-cloud information and comprehensively utilizes real-time and historical data of the traffic network. It can not only realize cross-domain/long-time perception, but also carry out the fast real-time calculation, which greatly releases the vehicle-side calculation pressure[8]. Therefore, it is foreseeable that ICVCCS will be an important support for the further improvement of PCC and open a novel research field for it.

Most of the existing reviews focus on economical driving[9, 10], energy-saving optimization[11, 12], energy management[13] of vehicles, etc., but few scholars review the field of PCC. In addition, with the development of ICVCCS, the advantages of ICVCCS-based PCC have been significantly highlighted, but there is no exploratory research in this field.

Based on the above analysis, this paper reviews PCC in different scenarios, including urban roads and freeways, and provides a comprehensive survey of PCC-related methods and strategies. Moreover, in order to demonstrate the advantages of ICVCCS-based PCC, three typical application kinds of research are briefly introduced in this paper. Specifically, first of all, from the theoretical level, a general overview of the PCC-relevant methodologies is given. Then, based on different scenarios, the research status of PCC is investigated and summarized extensively. Finally, the future trends and key issues in PCC, especially ICVCCS-based PCC, are proposed.

The remainder of this paper is organized as follows. In Section 2, the related methodology of PCC is summarized, including the construction of optimal problems based on predictive information and the commonly used solving methods. The PCC methods in freeways and urban traffic scenarios are elaborated in Sections 3 and 4, respectively. Section 5 introduces typical applications of ICVCCS on PCC. The outlook and future trends on PCC are elucidated in Section 6. Finally, the key conclusions are given in Section 7.

2 Methodology of predictive cruise control

In this section, based on a review of existing approaches, a general mathematical model for the construction of optimization problems based on predictive information is presented. Then, a summary of the commonly used methods for solving PCC problems is introduced.

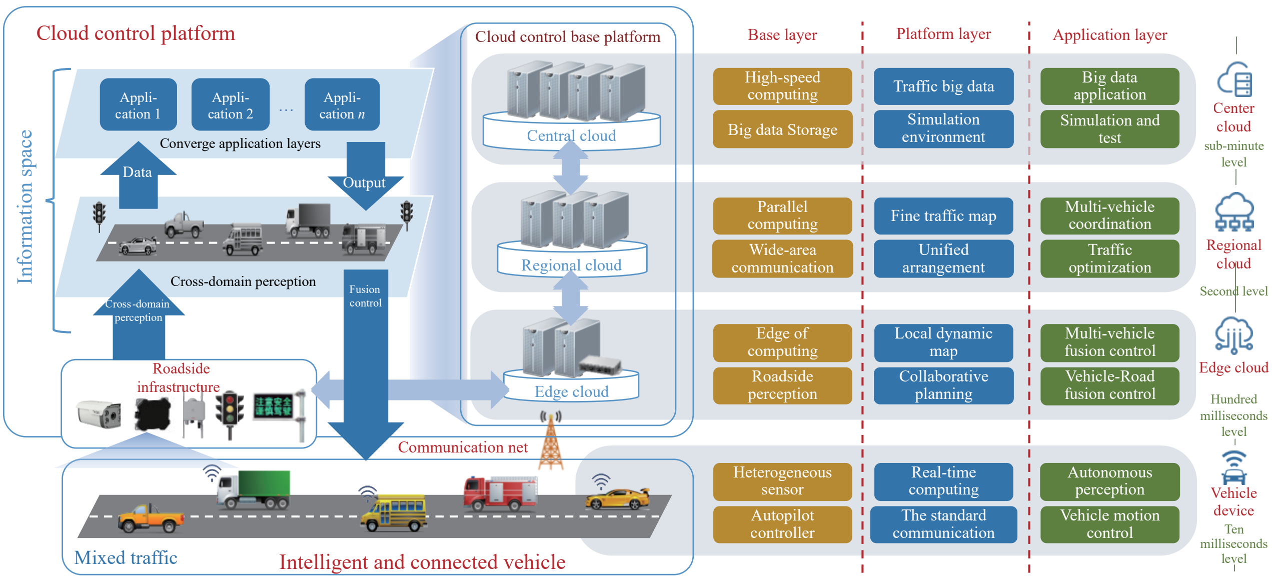


Fig. 1 Cloud control system architecture of intelligent connected vehicles

2.1 Construction of optimal problems based on predictive information

Excellent drivers are skilled at making optimal driving strategies based on complex traffic environments. Based on the background of this problem, some scholars[1, 14–16] have proposed the concept of PCC based on optimization and control theory by predicting dynamic and static traffic information in order to maximize the potential of optimal driving.

Predictive cruise control has been studied for many years. In the typical literature published in the past, Lattemann et al.[14] used a 3-dimensional road map to construct the optimal control problem of energy consumption to adjust the cruise speed, and firstly defined it as "predictive cruise control (PCC)". In the next studies, the scholars expanded on the concept. Asadi and Vahidi[1] performed PCC by using signal phase information to achieve optimal driving at intersections. Chu et al.[15, 16] further broadened the concept of PCC by incorporating traffic flow and surrounding vehicle states into the information available for PCC while considering multiple objectives, such as economy, safety, and comfort, in the construction of the optimization model. Based on previous research on PCC, this paper summarizes the information used in PCC as "predictive information", which includes both static road information and dynamic traffic information. Whatever information is used for PCC, the core of the problem is how to use this information to construct and solve the optimal control problem.

The predictive information available to PCC-equipped vehicles is shown in Fig. 2.

Fig. 2 shows that PCC can construct the optimal driving strategy using the above dynamic and static information to achieve optimal driving under different objectives. In the research of optimal driving strategy based on predictive information, the following three factors must be taken into account.

1) Objective function: A numerical measurement used to assess a vehicle's driving performance;

2) Vehicle model: It mainly includes vehicle dynamics and energy consumption models;

3) Constraint set: It contains static road constraints, dynamic traffic constraints, and vehicle performance constraints.

Through the summary of relevant methods, the general expression of the mathematical model is shown in (1)[1, 14–19].

$$\min J = \int (\omega_1 \times \zeta_1 + \omega_2 \times \zeta_2 + \cdots + \omega_n \times \zeta_n)\,\mathrm{d}t$$
$$\text{s.t.} \quad \begin{cases} \dfrac{\mathrm{d}\boldsymbol{x}}{\mathrm{d}t} = f_{\mathrm{vehicle}}(\boldsymbol{x}, \boldsymbol{u}, t) \\ \quad \{C_{\mathrm{vehicle}} \mid V_1, V_2, \cdots, V_n\} \\ \quad \{C_{\mathrm{static}} \mid S_1, S_2, \cdots, S_n\} \\ \quad \{C_{\mathrm{dynamic}} \mid D_1, D_2, \cdots, D_n\} \\ \varphi(x_0, x_{\mathrm{f}}) = 0 \end{cases} \tag{1}$$

where $\zeta_{(\cdot)}$ is the optimization objective, $\omega_{(\cdot)}$ is the weight of each optimization objective; $f_{\mathrm{vehicle}}(\cdot)$ is the vehicle dynamics model; $\boldsymbol{x}$ is the state variable, $\boldsymbol{u}$ is the control variable, t is the driving time; C_{vehicle} is the vehicle performance constraints, including engine power, torque, speed, transmission ratio, brake pressure, vehicle acceler-

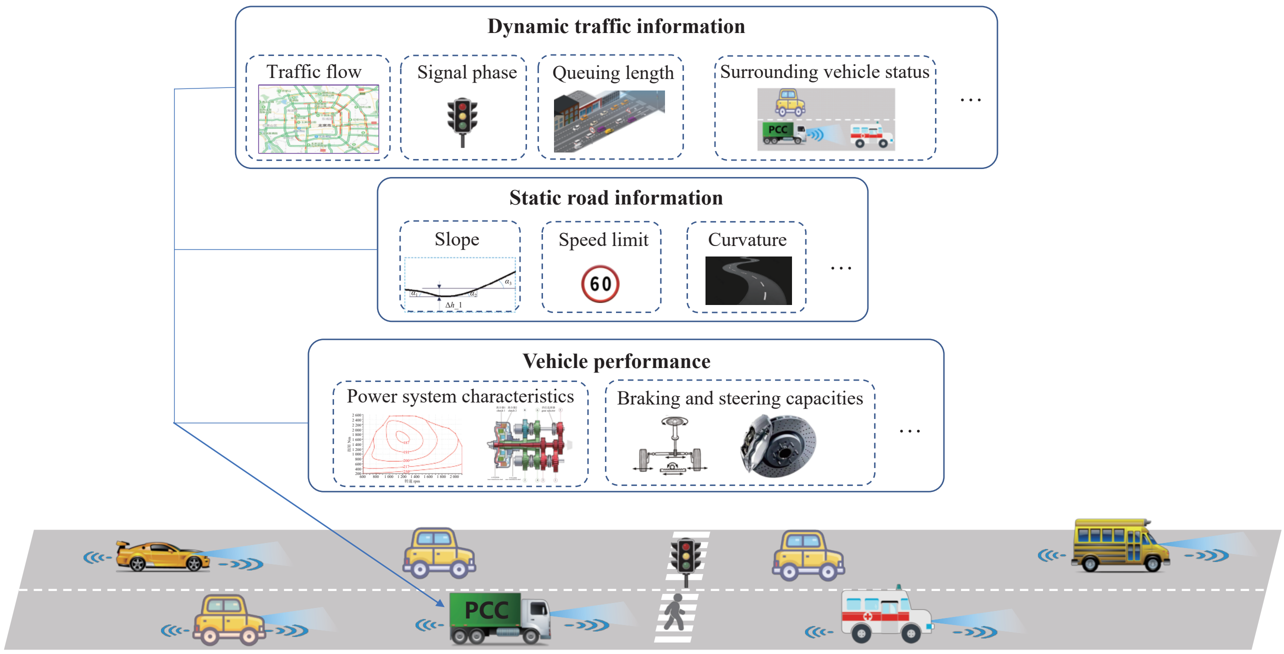


Fig. 2 Predictive information available to PCC-equipped vehicles

ation, etc., which are represented by $\{V_1, V_2, \cdots, V_n\}$, respectively; C_{static} is the static road constraints, including slope, curvature, speed limits, etc., which are expressed by $\{S_1, S_2, \cdots, S_n\}$, respectively; C_{dynamic} is the predicted dynamic traffic constraints, including traffic flow, signal phase, queuing number, and environmental vehicle speed and distance, etc., which are expressed by $\{D_1, D_2, \cdots, D_n\}$, respectively; $\varphi(\cdot)$ represent the initial and terminal boundary conditions.

