Leader-follower Optimal Control Method for Vehicle Platoons to Improve Fuel Efficiency

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***Abstract*—The automotive industry has experienced swift development with the rapid growth of the economy. The increasing number of vehicles has led to deteriorating road traffic conditions, increased consumption of nonrenewable energy, and excessive vehicle emissions. To tackle the problems of fuel efficiency and safety control for vehicle platoons, this study suggests a novel leader-follower optimal control method for vehicle platoons to improve fuel efficiency. Depending on where vehicles are in a platoon, they are classified into two categories: the leader vehicle and follower vehicles. The differing driving circumstances of these two types of vehicles are considered in this paper by using various control methods. On the one hand, the leader vehicle uses an approximate fuel consumption model to improve computational efficiency. At the same time, speed and acceleration are constrained to obtain the speed optimization curve. The follower vehicle uses a distributed receding horizon control method, which calculates the vehicle's speed optimization profile online. On the other hand, a linear following model is used to prevent collisions between vehicles and ensure the safety of the vehicle platoon. The simulation experiment has demonstrated that this speed optimization control method can reduce the fuel consumption of the vehicle platoon and ensure the safety of the vehicles.**

Keywords—Vehicle platoon speed optimization control; leader vehicles; follower vehicles; distributed re-ceding horizon control method; vehicle platoon fuel consumption control

I. Introduction

In recent years, all industries have experienced swift development with the rapid growth of the economy. The automotive industry is no exception. According to the Ministry of Public Security, by the end of March 2022, the number of motor vehicles in the country was expected to reach 402 million, including 307 million cars. Moreover, this growth projected 487 million motor vehicle drivers, including 450 million car drivers [1]. The increasing number of vehicles has led to deteriorating road traffic conditions, increased consumption of nonrenewable energy, and excessive vehicle emissions [2]. A typical approach to addressing these problems is to accelerate the development of intelligent transport systems, and vehicle platoon control technology has received widespread attention as an important component of these systems [3].

One useful means to address to improve fuel efficiency problem is to control vehicles in a common lane to run in platoons with small inter-vehicle spacing. Arranging vehicles into a queue with a smaller distance between vehicles can effectively improve traffic flow efficiency and reduce traffic congestion. At the same time, this strategy can also decrease the air resistance of vehicles in the vehicle platoon to reduce vehicle platoon fuel consumption and exhaust emissions. The coupling between vehicles during vehicle platoon operation is readily apparent, and vehicle platoon fuel consumption is greatly influenced by air resistance. Thus, appropriately controlling vehicle platoon speed can significantly reduce vehicle fuel consumption [4].

Platoon speed optimization control methods involve the use of advanced control algorithms and techniques for real-time monitoring and control of platoon speed. Common implementations of optimal platoon motion control include traditional proportional-integral-derivative control (PID), model predictive control (MPC), fuzzy control (FC), adaptive cruise control (ACC), rolling horizon control (RHC), and other methods. In addition, artificial intelligence techniques such as machine learning can be used to analyze and process the movement data of vehicles in a platoon, thereby improving the accuracy and efficiency of control. The platoon motion optimization control method has a wide range of promising applications in the fields of vehicle manufacturing and autonomous driving technology.

The remaining part of this paper is organized as follows: Section II briefly covers the related work. Section III is an introduction to the relevant models, including the fuel consumption model and the linear-following model. In Section IV, a leader-follower vehicle speed optimization control method for the vehicle platoon is given to reduce the overall fuel consumption of the platoon. This method includes two parts: the pilot vehicle speed optimization control method and the follower vehicle speed optimization control method. Section V presents the simulation validation and analysis. The practicality and effectiveness of the method are verified under simulation experiments and comparisons with other methods. Section VI presents the contributions and conclusions of this study.

II. Related Works

Initial research on fuel consumption-oriented speed optimization control methods focused on speed optimization control methods for a single vehicle. Many scholars have focused their attention on the influence of the road environment on vehicle fuel consumption. Regarding the study of fuel consumption of vehicles at signalized intersections, Xiaolin Tang et al. [5] proposed a multiobjective hierarchical optimal (MOHO) strategy by building a road model based on the real phase and position information of traffic signals. This strategy can improve passenger ride comfort and fuel economy. According to Ding Feng et al. [6], the established vehicle dynamic model and an instantaneous fuel consumption model can yield the ideal constant speeds corresponding to circular curves of various radii. Jiaqi Ma [7] et al. proposed a fuel consumption optimization method for connected and automated vehicles (CAVs) on rolling terrains. This method is based on established vehicle dynamics and fuel consumption models. The newly developed algorithm was validated on a CVA platform, and the eco-drive's fuel-saving benefits were quantified.

As vehicle fuel consumption is closely related to aerodynamic drag [8], controlling vehicles to run in platoons with small intervehicle spacing in a common lane is reasonable. In fact, this approach can effectively reduce the fuel consumption of a platoon. Multiple studies [9-12] have shown that platooning can reduce fuel consumption.

