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STABLE DRIFT-PLUS-PENALTY COLLABORATIVE TRACKING CONTROL FOR CONNECTED LOGISTICS PLATOONS BASED ON SPEED PLANNING

Yongqiang WANG[1], Fazhan TAO[1], Zhumu FU[1, 2], Longlong ZHU[1]

[1] Henan University of Science and Technology, College of Information Engineering, NO.263 Kaiyuan Road, Luoyang, 471023, Henan, China
[2] Zhongyuan University of Technology, NO.41 Zhongyuan Middle Road, Zhengzhou, 450007, Henan, China
Corresponding author: Zhumu FU, E-mail: fuzhumu@haust.edu.cn
Co-authors: Longlong ZHU, E-mail: zhu_long_long@foxmail.com; Fazhan TAO, E-mail: taofazhan@haust.edu.cn; Yongqiang WANG, E-mail: wang_yong_qiang@foxmail.com.

Abstract. To address the coordinated control problem of safety and comfort for connected logistic fuel cell hydrogen electric vehicles platoons in a vehicle-following environment, a Lyapunov drift-plus-penalty cooperative tracking control strategy based on speed planning is proposed. The designed algorithm is structured into two layers, the upper-layer controller, which aims to optimize energy consumption and comfort, utilizes the sequential quadratic programming algorithm to plan the overall future speed trajectory of the platoon of fuel cell hydrogen electric vehicles, while adhering to constraints on traction force and speed. The lower-layer controller focuses on platoon stability, employing Lyapunov optimization principles to transform the long-term stability control problem into a constrained optimization problem for each time slice. Using the drift-plus-penalty algorithm, the minimum Lyapunov drift and the objective function are resolved to establish the control command for tracking the platoon's position and speed trajectory. The proposed speed-planning-based distributed nonlinear fuel cell hydrogen electric vehicles platoon control strategy achieves low computational cost, enhanced comfort, and improved energy efficiency. Simulation results demonstrate that, compared to existing classical algorithms, the proposed speed-planning-based platoon control algorithm achieves higher computational efficiency, better comfort, and optimal fuel economy.

Keywords: speed planning, tracking control, sequential quadratic programming, Lyapunov drift plus penalty control.

1. INTRODUCTION

With economic globalization and the rapid advancement of e-commerce, traffic safety in logistics transportation has become an increasingly pressing concern, drawing significant attention from both academia and industry [1]. The electrification, automation, and connectivity of logistics fleets are widely regarded as promising solutions to mitigate these challenges, and they have gradually garnered growing interest and investment in recent years [2]. In particular, autonomous driving logistics fuel cell hydrogen electric vehicles (FCHEVs) with speed planning [3] are key technologies for enhancing comfort [4], reducing energy consumption [5], and decreasing traffic accident susceptibility in the future [6]. Nevertheless, developing a control framework that balances the goals of driving comfort, fuel economy, and driving safety remains a highly challenging issue.

In view of the complexity of traffic conditions and driving demands, effective speed planning (SP) methods are essential for achieving energy-efficient and comfortable power allocation in logistics platoons. In unconstrained traffic scenarios, SP has been advanced through techniques such as dynamic programming [3], genetic algorithms [7], Markov chains [8], fuzzy logic [9], and reinforcement learning [10], primarily targeting energy savings and accident reduction. However, developing a unified control framework that balances energy efficiency, driving comfort, and safety remains a significant challenge.

Meanwhile, with the advancement of connected and automated vehicle (CAV) technologies, significant transformations are occurring in the control techniques of vehicles [11]. These technologies optimize information exchange through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, improving road throughput and traffic efficiency, making traffic flow more smoothly [12]. Integrating CAV technology into logistics platoons significantly improves their performance but also introduces new challenges. Ensuring comfort and safety in high-speed autonomous driving, while minimizing energy consumption based on V2V or V2I information, is a crucial and demanding issue. The adaptive cruise control (ACC) system, utilizing V2V or V2I information, can adjust the longitudinal speed of vehicles to ensure a safe distance between platoons [13]. To improve performance in complex environments, adaptive cubature Kalman filtering enhances 3D multi-object tracking under uncertainty [14], while distributed fault-tolerant control ensures robustness against disturbances and sensor failures [15]. By combining speed planning with ACC technology, not only can better performance in energy efficiency be achieved, but also improvements in driving comfort and safety. Therefore, developing a comprehensive control framework integrating SP and ACC is crucial to address these issues simultaneously.