The key to constructing a PCC problem is to establish the analytic function of the optimization objective, state equation, and constraint set. The optimization objectives are safety, energy-saving, efficiency, comfort, etc.[20, 21] According to the number of optimization objectives, it can be divided into single-objective problems and multi-objective problems. Generally, in vehicle control, multiple optimization objectives are often transformed into single-objective problems by weighting[22, 23]. In order to adapt the weight factor according to the working conditions, some scholars propose a cost function with variable weight, which can improve the effect of optimal control. In addition, when determining the weight, some scholars have also proposed some common methods, such as fuzzy control[24], deep learning[25], genetic algorithm[26], etc.

The state equation needs to obey the dynamic characteristics of the vehicle. In order to pursue the simplicity of the equation, the vibration characteristics and mechanical deformation of the transmission system are generally ignored[27]. The constraint set, as shown in Fig. 2, mainly comes from the constraints of roads, traffic, and vehicles themselves. The road constraints are limited speed, slope, curvature, etc.[19, 28] Traffic constraints mainly refer to dynamic traffic information, including signal lights[29], surrounding vehicle status[30, 31], traffic flow[32], queue length[33], etc. The vehicle's constraints include the characteristics of the engine, transmission, braking and steering characteristics, etc.[34, 35]; the complex diversity of these constraints makes it extremely difficult to solve these problems.

2.2 Overview of solving methods

PCC problems based on predictive information are generally converted into optimization problems in mathematics, and then solved by mathematical theory. The solution method can be divided into analytic solution and numerical solution according to the form of solution. The calculus of variations[36, 37] and Pontryagin's minimum principle (PMP)[38, 39] are commonly used to solve the analytical solution. The constraints of the PCC problem often include integer, nonlinear, and time-varying constraints, and the objective function and state equation are mostly nonlinear functions, which is difficult to derive the analytical solution by using the formula. At present, numerical methods are used for solving PCC problems generally. Common numerical methods include dynamic programming (DP)[40–42], pseudo-spectral method (PSM)[43, 44], model predictive control (MPC)[45, 46], reinforcement learning (RL)[47, 48], heuristic algorithm (HA)[49, 50], etc.

DP is a powerful tool for tackling optimization problems. Its core idea is to divide the optimization choice problem into discrete and interrelated multi-step decision problems. The fundamental problem is the "curse of dimensionality". Storage and processing both expand rapidly for high-dimensional situations. To address this issue, a great number of researchers have improved DP, resulting in the development of approaches such as adaptive dynamic programming[51] and approximate dynamic programming[52].

PSM is a recently proposed effective solution method for optimal control problems that can efficiently translate these problems into nonlinear programming problems. In addition, PSM offers the advantage of having a high convergence accuracy[53]. This is extremely beneficial for the real-time online solution of predictive optimal control strategies.

MPC is similar to adaptive dynamic programming. General steps include 1) prediction model, 2) receding horizon optimization, and 3) feedback correction. Based on the prediction model, the state equation and the initial state value are corrected with the use of feedback information. The optimization period is determined in the receding horizon optimization, and the performance index is used to design an optimal control problem. Finally, the open-loop optimal control is solved, and the first control value in the solution sequence is implemented in the system.

RL-based predictive planning and control do not rely on precise mathematical models of the system[54]. By continuously obtaining the rewards and updated status of the decision from the external environment, the prediction performance is improved, and the dimensional disaster is averted to some extent. RL relies on the learning of a large amount of sample information to improve the accuracy of prediction, but due to the changeable traffic scene, the amount of predicted information is huge and irregular, which brings certain challenges to RL. As a result, it has certain limitations for the application of long-term predictive planning and control.

Another type of solution is one that can be solved by a heuristic algorithm by deforming the mathematical model of the PCC problems properly. Heuristic algorithms are a type of intelligent algorithm that simulates human or natural behavior in order to seek the solution space[55]. The heuristic algorithm has high solution efficiency and strong applicability, but its solution cannot guarantee optimality and cannot even explain the degree of approximation to the optimal solution.

3 Predictive cruise control in freeway scenarios

The freeway is a typical scenario for PCC applications. In this scenario, the road's geometric features are relatively simple, and the static road information of the whole road network is relatively stable. In addition, the vehicle driving state changes infrequently, and the traffic flow varies evenly. Thus, the dynamic traffic information is highly predictable. These features can make PCC highly effective.

According to the different control objects (single and multi-vehicle) and predicted information, this section offers a survey and review of the current state of PCC technologies.

3.1 Predictive cruise using static road information

The information on slope and speed limit in static road information has been widely used in PCC. However, since PCC algorithms require high real-time performance and robustness, most literature has not verified the algorithm in real vehicles. Some algorithms for real vehicle testing only consider single information (such as slope) and do not thoroughly study the comprehensive impact of multiple road information (such as slope, curvature, speed limit, etc.) on the optimal control of the vehicle during actual driving. Fully exploiting the static road information is not only of great significance for reducing the fuel consumption of fuel vehicles, but also has great potential for designing the energy management strategy of hybrid vehicles, which has become a hot research direction.

It is the most common practice to construct the slope-based PCC algorithm by using the optimal control method. Lattemann et al.[14] studied the influence of roads on vehicle fuel consumption and took the lead in constructing the optimal control model of vehicle fuel-saving driving based on road slope information. The simulation results show that the economy of vehicle driving can be improved by optimizing the vehicle speed. Hellström et al.[56, 57] constructed a look ahead control algorithm based on DP with fuel consumption and travel time as penalty terms. The effectiveness of the algorithm is verified by the heavy truck in Scania, with an average fuel-saving rate of 5%. Furthermore, the team conducted a comprehensive theoretical analysis of the computational complexity and numerical error of DP to improve the computational efficiency, which provided a new idea for the optimization calculation of the algorithm.

For the PCC application of static road information, MPC has also been widely studied. Kamal et al.[58] used the slope information, dynamics, and fuel consumption model to construct the nonlinear model predictive control problem and solved the optimal control sequence. The simulation results show that this method significantly improves the fuel economy of the vehicle. With the use of the high-precision map, Chu et al.[15] constructed slope-based PCC problem under the MPC principle. Compared with traditional ACC, the average fuel-saving rate was 8.73 %. In order to reduce the computational complexity of MPC, Guo et al.[59] proposed a fast MPC solution method. This method converts the nonlinear optimization problem into a two-point boundary value problem based on the maximum principle and then uses the characteristics of the controlled system to obtain the analytical expression of the optimal control sequence under the initial value of the co-state variable, which reduces the dimension and computational complexity of the optimal control problem. MPC and optimization methods are often combined to meet the optimality and real-time performance of algorithm design. Hellström[60] used the rolling optimization principle of MPC and the optimal solution method of DP to design a look-ahead control algorithm to realize the predictive fuel-saving control of vehicles. This method is now widely accepted by scholars.

For hybrid vehicles, there are also a large number of studies on predictive energy management using the obtained static road information. Alzorgan[61] used the road slope information to predict the future energy and power demand, and then optimized the power distribution between the internal combustion engine and the electric drive system so that the hybrid power system could operate more effectively and finally achieve the effect of fuel saving. Liu et al.[62] provided an integrated control method of the powertrain with the consideration of the driving mode into the entire loop with MPC. It effectively achieves the energy transfer regulation strategy under different intentions of the driver, improving transmission efficiency by 8.92% and saving fuel consumption by 4.9%. Based on MPC architecture, the predictive energy-saving driving of hybrid electric vehicles is realized in [63]. It uses the future slope information to predict the speed trajectory and then uses DP to solve the optimal torque distribution to optimize energy utilization.

With the application of cloud service platforms, some scholars have studied the PCC system based on the cloud in order to make full use of the rapidity of cloud computing and map service. Ozatay et al.[64] developed predictive speed planning algorithms based on cloud servers. Through the destination set by the driver, the cloud platform automatically obtains the road information, plans the recommended speed of the vehicle, and sends it to onboard controller so that the driver completes the speed following control. The test results verify the effectiveness of the proposed system and the fuel saving effect is obvious. Hou and Song[65] developed a predictive hierarchical energy management strategy based on vehicle-cloud communication, shown in Fig.3. Cloud uses traffic state information to predict future driving power demand and solves the optimal energy management strategy based on DP. At the vehicle level, an MPC algorithm is developed to deal with the uncertainty of control and reduce energy loss. The simulation results show that the proposed method is significantly better than the rule-based method, and the average driving energy consumption is improved by more than 40%. With the development of emerging tech-

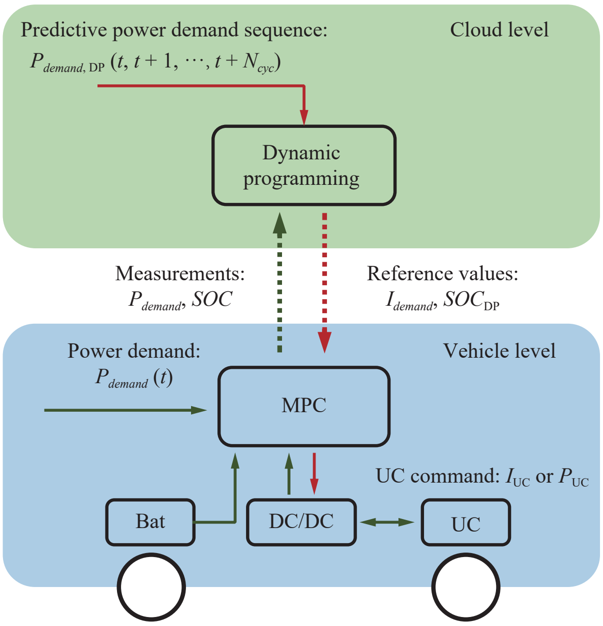


Fig. 3 Structure diagram of predictive hierarchical energy management strategy

nologies such as 5G communication and cloud computing, a suitable combination of the predictive cruise algorithm and the cloud system is considered an effective solution to the current problems such as map and cost.