In recent years, many scholars have focused their attention on the issue of vehicle platoon control. There are currently many control methods concerning vehicle platoons. The choice of vehicle In recent years, many scholars have focused on the issue of vehicle platoon control, and man control methods are currently available for vehicle platoons. The choice of vehicle control method usually depends on the specific control objectives, constraints, and environmental factors. Common control models include proportional-integral-derivative control [13, 14], adaptive cruise control [15, 16], and model predictive control [17-20]. These control methods have been extensively researched to reduce platoon fuel consumption. Communication delays will reduce the robustness of the vehicle platoon. Xu Zhu et al. [21] designed a distributed proportional-integral-derivative con-troller to improve the robustness of the vehicle platoon by obtaining strong stability conditions and upper bounds on communication delays. Cooperative adaptive cruise control (CACC) vehicles can improve the stability of the vehicle platoon and reduce emissions and fuel consumption. Yanyan Qin et al. [22] investigated the correlation between these two factors. Stability conditions for the vehicle platoon are calculated using car-following models to explore the relationship between stability and emissions. RHC and MPC are two methods based on predictive control, with the main difference being the design of the controller and how it is calculated. MPC achieves high-precision control of the system state by building a dynamic model of the system and using optimization techniques to solve for the state and control signals over several future time steps. RHC achieves high accuracy in the control of the system state by decomposing the control problem into a series of subproblems and solving each subproblem using a predictive model. Valerio Turri et al. [23] proposed a method that can dynamically calculate the optimal speed profile based on the fuel consumption of the vehicle platoon and enable real-time control of the vehicle platoon based on the DMPC method. In Chunjie Zhai et al.'s study [24], an ecological cooperative look-ahead control problem (Eco-CLC) based on distributed model predictive control (DMPC) was presented. The study addressed an autonomous vehicle platoon travelling on highways with varying slopes. Moreover, a particle swarm optimization approach with numerous dynamic populations increases computational efficiency. To improve the fuel economy of a parallel hybrid electric vehicle (HEV), Bo Zhang et al. [25] formulated a receding horizon control problem based on a cost function of energy consumption and optimized it with a sequential quadratic programming algorithm. The results of the simulation platform validate that the pro-posed strategy can improve fuel economy.

Existing efforts to optimize vehicle platoon speed for fuel consumption often focus on setting the speed of the leader vehicle as a reference speed for the follower vehicle and optimizing the speed of the vehicles in the vehicle platoon on this basis. However, adopting a fixed reference speed for the leader vehicle is not reasonable for realistic road conditions. In addition, most of the speed optimization control strategies for vehicle platoons have complex cost functions and additional constraints, resulting in reduced computational efficiency. Therefore, the construction of the optimization problem and improvement of computational efficiency warrant exploration.

To address the aforementioned issues and lower the vehicle platoon's fuel consumption, this study proposes a fuel consumption-oriented vehicle platoon speed optimization control method based on a fuel consumption model. To improve the efficiency of the calculation, a simpler approximate fuel consumption model is used for the pilot vehicle. Because the motion states of the following vehicle are constrained by the vehicle ahead, the follower vehicles use a distributed receding horizon control method. This technology, which is both forward looking and real time, enables the vehicle platoon's ideal speed profile to be forecasted in advance based on the current driving traffic scenario and road environment for fuel consumption.

III. Introduction to Related Models

A. Fuel Consumption Model

The fuel consumption model describes the relationship between vehicle driving and vehicle fuel consumption. Fuel consumption is influenced by the vehicle's performance (such as tractive effort, engine torque, mass, etc.), road features (such as the slope of a road), and traffic circumstances (traffic volume). Fuel consumption models can be broadly classified into three categories according to their form: instantaneous fuel consumption models, mode fuel consumption models, and average speed fuel consumption models. The instantaneous fuel consumption model is based on the relationship between fuel consumption and the instantaneous state of the vehicle. The fuel consumption model used in this study is such a model. The leader vehicle and the follower vehicle operate with different constraints and use different fuel consumption models. The leader vehicle is not constrained by the vehicle in front of it and uses a simpler fuel consumption model, which improves the efficiency of the calculation. Follower vehicles are also subject to more stringent constraints and use a more stringent fuel consumption model to enable the vehicle to travel safely and smoothly.

The fuel consumption model used in this study for the leader vehicle is an approximate fuel consumption model obtained by a quadratic approximation [26] to the Australian Rod Research Board (ARRB) model proposed by Akcelik. A special case of an approximate fuel consumption model is where just the square of the acceleration can be used as a proxy for minimizing fuel consumption. This particular approximate fuel consumption model reduces computational effort and increases computational efficiency. At the same time, the fuel consumption calculated with this fuel consumption model does not significantly differ from the actual fuel consumption. The expression for this parameter is shown below.

$$\tilde{f}(v(t),a(t))=\frac{1}{2}a(t)^2 \qquad (1)$$

$\tilde{f}(v(t),a(t))$ denotes the secondary approximate instantaneous fuel consumption. $v(t)$ and $a(t)$ denote the velocity and acceleration of the vehicle at moment t.