Several studies have integrated speed planning (SP) with adaptive cruise control (ACC) to improve energy efficiency, safety, and comfort. In [16], SP and ACC are combined to enhance energy efficiency while maintaining safe inter-vehicle spacing. [17] employs ADMM within an MPC framework to achieve real-time, terrain-aware speed planning and energy optimization for electric trucks. [18] uses MPC to optimize host vehicle speed based on preceding vehicle dynamics, improving fuel economy and safety. [19] proposes a hierarchical control strategy combining centralized eco-speed planning with distributed collision-free tracking to minimize fuel consumption. However, these approaches [17–19] inadequately address driving comfort, which significantly impacts driver and passenger fatigue. To balance energy efficiency, safety, and comfort, [20] introduces a hierarchical multi-objective eco-driving strategy for urban autonomous electric vehicles, while [21] and [22] propose hierarchical energy management strategies incorporating grey neural networks, fuzzy logic, and traffic prediction to optimize efficiency and comfort for plug-in hybrids. Nevertheless, [20–22] overlook computational burden, which is critical for real-time responsiveness. [23] decouples motion and powertrain dynamics to address safety, emissions, and computation. [24] leverages cloud-based speed planning for logistics fleets to reduce energy use and emissions, and [25] proposes a fast analytical solver for fuel-optimal speed trajectories in connected vehicles. Overall, computational efficiency remains influenced by algorithm complexity, solution methods, and hardware platforms. High computational efficiency often compromises optimization performance, while excessive computation burdens reduce real-time responsiveness. Striking a balance between the two remains a significant challenge. Lyapunov optimization addresses this by integrating stability theory with drift-plus-penalty techniques, enabling real-time, model-free decision-making without reliance on future information or system statistics. The method constructs virtual queues to represent constraint violations and minimizes the drift-plus-penalty expression at each time slot, achieving near-optimal performance while ensuring long-term stability. This approach supports online, distributed implementation and provides a principled way to manage multiple conflicting objectives under uncertainty. In contrast to many existing control strategies-such as fuzzy control for multiagent systems [26], path planning-based logic control [27], critic-only ADP methods [28], and robust cooperative platooning control [29] - it does not rely on predictive models or centralized coordination, making it particularly effective for large-scale multi-agent systems operating under uncertain and time-varying conditions. Due to its robustness and distributed nature, it has been widely adopted in wireless networks [30], cloud/edge computing [31], smart grids [32], and intelligent transportation systems [33], particularly in dynamic and uncertain environments.

Therefore, motivated by the Lyapunov optimization and practical effectiveness of the methods presented in in the literature above, there is a proposed control scheme for a connected automated FCHEVs based on optimized ACC and SP to solve the multi-objective coordinated optimization problem. The main contributions of this paper can be summarized as follows:

1) For high-speed scenarios of FCHEVs platoons, a Lyapunov drift-plus-penalty-based adaptive cruise control and speed planning framework has been developed. This framework is specifically designed to simultaneously enhance driving safety, passenger comfort, and traffic throughput in connected logistics FCHEV platoons under dynamic driving conditions.

2) To achieve a balanced trade-off between driving safety, passenger comfort, and traffic efficiency, a car-following algorithm based on Lyapunov optimization is proposed, which dynamically adjusts inter-vehicle following distances using real-time V2V and V2I communication. This enables real-time coordinated control and enhances adaptability to complex and uncertain traffic environments.

3) For the networked logistics fleet of FCHEVs equipped with ACC systems, a multi-objective optimization function considering both speed constraints and traction constraints is formulated to jointly address fuel economy and driving comfort. The Sequential Quadratic Programming (SQP) algorithm is employed to efficiently solve the optimal speed setpoints, thereby minimizing energy consumption while improving ride quality.

The remainder of this paper is organized as follows: Section 2 provides the problem statement and system modeling for networked logistics FCHEV platoons. Section 3 presents the main results of the optimal ACC and SP. Section 4 showcases simulation results to validate the proposed design schemes. The conclusion is presented in Section 5.