3.2 Predictive car following control

ACC is an extension of CC. The first generation of ACC maintained the relative distance to the vehicle in front by automatically adjusting acceleration and deceleration, which improved the safety of the cruise control system[66].

However, with the continuous updating of technology, scholars began to think about how to improve the economy and comfort of the ACC while ensuring safety. To some extent, when the economic goal is satisfied, most of the comfort goals are also satisfied, but there is an obvious conflict for safety. Multi-objective optimization refers to the difficulty of finding the best way to concurrently satisfy all of the objectives while dealing optimally with conflicting objectives[67].

Li et al.[68] added acceleration to the quadratic cost function and used a quadratic programming algorithm to compute the optimal control law numerically. Moreover, Li et al.[69] explored the fuel-saving mechanism of pulse-and-glide operation by considering both the internal combustion engine and step-gear transmission. The simulation results show that the algorithm achieves fuel savings of up to 8.9% compared to a linear quadratic controller when coasting in neutral gear. A dual-mode control strategy for unstable and stable conditions is proposed in [70]. It significantly improves the robustness and comfort of vehicle speed control and increases transmission efficiency by 7.98% to 9.98%. Luo et al.[71] effectively reduced fuel consumption and improved the following comfort by adding the variation of acceleration to the quadratic cost function and limiting it with constraint. Zhang and Ioannou[72] compared the difference between driver-driven and ACC for trucks and the effect of different spacing strategies on the following effectiveness. The findings demonstrate that both driving techniques attract insertions from surrounding lanes because of the potential for big gaps between the truck and the passenger car in front caused by the truck's low power. These insertions can cause additional disruptions that negatively affect fuel economy and pollution.

Although these methods have achieved remarkable results, they are all planned by the relative motion relationship between the front and rear vehicles, and the fuel-saving potential has not yet been completed. How to use future information or other information to plan the vehicle speed and thus further improve the energy-saving effect has become a hot topic of current adaptive cruise control research, called the predictive adaptive cruise problem.

Stanger and Re[73] constructed a fuel consumption model as a polynomial of vehicle speed and acceleration as a cost function, set upper and lower bounds on the following distance to ensure safety, and simulated the proposed method to decrease fuel consumption by 16% over the comparison PI control method. Schmied et al.[74] developed a second-order polynomial nonlinear autoregressive model to predict the speed of the vehicle in front, which further reduced fuel consumption. Although the fuel-saving effect of this method is obvious, the point that can not be avoided is that when the cruise function is turned on, the current following distance may not be within the upper and lower bound of its limited distance, which makes the method unable to solve for a feasible solution. Moser et al.[75] developed a conditional linear Gaussian model and trained it with actual measurement data to estimate the probability distribution of the future speed of the vehicle in front and introduced the process of constructing the fuel consumption model. Khayyam et al.[76] used road data to calculate vehicle energy consumption under various dynamic loads, such as wind resistance, slope, kinetic energy, and rolling friction, and included a look-ahead strategy to predict future road slopes. Simulation results show that the look-ahead approach effectively controls the vehicle speed and reduces the average fuel consumption by 3%. Weissgmann et al.[77] used a given route and calculated the optimal speed trajectory in advance using the DP algorithm by considering information such as speed limit, road gradient, and travel time during the optimization process. The MPC framework is used to control the traction of the main vehicle so that the vehicle speed follows the energy-optimal speed trajectory as much as possible, and the simulation shows that the method achieves high energy savings. However, the method is based on an offline solution and lacks the validation of practical applications. Turri et al.[78] used road slope information and the speed trajectory of the preceding vehicle to calculate the optimal engine torque and gearing requirements. The optimal control problem is realized by DP, and a simulation comparison of multiple longitudinal control strategies is performed, and the results show that the method can achieve fuel savings of 7%. Kamal et al.[79] predicted the front vehicle states for urban working conditions. The proposed approach was evaluated by observing intersection utilization, flow characteristics, and individual vehicle fuel efficiency in a typical urban traffic signal intersection. In addition, Kamal et al.[80] measured current road and traffic-related information to predict the future state of the vehicle ahead and maximize fuel economy by adjusting the safe headway or cruising at the optimal speed.

Today′s ACC strategies are no longer limited to considering information about the vehicle in front, but increasingly road traffic information, leading to further development of the potential for safe, economical, and efficient vehicle driving.

3.3 Predictive lane-changing control

The vehicle cruising and following behaviors discussed in the previous sections mainly focus on the control of longitudinal vehicle motion. However, in some traffic scenarios, controlling the longitudinal speed alone does not satisfy the vehicle travel optimization objectives. For example, if there is a continuous low-speed vehicle in front of the ego vehicle, the ego vehicle can only eliminate the influence of the vehicle in front of it on its driving and achieve the desired driving speed by changing lanes.

In recent years, various roadside units have become increasingly popular and perfect with the advancement of communication technology. The application of vehicle-vehicle communication, vehicle-road communication, and other communication technologies allows real-time information interaction between vehicles and vehicles, vehicles and roadside units, and vehicles and cloud platforms[81], which provides technical support for traffic state prediction. Using traffic state prediction information, vehicle lane-changing decisions and the lane-changing execution process can be optimized to effectively improve the safety and comfort of the vehicle during a lane change.

Depending on the usage of the obtained prediction information, predictive lane-changing control can be divided into two strategies: optimizing lane-changing decisions using longer time domain prediction information (e.g., more than 15 s) and optimizing lane-changing execution using shorter time domain prediction information (e.g., within 5 s).

Predictive control of lane-changing decisions generally does not focus solely on the action of lane-changing, but rather views lane-changing as a vehicle-driving maneuver option. It usually constructs a driving optimization problem, then solves this optimization problem to obtain the driving speed and lane-changing decision control sequence that optimizes the vehicle′s driving state in the future.

One of the characteristics of the MPC method is that it allows optimal control solutions considering both the predicted information of the vehicle and the traffic vehicles and the control system′s constraints[82]. This approach is compatible with the goals of predictive lane-changing decisions and has been widely used in related research. Kamal et al.[83] predicted the state of preceding traffic vehicles and established a travel cost function for the driving conditions of the controlled vehicle based on an MPC framework. They then designed a two-layer optimization scheme to calculate the acceleration control sequence and the lane-changing moment decision sequence, which optimizes the vehicle′s driving state. Finally, simulation experiments have verified that the method enables vehicles to anticipate lane-changing maneuvers when future changes in traffic conditions are predicted. Therefore, the average vehicle driving speed is higher and smoother, improving driving efficiency and economy. However, this method treats lane-changing execution as an instantaneous process, and it also has limitations like the road′s slope not being taken into account and the inability to guarantee computational real-time. In addition, the game theory approach has also been applied to the research on optimal control of predictive lane-changing decisions. Wang et al.[2] proposed an integrated control method for lane-changing and car-following based on receding horizon control and dynamic game theory. They designed a game problem that considers the behavioral decisions of the ego vehicles under the influence of the expected behavior of surrounding vehicles and determines the desired future lane sequence and acceleration sequence that minimizes a cost function reflecting future bad driving conditions. The method can be applied to non-cooperative scenarios (the controlled vehicles only optimize their costs) and cooperative scenarios (the controlled vehicles coordinate their decisions to optimize the overall costs of a microscopic traffic flow). Six scenarios were designed for simulation experiments. The results show that the driving cost of the vehicles controlled by this method is effectively reduced. However, when designing the cost function, the cost of the lane-changing behavior was set to a constant value, which ignored the differences between the lane-change scenarios and might affect the optimality of the lane-changing decision.

Optimizing lane-changing decisions based on longer time-domain prediction addresses the problems at the strategic level in the vehicle driving process. However, during the lane-changing process, the state of the surrounding vehicles will directly affect the safety of the lane-changing. In the high-speed lane-changing scenario, the states of the traffic vehicles may change significantly in a short period[84], and network delays can also seriously affect the control stability and lane-changing trajectory tracking accuracy of vehicles[85]. These situations will directly threaten the safety of the vehicle lane-changing, which is a problem that cannot be taken into account in longer time-domain prediction. Therefore, many existing studies have focused on the shorter period of the lane-changing process. Safe and collision-free lane-changing can be achieved by predicting the state of surrounding traffic vehicles, optimizing and adjusting the lane-changing trajectory planning, and tracking control.

Zhao et al.[86] transformed the collision avoidance path replanning problem into a nonlinear quadratic programming problem with velocity, angle, and angular velocity constraints based on the MPC algorithm. The optimization goal was to find the optimal path by minimizing the deviation of the actual vehicle trajectory from the reference trajectory and avoiding obstacles. The experiments demonstrate that the planned path could avoid obstacles. Nevertheless, the method in this paper only considers static obstacles and does not apply to dynamic obstacle scenarios. Luan et al.[85] proposed an uncertain model adaptive MPC algorithm to predict the control variables at the next sampling time for reducing the effect of target angle discontinuity considering the effect of random time delay. And hardware-in-loop simulation proved the stability and tracking accuracy of the algorithm.