However, when the vehicle is on the road, the fuel consumption of the vehicle depends not only on the acceleration of the vehicle but also on various other factors, such as engine speed, gear ratio, torque, and efficiency. The following approximate fuel consumption model is chosen for the fuel consumption model of the follower vehicle, as the movement ecology of the follower vehicle is more complex than that of the leader vehicle [27]. The fuel consumption model is expressed as follows:

$$f_{i,v}(t)=\begin{cases} b_0+b_1v_i(t)+b_2v_i^2(t)+b_3v_i^3(t)+ & a_i(t)\geq 0 \\ \hat{a}_i(t)(q_1v_i(t)+q_2v_i^2(t)) & \\ 0 & a_i(t)\leq 0 \end{cases} \qquad (2)$$

where b_0, b_1, b_2, b_3, q_0, q_1, and q_2 are parameters of fuel consumption model. When the acceleration $a_i(t)$ is greater than zero, the first part of the expression, $b_0+b_1v_i(t)+b_2v_i^2(t)+b_3v_i^3(t)$, represents the fuel consumption generated per unit time of the vehicle at velocity $v_i(t)$, and the second part, $\hat{a}_i(t)(q_0+q_1v_i(t)+q_2v_i^2(t))$, represents the additional fuel consumption generated by the corresponding equivalent acceleration $\hat{a}_i(t)$ at velocity $v_i(t)$. Moreover, $\hat{a}_i(t)=a_i(t)+a_G(t)$, $\hat{a}_i(t)$ denotes the equivalent acceleration related to the acceleration $a_i(t)$ and the acceleration $a_G(t)$ caused by the ramp. In this study, the ramp of the road is not considered; therefore $\hat{a}_i(t)=a_i(t)$.

B. Linear Car-Following Model

A car-following model uses kinetic theory to investigate the change in motion of followers if the vehicle in front of them changes its motion state when the platoon is driving in a single non-overtaking lane. A mathematical model [28] is also used to create a model that is more consistent with the actual vehicle motion. In a platoon, the leader drives in traffic situations with low traffic density and large workshop distances without being influenced by surrounding vehicles and in a free-motion state. The follower vehicles are affected by traffic rules, the performance of the vehicle, and the surrounding vehicles. To ensure safe driving, the speed of the follower vehicle is adjusted to avoid collisions with the vehicle in front of it; it cannot be driven at will by the driver's intentions and is not in a free-motion state. A diagram of the vehicle platoon's linear car-following model is shown in Fig. 1.

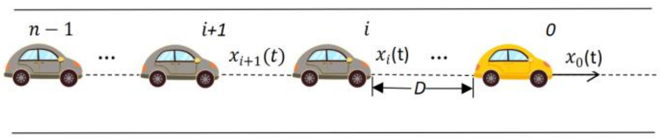

Fig. 1. Schematic diagram of the vehicle platoon's linear car-following model.

The vehicle platoon in Fig. 1 consists of $n-1$ vehicles, and $x_i(t)$ denotes the motion state of the follower vehicle i, $x_i(t)=[p_i(t),v_i(t),a_i(t)]^T$. The motion state $x_i(t)$ contains the position $p_i(t)$, the velocity $v_i(t)$, and the acceleration $a_i(t)$ of vehicle i. D denotes the distance between vehicles.

In the linear car-following model, when the motion of the previous vehicle changes, the motion of the follower vehicles also changes. If the reaction time is h, then the velocity of vehicle $i+1$ at moment $t+h$ can be expressed as:

$$\ddot{p}_{i+1}(t+h)=\lambda\left[\dot{p}_i(t)-\dot{p}_{i+1}(t)\right] \qquad (3)$$

Where $\lambda=\frac{1}{h}$, λ and h denote the response sensitivity and delay time. $\ddot{p}_{i+1}(t+h)$, $\dot{p}_i(t)$ and $\dot{p}_{i+1}(t)$ denote acceleration of the vehicle $i+1$ at time $t+h$, the velocity of the vehicle i and the velocity of the vehicle $i+1$ at time t respectively.

IV. Optimal Control Method of Vehicle Platoon Leading-Following Speed

The speed optimization problem for a platoon can generally be described as follows: given a starting point and an endpoint for each vehicle in the vehicle platoon, the overall vehicle platoon fuel consumption is minimized subject to certain constraints. In this study, a platoon of n vehicles is driven in a single lane for a distance on a road section without overtaking or changing behaviour. The communication topology chosen for this study is the predecessor-leader following type (PLF). This communication topology allows each follower vehicle to obtain information about the motion state of the leader vehicle and the previous vehicle. All vehicles in the platoon are divided into a leader vehicle and a follower vehicle. Different optimal control methods are employed for the leader vehicle and the follower vehicle to reduce the overall fuel consumption of the vehicle platoon along a specific segment of a one-way road. p_i, v_i, and a_i denote the position, velocity, and acceleration of vehicle $i(i=0,1,\ldots,N-1)$, respectively. l_i, d_i, and del_i denote the length of vehicle i, the desired workshop distance, and the error between the actual workshop distance and the desired workshop distance, with vehicle $i=0$ and others being followers. The leader vehicle must reach its final state within a time range of T, where x_e and v_e are the final positions and the vehicle's driving speed, respectively. The time range T is within a reasonable range and can be obtained using constraints.