2. PROBLEM FORMULATION AND SYSTEM MODELING

2.1. The dynamics model of platoon longitudinal

A longitudinal dynamic model of the vehicle has been established to describe the dynamic performance of the vehicle under the action of traction force F_t. Its description is as follows:

$$\begin{cases} \dot{p}_i = v_i \\ \dot{v}_i = \dfrac{1}{m_i}(F_t - F_a - F_r - F_g) \end{cases}, \tag{1}$$

where p_i, v_i and m_i represent the position, velocity, and mass of the i-th vehicle ($i \in \{1,2,3,4,5,6\}$), respectively, F_a, F_r and F_g denote air resistance, gradient resistance, and rolling resistance, respectively, which are expressed as follows:

$$\begin{cases} F_a = \dfrac{1}{2} C_d \rho A v_i^2 \\ F_r = f_r m_i g \cos\theta \\ F_g = m_i g \sin\theta \end{cases}, \tag{2}$$

where C_d represents the coefficient of air resistance; ρ stands for air density; A is the frontal area of the vehicle; f_r is the rolling coefficient; g represents the acceleration due to gravity; θ denotes the road gradient.

2.2. The model of energy consumption

In this paper, the vehicle travels continuously on a straight road, without performing any turning or lane-changing maneuvers. The energy consumed by the vehicle is only related to its own mass, rolling resistance during vehicle operation, and aerodynamic drag. Therefore, according to longitudinal dynamics, the required power $P_{dem}(t)$ can be calculated as:

$$P_{dem}(t) = \frac{1}{2} C_d \rho A v^3(t) + mg\sin(\theta)v(t) + f_r mg\cos(\theta)v(t) + m\,a(t)v(t). \tag{3}$$

3. OPTIMIZATION BASED SPEED PLAN AND STRATEGY ADAPTIVE CRUISE CONTROL

3.1. The two-layer framework includes platoon speed planning and platoon control

A framework for platoon adaptive cruise control and speed planning has been developed to address the unique characteristics of a FCHEVs platoon in internet-connected logistics, as shown in Fig. 1. The upper-level objective is to plan the speed for the platoon to minimize overall fuel costs while ensuring comfortable and safe vehicle operation. The lower-level requires the design of a platoon coordination controller to ensure the stability and comfort of the platoon, meeting the following two requirements:

1) A road-adaptive speed planning method is provided, which generates a reference speed profile v_p^* for a truck fleet with the aim of minimizing total energy consumption and enhancing passenger comfort. Specifically, the design of v_p^* should minimize the cost function, i.e., minimize $\min J = v_p^* F_t + \left| v_{p_{t+1}}^* - v_{p_t}^* \right| + \left| F_{t+1} - F_t \right|$.

2) A cooperative control method is provided for the platoon to prevent the amplification of spacing errors caused by the leading vehicle or other disturbances, while ensuring tracking of the given speed v with serial stability.