Many of today′s traffic vehicle state predictions use deterministic prediction methods, which assume that the predicted vehicle will move in a constant state over a limited time horizon. It would make the prediction results biased and unable to cope with sudden changes in the traffic environment. Therefore, it is necessary to consider the prediction of future state uncertainty. Suh et al.[87] proposed a stochastic MPC method (SMPC) for lane-changing motion planning and motion control of self-driving vehicles in complex driving environments. The probabilistic motion characteristics of other vehicles were analyzed by collecting driving data on real roads. In the vehicle state predictor, the possible positions of vehicles and their error covariance in a finite time horizon are predicted by an extended Kalman filter (EKF). Based on two indicators of safe time headway and safe distance, the current traffic information and predicted traffic information was used to evaluate the risk of lane-changing collision. And then, a safe driving area is established and the desired driving speed is matched. The simulation experiments reflected that the algorithm effectively improved the success rate of lane-changing, and that the algorithm robustness and lane-changing safety indexes were better than those of deterministic prediction methods. Experiments in real vehicles have verified that the method could control the vehicle to adapt to complex traffic flow conditions under automatic driving conditions in scenarios such as expressway ramp merging. Zhang et al.[84] proposed a trajectory planning algorithm for high-speed vehicles based on the trajectory prediction of the preceding vehicle motion. The trajectory prediction of the preceding vehicle based on the vehicle kinematic model and combined with the driving intention was performed by the unscented Kalman filter (UKF) method, and Gaussian noise was added to reflect the uncertainty of the prediction model. The relationship between the collision probability and the longitudinal position was calculated according to the predicted information. The Bessel curve was used to adjust the trajectory shape of the lane-changing, and the vehicle collision was effectively avoided. However, this method uses a simple kinematic model of the vehicle, which may not reflect the real-world situation in predicting the vehicle′s motion state.

In summary, both of these predictive lane change control strategies can improve the performance of the vehicle driving process in terms of efficiency, safety, and control stability. The research on the optimization of the lane change execution process based on predictive information is relatively mature. However, research on the predictive control problem of lane change decisions is still relatively few and the predictive models used are fairly simple. In addition, almost all of them are verified by simulation experiments only. In future research, based on the powerful computing capability of the cloud control system, a more accurate predictive model can be considered, and there is an opportunity to validate this algorithm in real vehicles.

3.4 Predictive cruise control of platoon

Predictive cruise control of the platoon (platoon-PCC) can be used to further strengthen the benefit of cloud-controlled PCC on the freeway. In the study of platoon-PCC, researchers have idealized the problem of platoon stability control, focusing instead on resolving the issues of platoon effectiveness and economy.

Many countries and regions have now launched research into heavy commercial vehicle platoon (HCVP) technology due to its practical needs and the enormous potential for energy efficiency. At present, most studies focus on platoon speed control, especially for high-speed scenarios in which platoon speed planning and prediction can be achieved through the use of static and dynamic traffic information. Furthermore, research indicates that decreasing the distances between vehicles in a platoon reduces the overall air resistance of the platoon, which can also reduce overall energy consumption. It has been shown that when commercial vehicles are kept at a distance of 10 meters, 10%–15% of fuel consumption can be saved[88], but too close a distance between vehicles traveling at high speed can pose significant safety risks due to the time lag associated with sensing, communication, control, and actuator response. In light of this, a number of researchers have focused their attention on the problem of optimizing speed and distance control in platoon driving in commercial vehicles based on road traffic data.

Currently, freeway scenarios mainly consider road slope, curvature, and road traffic flow conditions to design the platoon-PCC. Numerous studies have utilized model prediction methods to deal with complex nonlinear multi-objective platoon control systems due to their technical characteristics and advantages. Zhai et al.[23] proposed an economic collaborative look-ahead control strategy (Eco-CLC) based on a distributed model predictive controller (DMPC), which incorporates information on the slope of the road ahead to plan the optimal speed for the recommended platoon driving. Kamal et al.[58] proposed a model-based predictive economy driving system for a platoon whose fuel consumption is highly affected by the slope of the road. The system utilizes information regarding the topography of the road, a vehicle dynamics model, and energy consumption characteristics to calculate the economy speed profile. The results indicate that this control system can significantly reduce vehicle fuel consumption. Zhai et al.[89] proposed the Ecological cooperative adaptive cruise control (Eco-CACC) system to reduce the energy consumption of a heterogeneous vehicle platoon. The model-based predictive control solved the pilot vehicle control input optimization problem (CIO-LV), which considers platooning control objective constraints and driving comfort. An improved particle swarm optimization method is then used to quickly solve the optimal speed problem. The proposed Eco-CACC saves 6.35% of fuel in a heterogeneous vehicle platoon.

In addition to using the MPC strategy for platoon-PCC, many academics have concentrated on the DP method. It is a classic method for platoon-PCC that achieves a global optimal solution. Turri et al.[90] combined road slope and real-time vehicle states to plan a speed profile for optimal platoon energy consumption, which can save 12% of energy consumption compared to a traditional platoon. However, there is a dimensional disaster in the DP of platoon energy-efficient driving, and there are limitations in large-scale real-time applications. To address this issue, Li et al.[91] proposed to study energy-efficient driving control based on optimal control theory for simple platooning control. Compared to the traditional DP, the computation is faster, the DP dimensional disaster problem is avoided, and the energy-saving potential of the truck platoon is improved.

Recent research has also focused on the construction of hierarchical control architectures for platoon-PCC. On the one hand, the upper layer performs decisions and planning for the platoon, and its main task is the planning of the platoon′s economic speed. On the other hand, under the premise of ensuring the safety and stability of the platoon, the lower layer controller completes the policy following control based on the upper layer speed planning. Guo and Wang[88] investigated the speed planning and tracking control problem for HCVP on the freeway. A hierarchical control concept is proposed, in which a path-optimal speed planning procedure is performed at the upper layer and a speed tracking process is carried out at the lower layer. Yang et al.[92] developed a novel hierarchical Eco-CACC strategy in which the upper layer makes use of road slope, curvature, and the current platoon dynamics state (lateral and longitudinal) to plan the driving speed, and a conventional platoon ACC follow controller is performed in the lower layer. The experimental result shows that this hierarchical strategy can save more than 38.1% of energy consumption compared to the conventional cruise control method. Maged et al.[93] used optimal MPC as the upper-level speed planning to improve the platoon vehicle spacing and reduce the energy consumption of the platoon further. Linear proportional-integral-derivative (PID) is used as the lower-level speed-following controller to control the power output of each vehicle to achieve the optimal speed required. Under the hierarchical control architectures for platoon-PCC, two optimization models were proposed for connected and automated vehicles (CAVs) trajectory planning[94]. The first model predicts the traffic state of the freeway at future moments and optimizes the CAV desired speed profile. The model embeds CAVs and human-driven vehicles (HVSs) in the traffic flow model and optimizes them, taking full account of the effect of CAVs on HAV speed, thus reducing the energy consumption of the platoon. Ma et al.[95] proposed a hierarchical energy-efficient control architecture to reduce energy consumption and travel time. The upper layer considers information such as platoon length, signal phasing, road speed limit, and traffic flow to calculate the optimal speed control sequence. The lower layer introduces time-domain PCC to ensure safe vehicle spacing and to improve fuel efficiency while tracking the reference speed.

In summary, platoon-PCC is mainly concerned with platoon speed planning by combining static road slopes and the current platoon state. The future cloud platform can more efficiently solve the issue of platoon predictive speed planning. The cloud can be used to combine static and dynamic map information ahead to plan the speed of the platoon. Therefore, cloud-based platoon-PCC has enormous potential for energy-saving and improving the safety and stability boundaries of platooning systems.

4 Predictive cruise control in urban traffic scenarios

Urban road traffic is another important category of application scenarios for autonomous and assisted driving. The access rule and spatial-temporal constraints of intersections in the urban traffic network, unlike the freeway scenario, limit the continuous movement of vehicles on arterial roads. With the switching of traffic light signals, vehicles frequently experience braking and deceleration, idling-start-stop, and high-torque acceleration processes, which deteriorate energy consumption, ride comfort, and traffic efficiency. Thanks to intelligent and connected technologies, the driving vehicle can obtain the dynamic information of urban traffic networks in real-time. Utilizing this information can optimize the vehicle speed trajectory, thereby lowering energy consumption and emissions.

Intersections and expressway entrance ramps are typical scenarios for PCC applications. Therefore, the framework of the review in this section is described in Fig. 4 below.

4.1 Predictive driving control at a single signalized intersection

Many academics are interested in the significant benefits that can be brought to eco-driving and even traffic safety by using signal light information for vehicle speed trajectory optimization. Scholars have named such speed planning differently, such as green light optimal speed advisory (GLOSA)[96–99], economic-driving (Eco-Driving) at signalized intersections[100–103], eco approach and departure (EAD)[95, 104, 105], etc. They all essentially rely on signal phase and timing (SPaT) information to complete a non-stop through a signalized intersection. Limited by the communication technology, most of the related studies are based on dedicated short range communications (DSRC) for vehicle speed guidance at signalized intersections. Katsaros et al.[96] designed the GLOSA method based on DSRC and investigated the effect of communication distance on green light crossing optimization, verifying that GLOSA can reduce vehicle speed fluctuations and save travel time while improving traffic efficiency. Also, by obtaining real-time information about the traffic light through DSRC, Mandava et al.[106] proposed an arterial velocity planning algorithm to provide dynamic speed recommendations to drivers, achieving the maximum probability of encountering a green phase when a vehicle passes through a signalized intersection. Speed guidance in combination with DSRC has been practiced on real roads, Hao et al.[107] demonstrated in a field experiment in California, USA, that the proposed EAD method can save 6% of energy consumption and reduce 7%–18% of emissions when it is activated within the DSRC communication range. However, the DSRC technique for obtaining real-time information about signals has limitations. The finite communication range also narrows the distance over which vehicle speeds can be planned. It leads to many studies only optimizing for the upcoming intersection. Even the planning of consecutive intersections is a receding horizon optimization of individual intersections one by one, which is away from wide-area optimal programming. Moreover, early studies were mostly based on logical rules; e.g., Xia et al.[101] proposed a sinusoidal optimization rule for acceleration and deceleration; Asadi and Vahidi[1] passed through multiple consecutive intersections as much as possible with constant economic speed; Rakha and Kamalanathsharma[100] proposed the rule of either uniform variable-speed or uniform speed driving to compare the fuel consumption of different speed trajectories to determine the optimal economic vehicle speed. The same shortcoming as using the DSRC technique, the speed profile planned under rule-based speed profile cannot guarantee its self-adaptability and optimality for complex and changing scenarios.