A. Optimal Speed Control Method for Leader Vehicle

To minimize the fuel consumption of the leader vehicle, the following fuel consumption optimization problem is used to control the leader in this study.

$$\min J_0 = \int_0^T f(v_0(t), a_0(t))dt \quad (4)$$

where J_0 denotes the amount of fuel consumed by the leader vehicle while driving for T hours. $a_0(t)$ and $v_0(t)$ denote the leader vehicle's acceleration and speed at time t. T denotes the total driving time. $f(v_0(t), a_0(t))$ denotes the instantaneous fuel consumption of the leader vehicle. The instantaneous fuel consumption model used in this study is a special case, $f(v_0(t), a_0(t)) = \tilde{f}(v_0(t), a_0(t)) = \frac{1}{2}a_0(t)^2$.

Here, the Hamilton function is used to transform the optimization problem into an extreme value problem and to solve the leader vehicle equation of motion state, which contains the acceleration $a_0(t)$, the velocity $v_0(t)$, and the displacement equation $p_0(t)$, all of which are multiple functions of time t. The expressions are as follows:

$$a(t) = c_1 t + c_2 \quad (5)$$

$$v(t) = \frac{1}{2}c_1 t^2 + c_2 t + c_3 \quad (6)$$

$$p(t) = \frac{1}{6}c_1 t^3 + \frac{1}{2}c_2 t^2 + c_3 t + c_4 \quad (7)$$

Where c_1, c_2, c_3, and c_4 are constants in the equation. These four constants can be solved by known conditions (velocity v_{00}, position p_{00} at the initial moment of the leader vehicle and velocity v_{0e}, position p_{0e} at the end moment) and constraints.

The leader vehicle has certain constraints on speed and acceleration during the actual driving process.

For the safety of the vehicle, the velocity $v_0(t)$ needs to be limited and the speed constraint of the leader vehicle can be expressed as:

$$0 \le v(t) \le v_{\max} \quad (8)$$

To ensure the comfort of the passengers riding in the process of the vehicle, it is necessary to constrain the acceleration of the leader vehicle, and the constraint can be expressed as:

$$a_{\min} \le a(t) \le a_{\max}, (a_{\min} \le 0, a_{\max} \ge 0) \quad (9)$$

Where $v_{\max}$, $a_{\min}$, and $a_{\max}$ are the maximum speed of the vehicle, the minimum acceleration, and the maximum acceleration possible, respectively.

To meet the above condition restrictions, the total duration T of the journey must be within a reasonable range rather than an arbitrary time. If the velocity of the leader vehicle at the initial moment $v_{00} = 0$, the initial position $p_{00} = 0$, the velocity at the end moment $v_{0e} = 0$ and the final position $p_{0e} = X$, where X is a constant and T denotes the total distance traveled by the leader vehicle. If the starting velocity v_{00} and the starting acceleration a_{00} of the leader vehicle are other values, it is still possible to solve for a range of values for the total time T. The equations of states (6) and (7) for the leader vehicle allow the solution of the unknown parameter $c_1 = -\frac{12X}{T^3}$, $c_2 = \frac{6X}{T^2}$, $c_3 = 0$, $c_4 = 0$.

The acceleration for the leader vehicle is a monotonically decreasing function. When $t = 0$, equation (5) takes a maximum value. When $t = T$, the equation takes the minimum value. The range of T values can also be obtained using the acceleration constraint in (9).

$$\begin{cases} T \ge \sqrt{\dfrac{6X}{a_{\max}}} \\ T \ge \sqrt{\left|\dfrac{6X}{a_{\min}}\right|} \end{cases} \quad (10)$$

Similarly, the maximum and minimum values of the vehicle speed can be found in (6). When $t = 0$ or $t = T$, the speed equation takes the minimum value. The maximum point of the function is the maximum value when $t = -\frac{c_2}{c_1}$. Combining this with the velocity constraint, (8) gives a range of values for T.

$$T \ge \frac{3X}{2v_{\max}} \quad (11)$$

Combining (10) and (11) can be obtained from the leader vehicle driving the total time T range of values.

B. Optimization of the Speed of the Follower Vehicles

The fuel consumption minimization problem of the follower vehicles is solved using the distributed receding horizon control method. The time slice of size T_0 is in the time domain of the total platoon driving time T, which is considered the look-ahead domain of the vehicle. At the same time, the look-ahead domain T_0 is divided into M time slices h (h is the reaction time of the follower vehicles). When the optimal control sequences for the follower vehicles in the look-ahead domain are solved, the first step of the optimal control sequences is applied. The dynamic planning diagram is shown in Fig. 2 below.

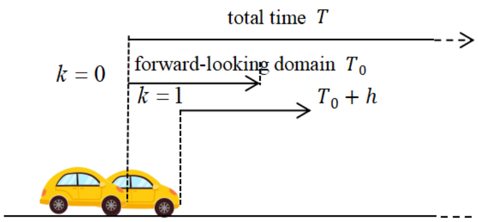

Fig. 2. Follower vehicle dynamic planning diagram based on the distributed receding horizon control method.