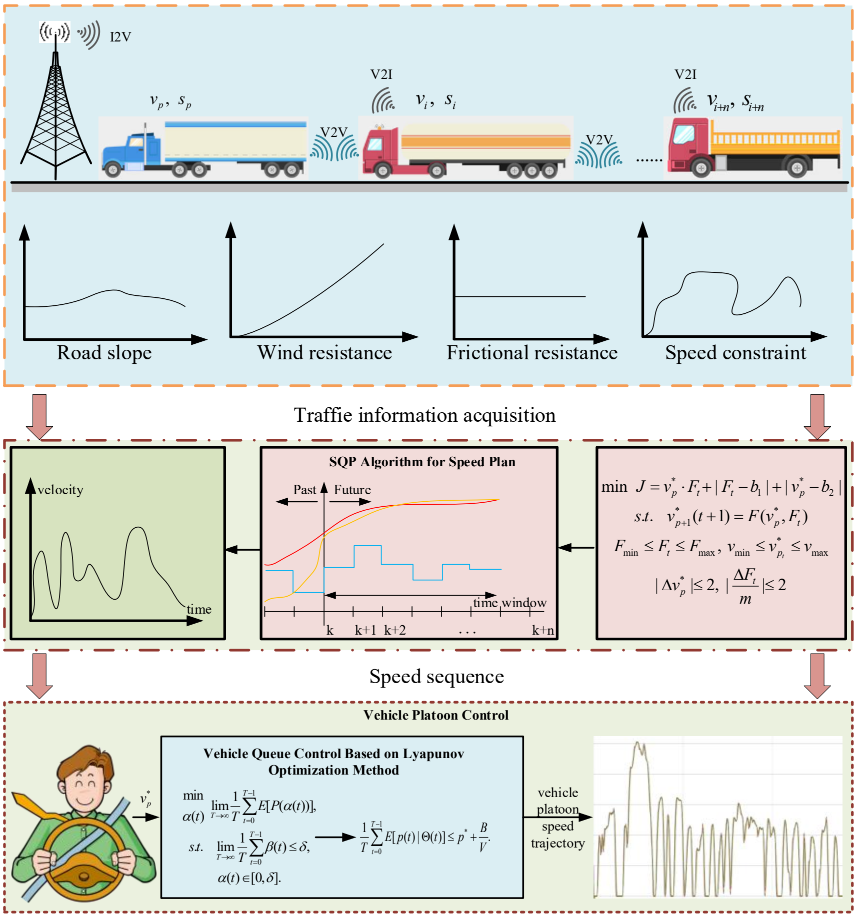


Fig.1 – Speed planning and vehicle queue control based on Lyapunov optimization.

3.2. Speed planning

Platoon speed planning aims to minimize energy consumption while ensuring driving comfort. This paper proposes a SQP-based method that treats the energy flow between the storage and power systems as a coupled entity, minimizing cumulative coupling power, speed variation, and traction variation, as defined in the objective function J. The optimization incorporates constraints including road gradient, aerodynamic drag, and comfort, and is formulated as follows:

$$\begin{gathered}\min J = v_p^* \cdot F_t + \left|F_t - b_1\right| + \left|v_p^* - b_2\right| \\ s.t. v_{p+1}^*(t+1) = F(v_p^*, F_t) \\ F_{\min} \le F_t \le F_{\max} \\ v_{\min} \le v_{p_t}^* \le v_{\max} \\ \left|\Delta v_p^*\right| \le 2 \\ \left|\frac{\Delta F_t}{m}\right| \le 2\end{gathered} \tag{4}$$

where b_1 and b_2 represent the traction and speed of the vehicle in the previous moment, respectively.

3.3. Distributed cooperative control method based on Lyapunov optimization

The objective is to assist following vehicles in determining their travel distance for each time period, as shown in Fig. 2.

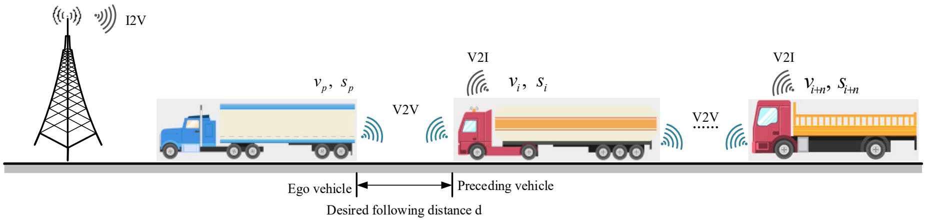


Fig. 2 – Connected logistics vehicle platoon.

This is achieved by using the long-term average inter-vehicle distance as the optimization criterion. Let $d_i(t) = p_{i-1}(t) - p_i(t)$ represent the actual inter-vehicle spacing between vehicle i (the follower) and its predecessor. Let $s_i(t) = \tau_h v_i(t) + d_0$ denote the desired spacing according to the ACC policy, where $\tau_h = 1.5$ is the time headway and $d_0 = 5$ m is the minimum distance. $p_i(t+1) = p_i(t) + v_i(t) \cdot \Delta t$ and $v_i(t+1) = v_i(t) + a_i(t) \cdot \Delta t$ represent the position and velocity updates. Define the spacing error as $e_s^{(i)}(t) = d_i(t) - s_i(t)$. The control objective is to minimize the following long-term average cost function:

$$J(a_i(t)) = \min_{a_i(t), i=2,\ldots,5} \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\left[\sum_{i=1}^{5} \left(e_s^{(i)}(t)^2 + \left(\frac{\mathrm{d}a_i(t)}{\mathrm{d}t} \right)^2 \right) \right]. \tag{5}$$

To ensure safety and physical feasibility, the controller must satisfy the following long-term constraints:

$$\begin{cases} \lim\limits_{T\to\infty} \dfrac{1}{T} \sum\limits_{t=0}^{T-1} \mathbb{E}[y_d^{(i)}(t)] \le 0, \quad i = 2,\ldots,6 & \text{(safety distance constraint)} \\ v_{\min} < v_i(t) < v_{\max}, \quad i = 2,\ldots,6 & \text{(velocity bounds)} \\ a_i^{\min} \le a_i(t) \le a_i^{\max}, \quad i = 2,\ldots,6 & \text{(acceleration bounds)} \end{cases} \tag{6}$$