As a result, more research has been carried out to optimize the eco-speed based on evolving mobile communication networks. Mahler et al.[108] showed that wireless communication technology using fourth generation and long term evolution (4G/LTE) improved the accuracy of SPaT data transmission, and in-vehicle GLOSA application further reduced fuel usage by 9.5%. The successful application of cellular networks in V2I breaks the communication distance constraint, allowing the vehicle to receive the SPaT for multiple future intersections on the driving path. Furthermore, the mature development of 5G communication technology gives us a higher expectation for high real-time control of ICV.

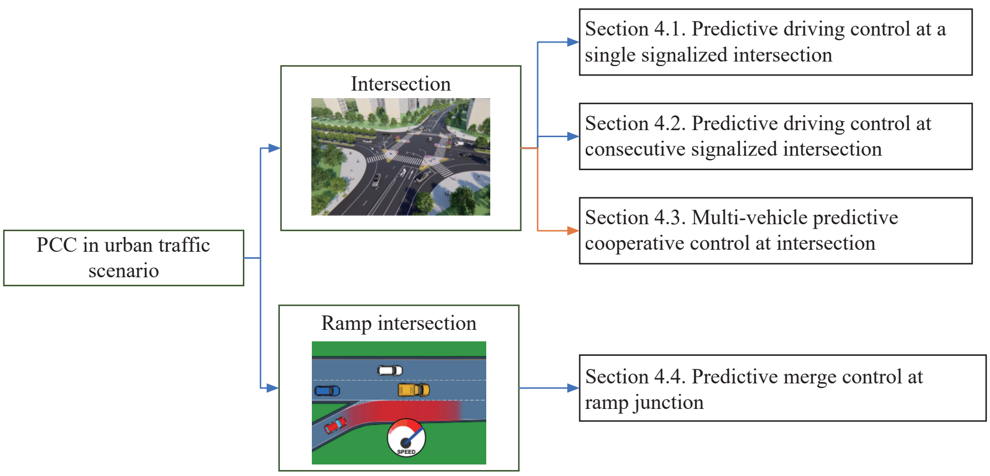


Fig. 4 Classification of PCC in urban traffic scenarios

4.2 Predictive cruise control at consecutive signalized intersections

Based on the development of communication technology, scholars have tried to solve the global optimal vehicle speed trajectory at consecutive intersections using more sophisticated optimization algorithms to achieve more integrated and diverse optimization objectives. Nunzio et al.[102] considered the restrictions of multiple traffic lights and speed limits, reduced the optimization domain with the pruning algorithm, and solved the analytical solution of the energy-efficient trajectory using the optimal control method. Miyatake et al.[109] numerically solved the optimal control problem for minimizing the energy consumption of electric vehicles at multiple signalized intersections based on Bellman dynamic programming. Similarly, Kamalanathsharma and Rakha[110] solved the optimal trajectory by proposing the multi-order DP algorithm combined with the A* algorithm, which improved solution speed and saved 19% of fuel consumption and 32% of travel time for multiple signalized intersections passage. DP has proven to be a valuable algorithm for solving such problems[111, 112]. Though there is a drawback to poor real-time performance, the optimal results it solves are still used as a benchmark by other algorithms. To avoid traversing the state space and control variable space, some scholars have tried to use heuristic algorithms to solve the problem. Luo et al.[113] investigated the speed optimization of a hybrid electric vehicle at consecutive intersections under intelligent traffic system (ITS) and proposed a genetic algorithm to solve the nonlinear optimization problem, which effectively improved fuel economy and traffic efficiency. Several scholars, such as Seredynski et al.[97], Zheng et al.[114], and Zhi et al.[115], have similarly used the genetic algorithm to achieve the optimization goal of energy saving and emission reduction. In addition, MPC[1], particle swarm optimization[116], and PMP[117, 118] are also suitable for solving the speed optimization problem at consecutive signalized intersections.

However, it is not difficult to find that many current studies solely consider the timing and phase of traffic lights, ignoring the impact of dynamic traffic flow on speed planning. To complete the optimization of control under the viewpoint of the ego vehicle, it is necessary not only to consider avoiding the nuisance caused to the traffic flow behind the ego vehicle and the waste of public road space resources because of its own continuous lower speed driving, but also to consider the impact of slow vehicles ahead or intersection queues on the economic vehicle speed trajectory planning and tracking control of the ego vehicle. Schuricht et al.[119] are enlightening in considering the effect of queue length at signalized intersections. Their queue length estimation technique based on induction loop sensor systems further improved the fuel-saving potential of a single-vehicle at a single-intersection by 28%. The algorithm proposed by Yang et al.[120] used the Lighthill-Whitham-Richard model to predict the queue length and dissipate time at the upcoming intersection, which significantly smoothed the vehicle speed trajectory and resulted in a further 11.4% fuel savings. He et al.[121] and Wu et al.[122], on the other hand, obtained the real-time queue length through the arterial traffic data collection system and solved the vehicle speed trajectory using a multi-stage optimal control model. However, they ignore the evolution of the traffic state, such as the queuing and dissipation of vehicles at an intersection, which will affect the driving performance of the controlled vehicle.

In summary of the literature, single-vehicle PCC on urban roads has been extended from single-intersection planning to multiple consecutive intersections, and in addition, scholars have begun to focus on the impact of environmental vehicles on the control of ego vehicles in recent years. Cloud control platforms can fuse wide-area dynamic traffic information to provide vehicles with a wider range and more rational decision-planning results, thus improving vehicle performance. As a result, combining the cloud control platform for PCC at multiple intersections will have a positive impact.

4.3 Multi-vehicle predictive cooperative control at intersections

Predictive cooperative control of multi-vehicle using traffic signals at intersection can also bring significant benefits to urban traffic systems. Dependent on V2X communication, cooperative adaptive cruise control (CACC) can improve information-sharing capabilities, thereby enhancing overall traffic efficiency. CACC can also benefit urban arterials by using appropriate algorithms to predict multi-vehicle behavior and optimize trajectories to divide and reorganize vehicle platoons before and after signalized intersections, thus maintaining small and safe headway time spacing.

With the use of traffic light information, energy consumption and pollutant emissions of multi-vehicle operation can be further reduced[123−126]. Dong et al.[123] proposed energy-efficient cooperative adaptive cruise control (Eco-CACC) based on V2X communication. An optimal speed decision is made in a fuel-efficient driving framework, and the algorithm also determines the optimal sequence of speed control for the platoon through a traffic light intersection based on traffic light signals and road speed limits. Yang et al.[120] developed a novel Eco-CACC that calculates fuel-optimized vehicle trajectories through signalized intersections by ensuring that the last vehicle in the platoon reaches the intersection stop line. The proposed Eco-CACC system can save up to 40% of vehicle fuel when the market penetration rate (MPR) of connected vehicles is 100%. Ma et al.[95] proposed an Eco-CACC, which combines the advantages of energy-efficient driving and follow-the-leader, resulting in an 8.02% improvement in the economy compared to manual driving with a constant acceleration strategy. In addition, a further 2.02% and 1.55% improvement in energy efficiency is achieved when the MPC and intelligent driver model (IDM) algorithms are used for the follow-along strategy. Cui et al.[124] explored the effect of ACC/CACC on fuel consumption and emissions at signalized intersections using the human driving model (HDM) following model. The numerical simulation results show that ACC/CACC has very high environmental benefits. Kamalanathsharma and Rakha[125] proposed that Eco-CACC enables multiple vehicles to operate on a fuel-optimal trajectory. Based on experimental validation, fuel consumption levels were reduced by up to 30%. Du et al.[126] proposed a coupled vehicle-signal control (CVSC) method to simultaneously optimize traffic signal timing and the trajectory of CAVs with the objectives of improving traffic efficiency and energy-saving, respectively. When the CAV penetration rate is greater than 40%, the method can save 6%–14% in fuel consumption and increase the average vehicle speed by 1%–5%.

In addition to the problem of focusing on energy consumption at intersections, the issue of intersection throughput efficiency has also attracted the attention of many scholars[127–130]. Liu et al.[127] have developed a cooperative signal control algorithm that uses a CACC dataset collected by conventional fixed traffic sensors to predict future traffic conditions. Average vehicle speeds and miles traveled per gallon of fuel consumed can be increased by more than 10% when CACC penetration rate is 100%. Günther et al.[128] proposed a method to optimize the behavior of multi-vehicles at signal intersections. The objective of the optimization is to reduce the number of stopped vehicles bypassing the stop line. Lazar et al.[129] proposed the CACC for multiple vehicles waiting at a red traffic light, thus starting to accelerate in a coordinated manner after the traffic light turns green. This coordinated initiation allows more vehicles to pass through the intersection during the green light window compared to manual driving. A decentralized CACC using V2X has been proposed in [116]. The algorithm improves traffic efficiency and throughput at intersections by reorganizing the vehicles around the intersection to pass as a platoon. Bie and Qiu[130] proposed a CACC algorithm that divides vehicles into connected vehicle platoons while maintaining the highest traffic throughput and the lowest disruption to mainstream traffic.

In summary, research has demonstrated that combining signal light information and traffic flow to predictive cooperative control of multi-vehicle can significantly improve urban transportation efficiency. Additionally, ICV penetration rate has a profound impact on energy consumption and efficiency improvements. Researchers will study how to integrate rich road traffic information and develop more efficient strategies for multi-vehicle formation in the future. By integrating rich road data, sensing, and processing information about road traffic conditions in real-time, the cloud platform supports multi-vehicle formation decisions, as well as achieving a larger and more efficient objective for road access. In the future, research will focus on the combination of multi-vehicle collaboration at intersections and the cloud platform.

4.4 Predictive merge control at ramp junction

Urban and suburban expressway ramp entrances are also typical scenarios of predictive planning and control. By predicting the traffic situation and coordinating the vehicle trajectory around the ramp zone, driving safety and traffic efficiency can be significantly improved, and fuel consumption and emissions can be further reduced[131]. Predictive planning and control methods for ramp merge zones can be divided into centralized and decentralized[132]. The centralized predictive planning strategy uses the central controller to collaboratively optimize the optimal trajectory of each vehicle passing the ramp junction with the goal of global optimality. The decentralized uses the obtained vehicle state information on the ramp and the main road to optimize the driving trajectory of the ego-vehicle, respectively. Two typical centralized and distributed merging strategies are shown in Figs. 5 and 6.