The total fuel consumption of the vehicles moving in the forward-looking domain at time T_0 is minimized if the total fuel consumption of each subsequent vehicle is minimized at time T_0. The overall fuel consumption of the vehicles throughout all of the time T is minimized if the total fuel consumption of all the vehicles throughout the for-ward-looking domain T_0 is minimized. Thus, the speed optimization problem based on the combined fuel consumption of the vehicles in front of it can be changed into a speed optimization problem based on the fuel consumption of each vehicle. Eq. (12) shows the total fuel consumption J_1 for all follower vehicles driving T_0. The optimal control problem for single-follower driving T_0 is shown in (13).

$$J_1 = \sum_{i=1}^{n-1} \int_t^{t+T_0} f_{i,v}(x_i(s), u_i(s))ds \tag{12}$$

$$\min F = \min \sum_{i=1}^{n-1} \int_t^{t+T_0} F_i(x_i(s), u_i(s))ds \tag{13}$$

where F_i denotes the cost function of the follower vehicle i, expressed as follows:

$$F_i = \psi_i f_{i,v}(x_i(t)) + \frac{1}{2}\beta_i(u_i(t))^2 + (r_i(t) - y_i(t))^T (r_i(t) - y_i(t)) \tag{14}$$

where the first term relates to the fuel consumption of the vehicle. β_i and ψ_i denote the corresponding weights and are constants. $f_{i,v}(x_i(t))$ denotes the immediate fuel consumption of the follower vehicle i. It is obtained through (2).

$u_i(t)$ is the vehicle's control input in the second period. The nonlinear model [29] was transformed into a linear model by using a linear feedback technique [30]. The computation is simplified. The structural formula is defined as follows:

$$u_i(t) = k_1 v_0(t) - k_2 v_i(t) + k_3 a_0(t) - k_4 a_i(t) \tag{15}$$

Where k_1, k_2, k_3, and k_4 denote various parameters. $v_0(t)$ and $a_0(t)$ denote the leader's velocity and acceleration in a platoon, respectively.

The third term is related to minimizing the difference between the reference output and projected value. The prediction error is assumed to be the difference between the predicted output $y_i(t)$ and the reference output $r_i(t)$. This quantity of feedback is added to achieve feedback correction. $x_i(t) = [p_i(t), v_i(t), a_i(t)]^T$ denotes the motion state of vehicle i in the platoon at time t. $p_i(t)$, $v_i(t)$ and $a_i(t)$ denotes the position, speed, and acceleration of vehicle i at time t. $y_i(t) = [v_i(t), a_i(t)]^T$ denotes the predicted output, including the speed and acceleration of the follower vehicle i at time t. $r_i(t) = [v_{0i}(t), a_{0i}(t)]^T$ denotes the output of the follower vehicles, i.e., the desired speed and acceleration of the follower. It is obtained using the linear following model.

With the PLF communication topology, the leader vehicle can broadcast messages to all follower vehicles. When the motion state of the leader vehicle changes the motion state of all followers also changes. Their reaction times are the same, both being h. The reference speed and acceleration output of the follower vehicle in a platoon at time t can be obtained from the leader vehicle and the current vehicle speed and position at the previous moment, as follows:

$$a_{0i}(t) = \lambda(v_0(t-h) - v_i(t-h)) \tag{16}$$

$$v_{0i}(t) = \lambda(p_0(t-h) - p_i(t-h)) \tag{17}$$

where $\lambda = \frac{1}{h}$, $a_{0i}(t)$, $v_0(t-h)$, and $v_i(t-h)$ signify the sensitivity, the follower vehicle's acceleration at time t, the leader vehicle's velocity, and the follower vehicle's velocity at time $t-h$, respectively. The symbols $v_{0i}(t)$, $p_0(t-h)$, and $p_i(t-h)$ denote the velocity of vehicle i at time t, the position of the leader vehicle, and the position of the follower vehicle i at time $t-h$.

The forward-looking domain T_0 is split into M time slices to numerically solve the optimal control issue. Euler's approach is then used to discretize the vehicle's motion state. A Hamiltonian function is constructed from the equation of the state and cost function of the vehicle. The prediction output equation can be solved according to the control equation, the costate equation, and the state equation. The constructed Hamiltonian function is solved iteratively to provide the predictive motion state equation, as shown in (18).

$$\begin{aligned} &y_{i,k+1}(t) = (A_i h + I_3)^{k+1} x_{i,0}(t) + \sum_{j=0}^{k} (A_i h + I_3)^{k-j} B_i h u_{i,j}(t), \\ &k = 0, 1, \ldots, M-1 \end{aligned} \tag{18}$$

where $x_{i,0}(t) = [v_{0,i}(t), a_{0,i}(t)]$ denotes the current state, and I_3 is a third-order unit matrix.

According to (18), the predicted motion state equation can be represented by the current state information $x_{i,0}(t)$ and the future control sequence $u_{i,j}(t)$ together. The necessary condition for solving the optimal solution of the equation is that the control equation $\frac{\partial H}{\partial u_i}=0$. The optimal control series is obtained by an iterative algorithm. The first step in obtaining the optimal series is then applied as the control input for the next moment of the platoon.

V. Simulink Simulation Verification and Analysis

A. Experiments and Simulink Simulation

Three main methods are available for studying the fuel economy of vehicles: wind tunnel experiments, road experiments, and simulation methods. Among these three methods, wind tunnel experiments provide more accurate control of the influences that affect vehicle platoon fuel consumption. Road experiments are more realistic and reliable. Simulation experiments are more cost-effective, safer, and simpler than the other two methods. Therefore, this study chose to verify the feasibility of the method through simulation experiments.