These constraints ensure that a minimum safety distance is maintained between consecutive vehicles, all vehicles operate within feasible speed and acceleration ranges, and the system avoids unsafe operations. To ensure the long-term constraints are satisfied, this paper employs a Lyapunov optimization framework that transforms the constraint enforcement problem into a queue stability problem. This approach systematically penalizes constraint violations while optimizing the desired control objectives. The queue input $y_d^{(i)}(t)$ is determined by the deviation between the actual distance $d_i(t)$ and the desired safety distance $s_i(t)$:

$$y_d^{(i)}(t) = s_i(t) - d_i(t). \tag{7}$$

For each follower vehicle $i \in \{2,\ldots,6\}$, this paper defines a virtual queue $Q_d^{(i)}(t)$ to track safety distance violations. The virtual queue updates dynamically as:

$$Q_d^{(i)}(t+1) = \max(Q_d^{(i)}(t) + y_d^{(i)}(t), 0). \tag{8}$$

This mechanism ensures that persistent spacing violations accumulate in the queue, prompting corrective control actions to stabilize the system. To analyze and control the system's stability, this paper introduces a Lyapunov function $L(\Theta(t))$, where $\Theta(t) = [Q_d^{(2)}(t), Q_d^{(3)}(t), Q_d^{(4)}(t), Q_d^{(5)}(t), Q_d^{(6)}(t)]$ represents the collective state of all virtual queues:

$$L(\Theta(t)) = \frac{1}{2} \sum_{i=2}^{6} Q_d^{(i)}(t)^2. \tag{9}$$

The Lyapunov drift $\Delta(\Theta(t)) = L(\Theta(t+1)) - L(\Theta(t))$ measures the change in system stability over time. To balance constraint satisfaction and control performance, this paper minimizes a drift-plus-penalty expression at each time step:

$$\Delta(\Theta(t)) + V \cdot J(a_i(t)), \tag{10}$$

where V is a tunable parameter that adjusts the trade-off between constraint enforcement and control smoothness.

Using Lyapunov drift theory, this paper bounds the drift term as:

$$\Delta(\Theta(t)) \le B + \sum_{i=1}^{5} Q_d^{(i)}(t) y_d^{(i)}(t), \tag{11}$$

where $B = \frac{1}{2}\sum_{i=1}^{5}\max(y_d^i(t))^2 = \frac{1}{2}\cdot 5\cdot[5]^2 = 62.5$ is a constant representing the worst-case squared constraint violations. The optimal controller $a^*(t) = [a_2(t), a_3(t), a_4(t), a_5(t), a_6(t)]$ is derived by solving the following optimization problem using the SQP method:

$$a^*(t) = \arg\min_{a_i(t), i=2,\dots,6}\left[B + V \cdot J(a_i(t)) + \sum_{i=2}^{6} Q_d^{(i)}(t) y_d^{(i)}(t)\right], \tag{12}$$

subject to the acceleration limits $a_i^{\min} \le a_i(t) \le a_i^{\max}$. This formulation ensures that the controller not only maintains safety and stability but also achieves smooth and efficient vehicle motion.

3.4. Theoretical performance and stability guarantees

At each time slot, the controller minimizes the drift-plus-penalty expression [34]:

$$\Delta(\Theta(t)) + V \cdot J(a_i(t)). \tag{13}$$

Taking expectations and summing over all time slots $t = 0$ to $T-1$, the following inequality is obtained:

$$\sum_{t=0}^{T-1}\mathbb{E}\left[\Delta(\Theta(t)) + V \cdot J(a_i(t)) \mid \Theta(t)\right] \le T \cdot B + V \cdot \sum_{t=0}^{T-1}\mathbb{E}\left[J(a_i(t)) \mid \Theta(t)\right]. \tag{14}$$

Using the definition of Lyapunov drift:

$$\sum_{t=0}^{T-1}\mathbb{E}\left[\Delta(\Theta(t))\right] = \mathbb{E}\left[L(\Theta(T)) - L(\Theta(0))\right]. \tag{15}$$