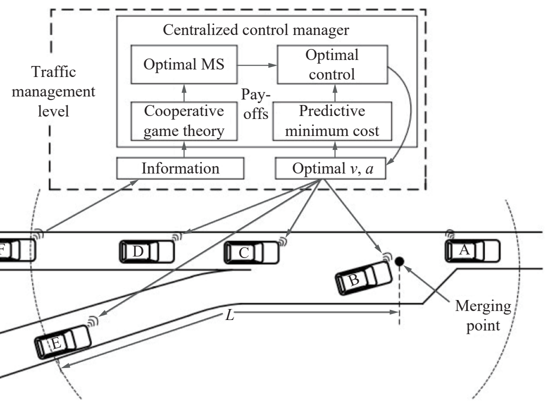


Fig. 5 Typical centralized architecture of ramp predictive planning strategy[133]

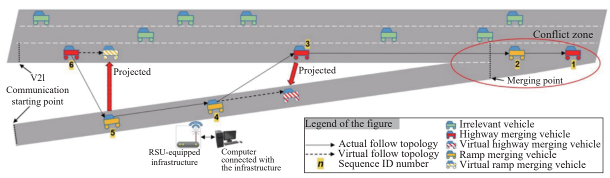


Fig. 6 An illustrative example of decentralized predictive planning on ramp merging zone[134]

In centralized strategies, the optimal control problem is often constructed as a global state optimization problem for all vehicles on the ramp and main road. Rios-Torres and Malikopoulo[135] planned the merging trajectory of vehicles by constructing an unconstrained ramp merging optimal control problem and derived its analytical solution using Pontryagin′s minimum principle. Pei et al.[136] proposed a DP-based efficiency calculation method for quickly solving the optimization problem of vehicle sequence in ramp merge zones. The simulation results demonstrate that the complexity of the algorithm is reduced while the global optimality is enhanced. Jing et al.[133] formulated the cooperative game as a globally optimal merging problem to minimize the global payoff. Then, the problem is decomposed into a multi-layer game event, and the optimal merging sequence is determined by predicting the minimum cost of merging behavior under different strategies. Ding et al.[137] proposed a rule-based coordination algorithm to solve the problem of the optimal merging sequence with an approximate optimal solution. Liao et al.[138] built a digital twin model of ramp cooperative control. The model is verified by vehicle-cloud communication. The results show that compared with the benchmark model without speed guidance, it significantly improves the safety and fuel saving of ramp entry.

Although the centralized strategy can perform global optimization, the computational burden of the whole system is large. When the traffic flow is large, and the number of lanes is large, it is difficult to guarantee the characteristic of high real-time. In the distributed planning strategy, the controlled vehicle plans its own trajectory by sensing the state information of the surrounding vehicle. Wang et al.[139] proposed a distributed collaborative planning method. After the sequence arrangement of vehicles in the ramp control area, the speed and position of the ego vehicles are controlled based on the distributed consensus-based merging method, which realizes safe and efficient merging. Furthermore, the team verified the ramp collaborative fusion system by building a 3D Unity virtual simulation platform and compared it with the hardware-in-the-loop of human drivers, which fully verified the superiority of the system[134]. In addition, Liao et al.[140] also used Unity to perform simulation validation of a game theory based ramp merging strategy by building a unity-SUMO integrated platform. In addition, in order to improve the control accuracy, the MPC method is introduced into the trajectory planning problem. In view of the fusion sequence determined by the distributed architecture, Ntousakis et al.[141] optimized the optimal trajectory of each vehicle in the fusion region and corrected the existing signal disturbance by the MPC method. Compared with the trajectory optimization model of ACC, the advantages of the proposed method were verified.

In order to make full use of the advantages of decentralized and centralized control methods, some scholars have begun to design some hybrid systems and have practiced in multi-lane scenarios. Xiao and Cassandras[142] firstly performed a global sequence arrangement for all vehicles in the ramp area based on the FIFO principle. Then, based on the distributed principle and merging order, the driving trajectories of all ego vehicles are calculated by constructing an optimal control problem with the goal of minimizing travel time and energy consumption. In [143], a hybrid control system combining centralized and distributed control was designed for the coordination between the main road and ramp vehicles. The system divides the space on the main road of a multi-lane expressway into moving slots, and the vehicle merging problem is transformed into the allocation of vehicle slots.

To sum up, many scholars have made a lot of contributions to the predictive planning and control of on-ramp merging in recent years. However, most of the problems have been simplified, and the control of on-ramp convergence considering multi-lane and mixed traffic needs to be further developed. In addition, most of the verification methods either only perform offline simulations of software or perform hardware-in-the-loop in real environments, and there are relatively few methods that can be verified in real traffic.

5 Typical applications of ICVCCS-based PCC

5.1 General architecture of ICVCCS-based PCC

The efficient operation of predictive cruise systems needs the support of road maps and computing power. The cloud platform has powerful computing resources to meet the real-time operation of the system. In addition, the cloud platform can be interconnected with the map server, and the map call and update are convenient. Therefore, with the development of wireless communication technology, the design of the system architecture using cloud platforms is considered an important solution for further development of the PCC system.

Based on the PCC research cases in different scenarios investigated above, some scholars have tried to optimize the PCC system by using the vehicle-cloud two-layer structure. Li et al.[8] proposed an energy-saving cruise system based on the cloud control system. The cloud platform performs high-intensity computing power, and the vehicle platform performs command control, thus realizing the full utilization of the advantages of the vehicle-cloud. The real vehicle experiment proves the feasibility and effectiveness of the system architecture. Likewise, Ozatay et al.[64] also place intensive computing in the cloud. The cloud calculates the optimal speed according to the destination set by the vehicle. The test results show that the system can achieve 5%–15% fuel savings compared to the benchmark system.

In short, the hierarchical architecture is basically used to reconstruct the PCC system. The PCC algorithm is arranged in the cloud to realize the fast operation of the algorithm and map service. Then, the predicted optimal control sequence is sent to the vehicle by wireless communication. The vehicle side analyses and controls the control sequence to achieve safety, energy-saving, and efficiency.

By analyzing the functions of vehicle-cloud in the existing literature, the hierarchical architecture of the PCC system is proposed based on the concept of the cloud control system, as shown in Fig. 7. Based on the ICVCCS architecture, the predictive cruise system is split according to the cloud control base platform (CCBP) and application platform (CCAP). In addition, in the cloud control platform, PCC needs a real-time operation, so it is arranged on the edge cloud with high real-time operation. CCBP mainly provides map services for the PCC system, including a static map and a local dynamic map. It should be noted that due to the changeable traffic state, the edge cloud needs to monitor the real-time road traffic situation according to the roadside sensing unit and generate a local dynamic traffic map. Different types of PCC algorithms are arranged in CCAP, such as predictive fuel-saving control, multi-vehicle collaborative control, and predictive speed planning at intersections. These algorithms call the required map information from CCBP in real-time as needed. CCAP sends the calculated optimal control strategy to the vehicle through wireless communication based on the edge cloud to realize the hierarchical PCC of the vehicle-cloud.

5.2 Predictive energy-saving cruise control

Road slope is widely used in PCC. This section briefly introduces the design of a cloud-based predictive energy-saving cruise control system (CPCC) based on the ICVCCS architecture for energy-saving driving. In addition, in order to verify the effectiveness of the system, real vehicle experiments with a total of more than 6 000 km are carried out by using trucks with different weights.

The realization of the CPCC system needs to analyze the function between vehicle and cloud reasonably in order to ensure the effective use of their respective advantages. The strengths of a cloud control platform (CCP) are that it has powerful computing and data integration abilities. In addition, CCP can provide convenient and real-time updated map services. Therefore, it would be a great solution to deploy the energy-saving cruise (ESC) algorithm and map in CCP. The vehicle platform mainly parses the control commands sent by the cloud and monitors the cruise state based on state transition conditions constantly. The schematic diagram of the vehicle-cloud layered architecture is shown in Fig. 8.

The ESC algorithm calculates the optimal speed for future driving by obtaining road slope information from the map dataset. Then, the speed command is sent to the vehicle side via the 4G/5G network. After receiving the information in the cloud, the Telematics BOX (T-BOX) is analyzed and sent to the power system controller to realize the speed following control. Moreover, the real-time running data of the vehicle is also synchronously uploaded to the cloud to realize the closed-loop iterative control.

The test road is 36 km from the Yiyuan to Zhuge service area on the G22 freeway in Shandong, China. The system server is located in Beijing. The change of road el-

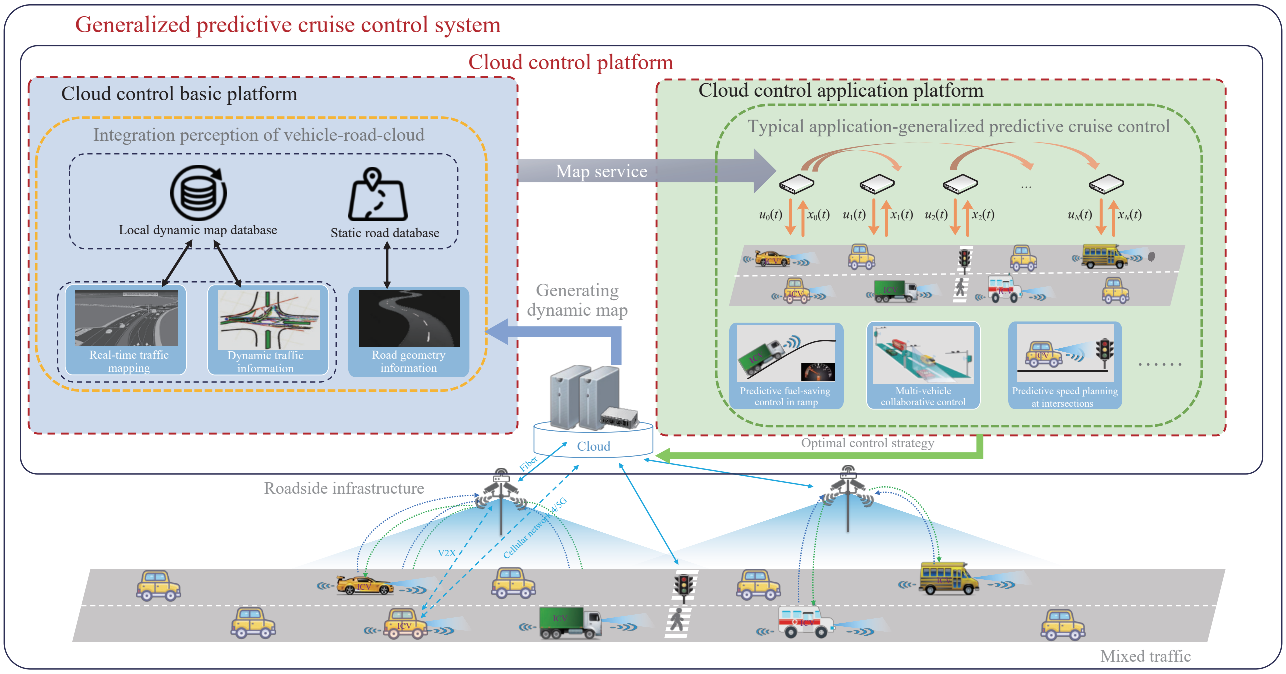


Fig. 7 General architecture of the predictive cruise system based on cloud control