The vehicle platoon in the simulation experiment consists of ten vehicles. The vehicle platoon traveled $2000m$. The powertrain model parameters of the vehicles are shown in Table I.

TABLE I. Vehicle Powertrain Model Parameters

Vehicle Parameters	Identifier	Data	Unit
Mass	m_i	1464	kg
Air Resistance	ρ	1.29	kg/m^3
Cross-sectional Area	A_i	2.2	m^2
Drag Coefficient	c_{di}	0.35	–
Mechanical Drag	d_{mi}	5	N
Time Constant of an Engine	ζ_i	0.25	–

Set the controller parameters to meet the requirements: $k_1=0.2516$, $k_2=0.51175$, $k_3=0.2601$, $k_4=0.1021$, $M=150$. To ensure the safe movement of the vehicle platoon, according to the speed regulations, vehicles in a platoon should not exceed $50km/h$ on a one-way urban road. Therefore, the speed constraint for the leader vehicle is $0\le v_i\le 13.9m/s$. At the same time, a typical vehicle can currently accelerate from zero to $100m/s$ in $10s$. The average acceleration is $2.2778m/s^2$. The maximum acceleration can be up to $6m/s^2$. As a result, the acceleration of a typical vehicle when braking is $-6m/s^2$. Therefore, the acceleration constraint is $-6m/s^2\le v_i\le 6m/s^2$. According to the literature [23], the acceleration restriction is typically set to $-2m/s^2\le v_i\le 2m/s^2$ to make passengers feel comfortable. The leader vehicle's maximum velocity and acceleration are as stated above. The range of values for the total duration can be deter-mined by combining (10) and (11). This study's total running time is $T=250s$.

Under the direction of the integrated controller, Simulink simulations can be used to determine the acceleration-time curve and velocity acceleration-time curve for each vehicle in the vehicle platoon, as shown in Fig. 3 and Fig. 4. From Fig. 3, it is noticed that that each vehicle in the vehicle platoon will swiftly finish the speed-up. All vehicles' acceleration values fall within the range $-0.8m/s^2\le v_i\le 0.8m/s^2$. The vehicles' consistent acceleration improves the comfort of the passengers. From Fig. 4, the speed of all vehicles satisfies the speed constraint for vehicles traveling on a one-way urban road, which should not exceed $50km/h$. The vehicles in the vehicle platoon converge at the same speed for all vehicles and stabilize within the vehicle platoon at around ten seconds.

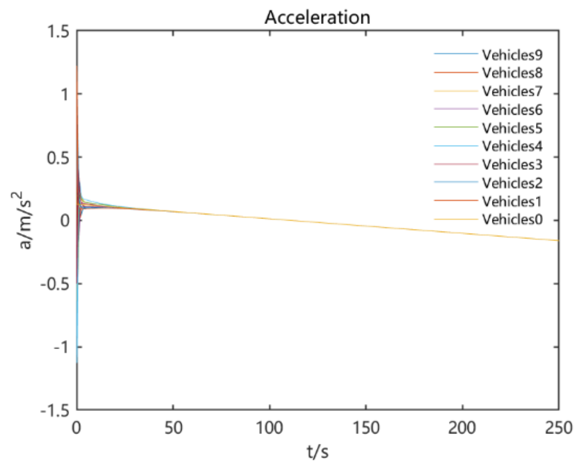

Fig. 3. Acceleration-time curve.

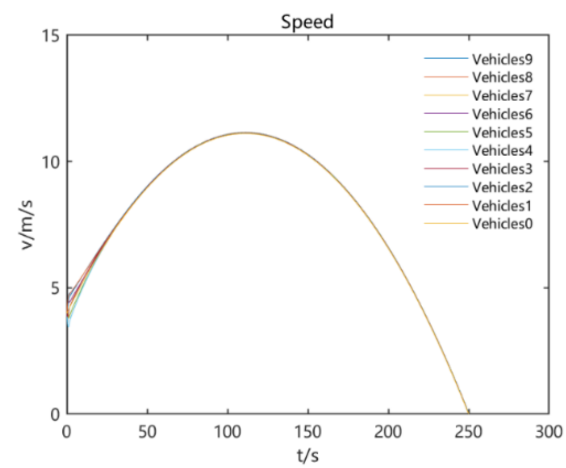

Fig. 4. Velocity-time curve.

For the follower vehicles in the platoon, use the parameters in the fuel consumption model: $b_0=0.1569$, $b_1=2.450\times10^{-2}$, $b_2=-7.4152\times10^{-4}$, $b_3=5.975\times10^{-5}$, $q_0=7.224\times10^{-2}$, $q_1=9.681\times10^{-2}$, $q_2=1.078\times10^{-3}$. The vehicle length is $D=3m$. According to the Road Traffic Safety Law of the People's Republic of China, when the speed is below $50km/h$, the safe distance between vehicles is not less than $50m$. Therefore, this study sets the desired vehicle distance $od_i=60m$. The fuel consumption-time curve for the vehicle platoon is shown in Fig. 5. Compared to other controllers, the vehicle platoon using the controller provided in this study consumes less fuel and saves significantly on fuel consumption. The curve of the workshop distance error over time is shown in Fig. 6, with the maximum workshop distance error not exceeding 8 meters. The workshop distance is still within the safe workshop distance range, ensuring the vehicle platoon's safety.