Given that $L(\Theta(0)) = 0$, this simplifies to:

$$\sum_{t=0}^{T-1}\mathbb{E}\left[\Delta(\Theta(t))\right] = \mathbb{E}\left[L(\Theta(T))\right]. \tag{16}$$

Substituting into the inequality above yields:

$$\mathbb{E}\left[L(\Theta(T))\right] + V \cdot \sum_{t=0}^{T-1}\mathbb{E}\left[J(a_i(t)) \mid \Theta(t)\right] \le T \cdot B + V \cdot \sum_{t=0}^{T-1}\mathbb{E}\left[J(a_i(t)) \mid \Theta(t)\right]. \tag{17}$$

Rearranging terms gives:

$$\mathbb{E}\left[L(\Theta(T))\right] \le T \cdot B. \tag{18}$$

Since $L(\Theta(T)) \ge 0$, dividing both sides by T and taking the limit leads to:

$$\lim_{T\to\infty}\frac{1}{T}\mathbb{E}\left[L(\Theta(T))\right] \le B. \tag{19}$$

This results in the final bound:

$$\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\left[J(a_i(t)) \mid \Theta(t)\right] \le J^* + \frac{B}{V}. \tag{20}$$

Therefore, the controller guarantees that the long-term average performance remains within a bounded gap from the optimal solution J^*, with convergence rate $O(1/V)$. This indicates that increasing V brings the controller closer to optimality, albeit at the cost of slower convergence.

The formal proof of queue stability under the drift-plus-penalty algorithm proceeds as follows. From the Lyapunov drift inequality:

$$\Delta(\Theta(t)) \le B + \sum_{i=2}^{6} Q_d^i(t) y_d^i(t) . \tag{21}$$

The expectation is taken and summed over all time slots:

$$\sum_{t=0}^{T-1} \mathbb{E}\left[\Delta(\Theta(t))\right] \le T \cdot B + \sum_{t=0}^{T-1} \mathbb{E}\left[\sum_{i=2}^{6} Q_d^i(t) y_d^i(t)\right]. \tag{22}$$

Expanding the left-hand side using the Lyapunov function:

$$\sum_{t=0}^{T-1} \mathbb{E}\left[\Delta(\Theta(t))\right] = \mathbb{E}\left[L(\Theta(T)) - L(\Theta(0))\right]. \tag{23}$$

Given that $L(\Theta(0)) = 0$, it follows that:

$$\mathbb{E}\left[L(\Theta(T))\right] \le T \cdot B . \tag{24}$$

Substituting the definition of the Lyapunov function:

$$\frac{1}{2}\sum_{i=2}^{6} \mathbb{E}\left[(Q_d^i(T))^2\right] \le T \cdot B . \tag{25}$$

Applying the Cauchy-Schwarz inequality:

$$\left(\sum_{i=1}^{5} \mathbb{E}\left[Q_d^i(T)\right]\right)^2 \le 5 \cdot \sum_{i=1}^{5} \mathbb{E}\left[(Q_d^i(T))^2\right] \le 2 \cdot 5 \cdot B \cdot T . \tag{26}$$

Taking square roots and dividing both sides by T, the following result is obtained:

$$\lim_{T\to\infty} \frac{\sum_{i=1}^{5} \mathbb{E}\left[Q_d^i(T)\right]}{T} \le \lim_{T\to\infty} \sqrt{\frac{2 \cdot 5 \cdot B}{T}} = 0 . \tag{27}$$

Given that $Q_d^i(t) \ge 0$, it follows that:

$$\lim_{T\to\infty} \frac{\mathbb{E}\left[Q_d^i(T)\right]}{T} = 0, \quad \forall i . \tag{28}$$

This completes the proof of queue stability under the drift-plus-penalty algorithm.

4. RESULTS AND DISCUSSION

To evaluate the proposed method for a connected logistics FCHEV platoon, simulations are conducted in MATLAB/Simulink using vehicle parameters from Table 1. Speed planning is first performed under varying road gradients. Then, a platoon model with the control strategy is implemented over a full driving cycle, and system performance is analyzed. The Lyapunov drift-plus-penalty controller is evaluated against MPC, H∞, fuzzy, and PID controllers [35] as benchmarks to verify its effectiveness.