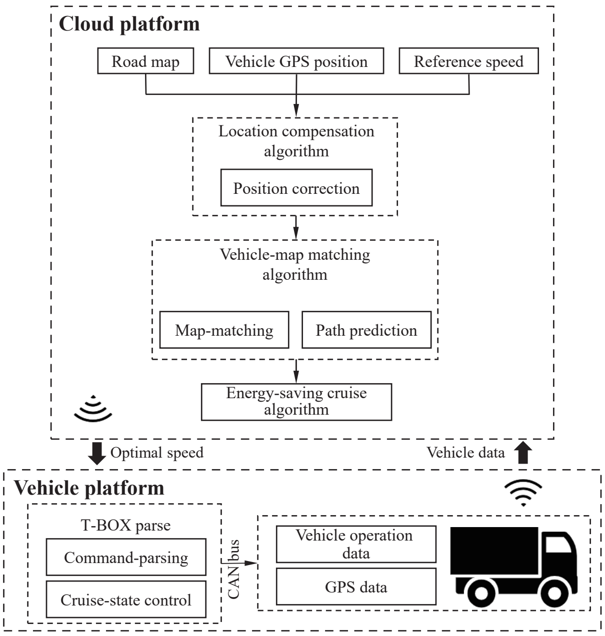


Fig. 8 Schematic diagram of cloud-based predictive energy-saving cruise control system

evation is shown in Fig. 9, which can meet the slope requirement of the algorithm test.

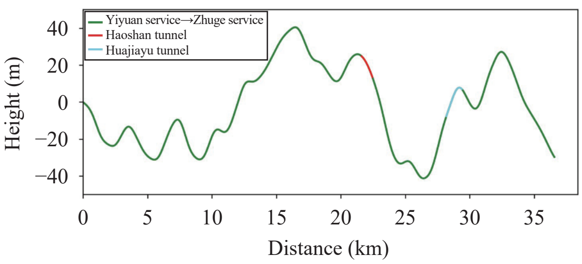


Fig. 9 Height variation of the experimental road

Due to the large amount of experimental data, this section only shows some test results of 49 tons of heavy trucks, as shown in Table 1.

The experimental results show that the fuel-saving rate of the proposed CPCC system is 2%–6% compared with CC, with little difference in travel time, which verified the reliability and validity of the CPCC system.

5.3 Predictive lane-changing control of the platoon

For the predictive lane-changing control of the platoon in the freeway scene, a vehicle-cloud layered control strategy is designed: The cloud is the decision-making layer. Based on the long-term prediction of real-time traffic conditions and the platoon operation status, the longitudinal speed and lateral lane-changing strategies are generated, then send them to the platoon; the platoon is the execution layer. The trajectory planning and tracking control are carried out in accordance with the cloud's strategy, and the platoon's movement status is uploaded, forming a closed-loop vehicle-cloud collaborative control.

Table 1 Partial experimental results

Mode	Item	Distance (km)	Time (s)	Fuel consumption (L)	Fuel-saving rate (%)
CPCC	1	36	1 833	14.572	−2.45
	2	36	1 822	14.168	−5.16
	3	36	1 811	14.042	−6.00
	4	36	1 851	14.309	−4.22
	5	36	1 841	14.302	−4.26
	6	36	1870	14.044	−5.99
CC	Average value	36	1 845	14.938	Baseline

The platoon's predictive lane-changing control system has two communication topologies: the communication topology between the platoon and the cloud and the communication topology within the platoon. The communication topology between the platoon and the cloud adopts the direct-connected star topology, which is used to upload the platoon's movement status in real-time and send cloud decision-making. The communication topology within the platoon is the predecessor-leader following topology, which is used for platoon control.

To verify the proposed predictive lane-changing algorithm, a two-lane condition is designed. As shown in Fig. 10, the left lane is the fast lane with a speed limit of 120 km/h, and the right lane is a slow lane with a speed limit of 100 km/h. There is a slow car (blue car) 800 meters ahead of the controlled platoon (yellow car), and it gradually affects the driving of vehicles behind it.

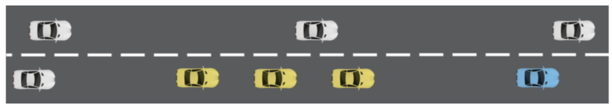
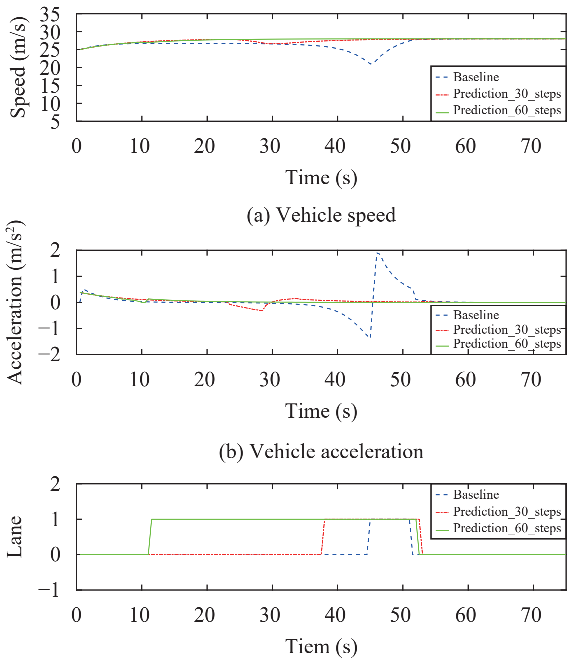


Fig. 10 Simulation conditions

The designed working conditions are simulated using the microscopic traffic flow simulation software SUMO, and the simulation step is 0.5 s. The predictive lane-changing algorithm was compared to a baseline using the IDM car-following model and the LC2013 lane-changing model[144]. Among them, the sampling interval of the predictive lane-changing algorithm is 0.5 s, and the performance of prediction 30 steps and prediction 60 steps are tested, respectively. The speed, acceleration, and lane of the leader of the platoon are shown in Fig. 11.

In Fig. 11, the blue dotted line represents the platoon using the IDM car-following model and the LC2013 lane-changing model, the red dot-dash line represents the platoon using the predictive lane-changing algorithm with a prediction horizon of 30 steps, and the solid green line



(a) Vehicle speed

(b) Vehicle acceleration

(c) Vehicle lane

Fig. 11 Simulation result diagram

represents the platoon using the predictive lane-changing algorithm with a prediction horizon of 60 steps. The speed and lane curve shows that due to the influence of the slow vehicle ahead, the platoon that does not use the predictive lane-changing algorithm will have a greater speed attenuation. The platoon using the predictive lane-changing algorithm can predict the impact of the slow vehicle on the platoon, implement acceleration/deceleration, and lane change in advance, the speed is basically not attenuated, and the driving efficiency is higher. From the acceleration curve, it can be seen that the platoon's acceleration with the predictive lane-changing algorithm changes more smoothly, providing better driving comfort and being more friendly to the surrounding traffic flow environment.

5.4 Predictive cruise control at signalized intersections

For predictive cruising of cloud-based signalized intersections, the designed traffic signal system needs to upload phase and timing information to the cloud in real-time, which is different from the previous literature that uses V2I technologies to transmit SPaT information to vehicles. We believe that vehicle decision-making and planning functions should be moved to the cloud and that SPaT, which is useful for driving at signalized intersections, should also be uploaded there. Furthermore, the road information (e.g., road grade, speed limit) provided by the high-precision map and the self-vehicle information uploaded by the ego vehicle are also essential in the velocity planning process. In the cloud, we also need to utilize the traffic status changes sensed by the roadside devices and the surrounding vehicle information, which is beneficial for us to predict queuing situations at intersections. After weighing the multi-objective optimization, the cloud will eventually issue the optimal vehicle trajectory to the ego vehicle, which will be tracked by the driver or vehicle control system.

Following the development of a predictive cruising framework for urban continuous signalized intersections based on the cloud control system, a simulation scenario of passing through three consecutive intersections was built, as shown in Fig. 12. Combined with the characteristics of the IDM car-following model, a queue length prediction model is proposed based on the traffic shockwave theory, which calculates the queue length, the farthest distance of the queue, and the queue dissipation time[120]. The queue dissipation time is equivalent to the red-light phase time extended by the corresponding length, taken into account in our velocity planning algorithm. Taking electric vehicles as the research object, we combine longitudinal vehicle dynamics, energy consumption model, and braking energy recovery strategy to solve the optimal vehicle velocity profile using the DP algorithm.