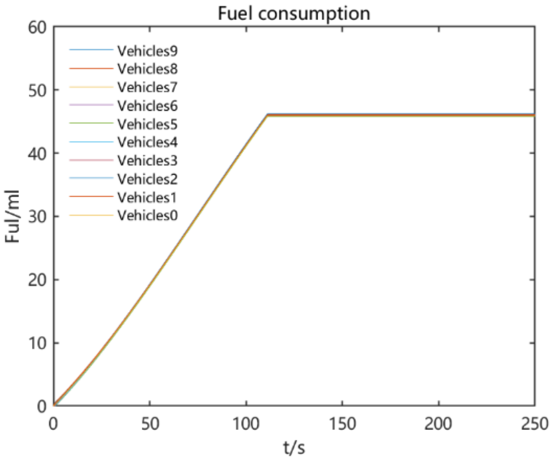

Fig. 5. Fuel consumption-time curve per vehicle.

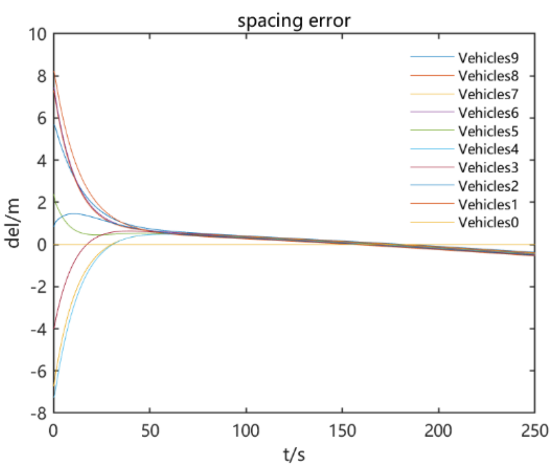

Fig. 6. Workshop distance error-time curve.

B. Analysis and Comparison

The following comparison will focus on five characteristics of the four controllers, including (1) the utilization of vehicle platoon technology. Using vehicle platoon technology, a collection of vehicles is arranged into a platoon beside a workshop. It is essential and of considerable practical value to use the platoon as a focal point for vehicle speed optimization problems because it has major benefits in the four key areas of enhancing traffic capacity, decreasing emissions and traffic accidents, and reducing fuel consumption. (2) The optimization of the speed of the leader vehicle is also considered. The current literature on optimal vehicle platoon speed control often focuses on setting the speed of the leader vehicle as a reference speed for the follower vehicles. Adopting a fixed reference speed for the leader vehicle is not reasonable in light of actual traffic conditions. In this study, speed optimization is applied to the lead vehicle of a vehicle platoon on this basis. (3) The possibility of boosting the computational effectiveness is also considered. Increasing the computational efficiency is crucial since solving fuel consumption-focused speed optimization problems can be computationally taxing due to complex traffic conditions and a large number of moving vehicles. (4) Predictive control is then applied. The vehicle's movement is analysed and processed by predictive control. The speed of the vehicle can be quickly changed when unforeseen circum-stances arise. (5) Lastly, the decision to increase fuel effectiveness is made. Since oil is a nonrenewable energy source, energy usage needs to be decreased. Fuel consumption and vehicle emissions should be lowered. It is essential to increase vehicle fuel efficiency and environmental protection.

In the same simulation environment, the integrated controller in this work is contrasted with the three controllers in the following literature based on five factors. Table II presents the outcomes.

TABLE II. COMPARISON WITH OTHER CONTROLLERS IN TERMS OF FUNCTIONALITY

Characteristics	**this paper**	**Literature [27]**	**Literature [24]**	**Literature [23]**
Using platoon technology	√		√	√
Speed optimization of the leader vehicle	√			
Improving computational efficiency	√	√	√	
Enabling predictive control	√		√	√
Improving fuel efficiency	√	√	√	√

The literature [27] focuses on enhancing the calculating efficiency. While the computations are simplified, significant fuel savings are achieved, but this process applies to a more demanding environment. The literature offers a state-constrained multi-objective switching control approach [24]. In addition to increasing fuel efficiency, it can also increase vehicle stability and safety. The leader vehicle's state of motion is known and used as a reference state for the follower vehicles in this procedure. State limitations are prevalent in the control strategies suggested in the literature [23]. State limitations decrease efficiency and raise computing complexity. By classifying the vehicle platoon's vehicles and streamlining calculations while enhancing computing efficiency, the controller in this study increases the vehicle platoon's fuel efficiency. Due to the lack of vehicles in front of the leader vehicle, it has a relatively simple traffic environment. The leader vehicle fuel consumption model is simplified to improve the efficiency of the calculation. Speed and acceleration constraints are also added to improve the safety of the vehicle. For the follower vehicles, the distributed receding horizon control method is used, which is forward looking and real time.

Vehicle fuel consumption is one of the most important indicators of vehicle fuel economy, reflecting the fuel consumption of the vehicle during the driving process. Vehicle fuel consumption as an evaluation indicator of the method plays an important role in evaluating vehicle performance and energy efficiency. Under the same simulation environment, the fuel consumption of each vehicle in the platoon under the classification controller in this paper is calculated and compared with that under the controllers set up in other literature according to the fuel consumption model, as shown in Fig. 7. The data relating to the total fuel consumption of the platoon under the controllers set up in other literature is analyzed, and the results in Table III show that the reduction in fuel consumption of the platoon under the action of the classification controller is significant.