Table 1

Vehicle parameters

Parameters	Value
average mass (m_p)	$40\,\mathrm{t}$
rolling resistance coefficient (c_r)	3×10^{-3}
vehicle cross-sectional area (A_p)	$10\,\mathrm{m}^2$
air density (c_p)	$0.25\,\mathrm{s}$
air drag coefficient (c_λ)	$1.29\,\mathrm{kg}\cdot\mathrm{m}^{-3}$
speed limits	$v_{p,\max}=25\,\mathrm{m/s}$, $v_{p,\min}=20\,\mathrm{m/s}$

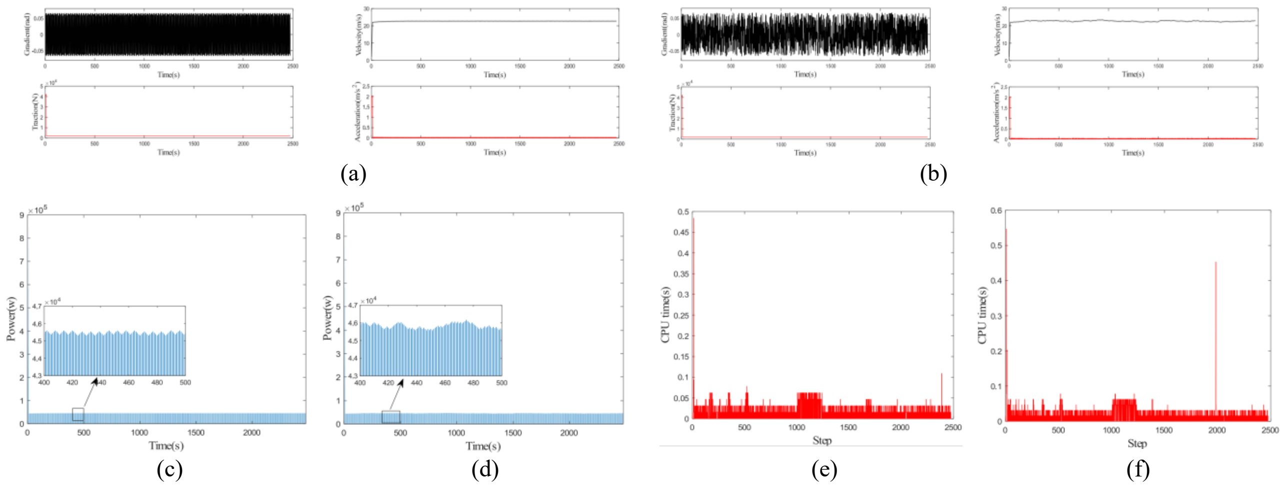
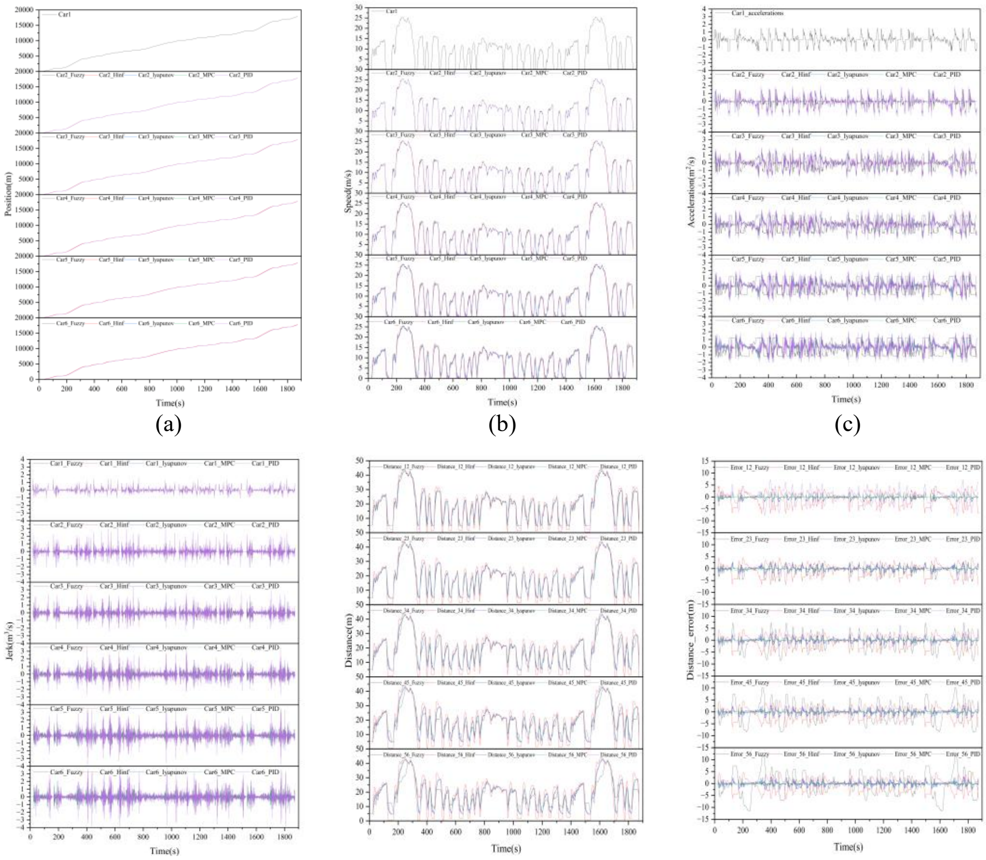