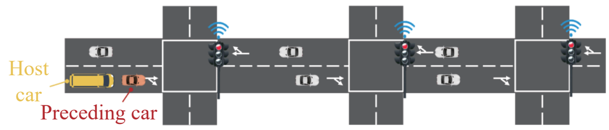
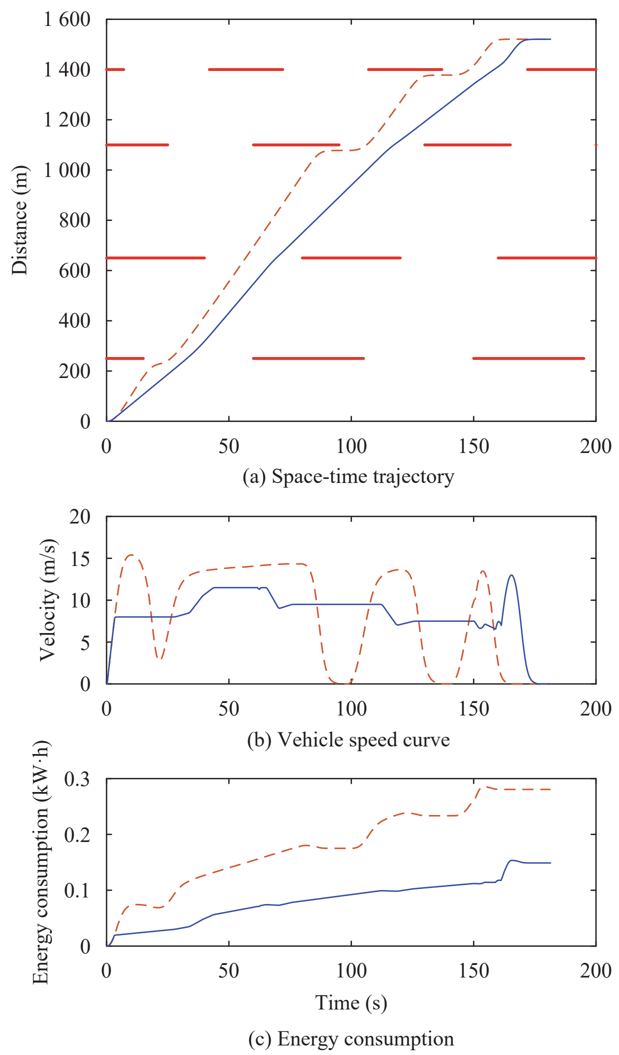


Fig. 12 Simulation scenario diagram

A scene where an environmental car is driving in front of the controlled vehicle is designed, and the speed planning based on DSRC technology (300 m communication distance) is compared with our proposed cloud-based predictive cruise control, as shown in Fig. 13.

It can be seen from Fig. 13 that the proposed PCC algorithm accurately predicts the queuing situation at the intersection ahead. Through the prediction of the dissipation time, the interference of the queue to the ego vehicle is effectively avoided. Benefiting from the planned velocity profile by acquiring SPaT information, the CCS-based car controls the speed tracking to 10 m/s or less without causing too much speed fluctuation. The planning result avoids unnecessary hard decelerations/accelerations before and after the stop line, just like the driving trajectory exhibited by the preceding car, which is the main reason for the huge energy consumption. The DSRC technology, on the other hand, cannot predict the changes in traffic state and provide information to the vehicle about the traffic dynamics; therefore, the DSRC-based car inevitably follows the queue due to the stagnation of the preceding car. Ultimately, as shown in Table 2, the vehicle based on cloud-supported PCC saves 60.02% energy consumption compared to the preceding vehicle and 43.97% energy consumption compared to the vehicle using DSRC vehicle-road collaboration technology.



(a) Space-time trajectory

(b) Vehicle speed curve

(c) Energy consumption

Fig. 13 Simulation results of three continuous intersections

Table 2 Performance on all vehicles

Comparative object	Travel time (s)	Waiting time (s)	Cost (kW·h)
CCS-based	140.8	–	0.110 5
DSRC-based	137.6	2.7	0.197 2
Preceding car	137.4	29.5	0.276 4

Moreover, it significantly reduced intersection waiting time and congestion.

6 Outlook and future trends

6.1 PCC in freeway scenarios

Useful and predictable road traffic information is the key to improving the decision-making, planning and control effect of the PCC system. The relatively stable change of vehicle behavior and driving state on the freeway is the primary scenario for PCC to demonstrate its capabilities. The road geometry information contained in the static map data has been fully incorporated into the PCC. However, in actual vehicle operation, various real-time dynamic traffic information, such as traffic flow, ambient vehicle driving states, and accidents, have a substantial impact on PCC, but PCC has not completely exploited these data. Therefore, in the future, it is necessary to extensively study the impact of dynamic traffic environment on PCC. Furthermore, the strategy of PCC, obtained by using static map information, is adjusted in real-time based on time-varying dynamic traffic. There are some specific optimization scenarios, such as overtaking driving based on global traffic state, optimal lane selection, optimal speed planning based on traffic flow prediction, etc.

However, as the information applied to PCC becomes increasingly comprehensive, the design of PCC algorithms becomes more complex, which poses a great challenge to the performance of the on-board controller. Therefore, it is necessary to combine artificial intelligence, cloud computing, wireless communication, and other technologies to provide more reliable and rapid support for the operation of the PCC system, which will be a new subject to study how to apply these technologies to PCC systems.

6.2 PCC in urban traffic scenarios

First, the single-vehicle driving control should be extended to the full road traffic system with the purpose of maximizing traffic efficiency. Therefore, multi-vehicle and traffic signal cooperative control will be essential research fields. Second, new energy vehicles, with more advanced connected technologies, are an important carrier and more urgent demand side for predictive energy-saving driving. Due to the limited capacity and cost of on-board power batteries, it is difficult to support a higher level of driving range. While based on the intelligent connected technologies, the predictive cruise enables a longer driving range equivalently without increasing the cost of a single-vehicle battery, which is obviously of great value to the high-efficiency and energy-saving goals for future intelligent vehicles and intelligent transportation. Consequently, urban energy-saving driving should be tilted from research on traditional fuel vehicles to new energy vehicles. Third, the promotion of ICV is crucial for PCC. More precise vehicle speed control brings better energy-saving effects, and a higher ICV penetration rate will lead to higher system gains, which has been verified in [120].

Finally, we would like to point out that the cloud control system can better support us in realizing the decision-planning-control of vehicles in urban traffic scenarios. The cloud platform can not only sense the changes in traffic state at several future intersections, but also collect information about surrounding vehicles. This way of real-time information mapping will help us to accurately predict the variety of traffic flows and then adjust our driving strategy. At the same time, the powerful computational scheduling capability of the cloud platform will help us to use more complex optimization algorithms, handle more dynamic information about vehicles, coordinate conflicts with surrounding vehicles, and guarantee the safety of service vehicles. Therefore, our subsequent research will be carried out in conjunction with the cloud control platform to a greater extent.

6.3 PCC based on ICVCCS

The design goal of the cloud control system is to realize interconnection and collaborative control by integrating intelligent transportation with intelligent vehicles. The cloud control platform not only solves the difficulties of limited vehicle prediction range and real-time calculation, but also greatly reduces the hardware cost of vehicle terminals. In addition, in the three-tier four-level cloud control architecture, the edge cloud, the regional cloud, and the central cloud can realize different predictive cruise system functions. For example, the edge cloud can support the cruise control of vehicles in a small range, the regional cloud can realize the collaborative predictive cruise of large-scale multi-vehicle groups, and the central cloud can manage the data of PCC users and optimize the PCC algorithm based on the historical PCC data. Therefore, it is foreseeable that the ICVCCS-based PCC will be an inevitable trend and will be used as an important auxiliary application for high-level autonomous driving.

7 Conclusions

This paper provides a comprehensive and systematic review of the research methods and advances related to predictive cruise control of vehicles in freeway and urban traffic scenarios. Based on the principle of cloud control systems, the general architecture of cloud-controlled predictive cruise control is proposed, and three typical applications are introduced. A summary is as follows.

1) PCC problems are often modelled as optimization problems with predictive information as a dynamic and static constraint. Due to the complexity of the problem, only numerical solutions can be taken, and commonly used solutions include DP, PSM, MPC, RL, HA, etc.

2) The use of static road information for predictive cruise control in highway scenarios can mostly be done in real-world experiments and can be promoted in the industry. However, for driving behaviors that require PCC planning using dynamic traffic information, such as following and lane changing, the models constructed suffer from many assumptions and simple considerations due to the unpredictability and complexity of the traffic state, and therefore only exist in the simulation stage, with few people having completed real-world testing and verification. For platoon PCC research, the difficulty lies in balancing optimal predictive driving and platoon stability control, and there are also problems with heterogeneous platoons that are difficult to model. A hierarchical control architecture is often used, with decision-making, planning and control effect at the top and platoon stability control at the bottom.

3) In urban traffic scenarios, PCC is used at intersections and ramps. At signalized intersections, the green wave passing is mostly used as the main control objective, taking into account factors such as queue length and dissipation time, traffic flow density, surrounding vehicle status, etc. The problems are similar to those of the highway scenario, where the unpredictability of the traffic environment limits the effectiveness of the control. Predictive cooperative control of multiple vehicles using traffic information at signalized intersections can further improve the efficiency of urban traffic, but cooperative multi-vehicle control strategies are still a difficult problem. At the ramp, PCC studies the predictive optimal ramp merging problem. At present, it is often studied in accordance with the strategy of collaborative control, which is divided into centralized, distributed, and hybrid method. The difficulty lies in solving the cooperative control strategy under a large number of lanes, different permeability, and traffic density.

4) The general architecture of PCC based on ICVCCS is proposed and three typical applications, such as energy-saving, lane-changing, and speed-planning at intersections, are given. The effectiveness of the proposed method is verified by real vehicle experiments and simulation tests. Based on those examples, the advantages of ICVCCS-based PCC are demonstrated, and new ideas for the development of PCC are given.

Acknowledgements

This work was supported by the National Key Research and Development Program, China (No. 2021YFB2501000).

Declarations of conflict of interest

The authors declared that they have no conflicts of interest to this work.

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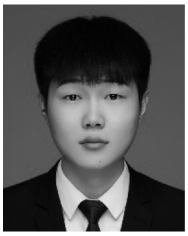

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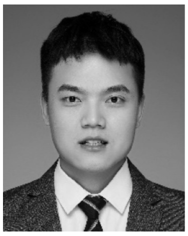

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