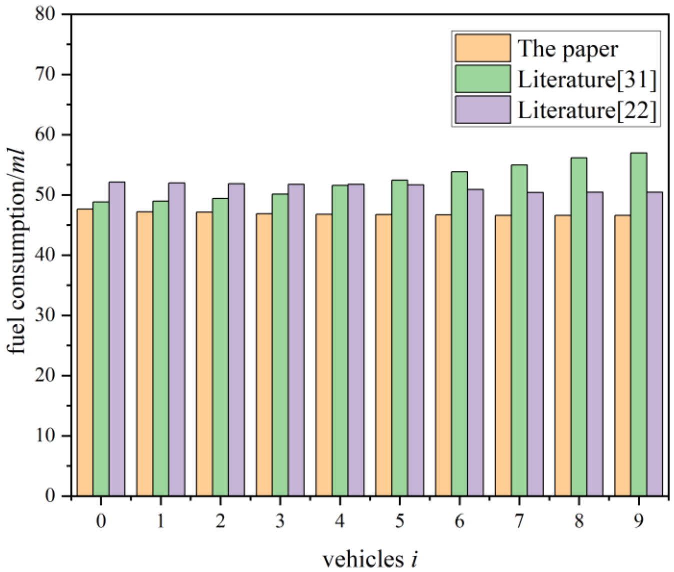

Fig. 7. The fuel consumption of the vehicles in the platoon based on the classification controller in this paper was compared with fuel consumption under controllers set up in other literature.

TABLE III. COMPARISON OF VALUES WITH OTHER CONTROLLERS IN TERMS OF FUEL CONSUMPTION

Fuel consumption	this paper	Literature [31]	Literature [22]
Total value	468.81	523.13	513.29
Average value	46.88	52.31	51.32
Minimum value	46.60	48.81	50.40
Maximum value	47.62	56.91	52.12
Median value	46.76	51.99	51.71
Standard deviation	0.33	3.03	0.70

VI. DISCUSSION

This section includes the main conclusions obtained during the experimentation. Furthermore, future work is included on how to continue the line of research, based on the premises of this article.

A. Conclusion

This paper is mainly oriented toward a vehicle platoon fuel consumption problem and the platoon fuel consumption problem. A novel leader-follower optimal control method for vehicle platoons to improve fuel efficiency is proposed. The vehicles are divided into leader vehicle and follower vehicles according to their position in the platoon and are controlled differently and optimally.

Firstly, the leader vehicle uses a relatively simple fuel consumption model to simplify the fuel consumption model of the vehicle and the optimization problem oriented to fuel consumption, improve the efficiency of the method calculation, and shorten the time for the vehicle to obtain the queue information. The vehicle transmits information about its movement status to other vehicles around it promptly so that the vehicle itself and surrounding vehicles can react accordingly to unexpected situations and reach safe driving purposes.

Secondly, the follower vehicles, being constrained by the vehicle in front, can choose a more complex and accurate fuel consumption model and a more sophisticated speed optimization control algorithm for real-time control based on the motion of the vehicle in front. The follower vehicles use a distributed rolling horizon control method. This method decomposes the global control problem into several local control problems through collaboration between vehicles in the platoon and achieves the global control objective through local control of each vehicle. It solves the optimal speed profile of the platoon online and is more real-time.

Finally, to ensure the safety of the platoon, the speed, and acceleration of the leader vehicle are constrained. The dynamic model of the vehicle queue is combined with a car-following model to ensure the safety of the platoon and a distributed rolling horizon control method to minimize the overall fuel consumption of the platoon.

The method reduces vehicle crashes and enhances vehicle platoon safety. This method has been developed based on experimental and simulation results to in-crease computational efficiency and decrease vehicle platoon fuel consumption. Additionally, the vehicle platoon's general safety is guaranteed.

B. Future Work

Due to the non-renewable nature of energy and the increase in air pollution, fuel consumption-oriented research, whether for vehicles or platoons, has practical significance and a wide range of application scenarios. However, as the actual road conditions are more complex and variable, there is still a gap in the actual application, and the research is not comprehensive enough. Combining the research results of this paper, the following outlook is given for the future research of fuel consumption-oriented vehicle and platoon movement optimization control methods:

1) Further optimisation of the control algorithm: For different vehicle types and driving conditions, more precise and efficient control algorithms should be developed to make the vehicle more energy efficient during the driving process. At the same time, it should be considered that the control method can be applied to roads with gradients, signals, etc. that are closer to reality.

2) Exploring new optimisation strategies: The current approach to optimized motion control is mainly based on model-based predictive control. In the future, more flexible and efficient optimization strategies, such as deep learning-based control methods and neural network-based control methods, can be explored to further improve the efficiency of vehicle and platoon motion and fuel consumption reduction.

3) Enhanced stability control of the platoon: The platoon is more stable and does not transmit this disturbance, which is amplified by the disturbance that occurs in the leader vehicle.

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