Fig. 3 – Platoon speed planning based on designed road slope curves: a) speed planning based on periodic slope; b) speed planning based on random slope; c) power distribution based on periodic slope; d) power distribution based on random slope; e) CPU times of periodic slope; f) CPU times of randomtime slope.

As shown in Figs. 3a and 3b, the speed planning simulation for a logistics platoon with homogeneous connections is conducted on a road with a designed slope profile ranging from – 0.066 to 0.066 radians, following highway standards. The road includes both periodic and random slope segments, with the periodic slope yielding a smoother speed curve. Power distribution during long driving cycles, depicted in Figs. 3c and 3d, shows smaller fluctuations under periodic slopes. The speed planning time is 30.47 s for periodic slopes and 29.25 s for random slopes, as shown in Figs. 3e and 3f.

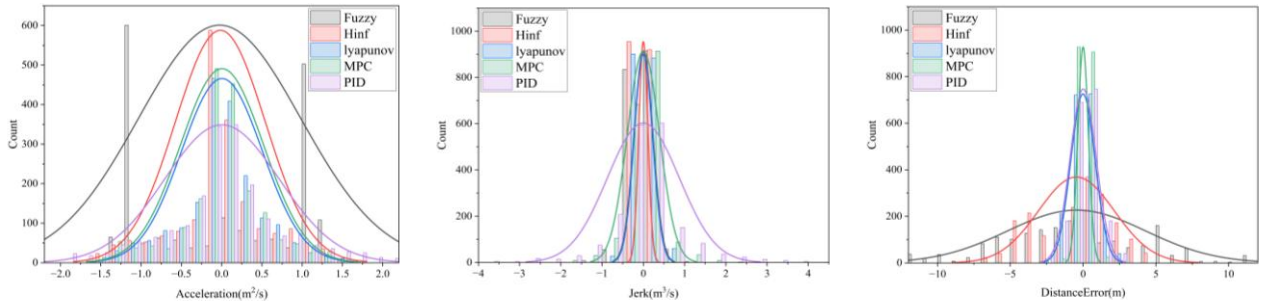
As shown in Figs. 4a, 4b, 4d and Fig. 5b, the five controllers exhibit varying long-term position tracking and speed regulation performance. The MPC controller achieves the best performance, with minimal jerk fluctuations of ± 1 $\mathrm{m/s^3}$ and 90% of data within ± 0.5 $\mathrm{m/s^3}$, indicating high stability and a narrow, symmetric distribution. The Lyapunov-optimization controller shows good symmetry with a slightly broader range of ± 1 $\mathrm{m/s^3}$. The H∞ controller demonstrates moderate performance, with intermittent peaks up to ± 2 $\mathrm{m/s^3}$ at 300 s, 900 s, and 1500 s, and a bimodal distribution featuring primary peaks within ± 0.8 $\mathrm{m/s^3}$ and secondary peaks at ± 2 $\mathrm{m/s^3}$. The fuzzy controller exhibits more pronounced fluctuations, reaching ± 3 $\mathrm{m/s^3}$, with the widest distribution from –3 to 3 $\mathrm{m/s^3}$. The PID controller performs the poorest, showing frequent severe oscillations up to ±4 $\mathrm{m/s^3}$, especially during 0–200 s and 1200–1400 s and a flat distribution spanning –4 to 4 $\mathrm{m/s^3}$, highlighting its inferior jerk control.



(a) (b) (c)

(d) (e) (f)

Fig. 4 – Vehicle platooning behaviors in FTP75 condition: a) position; b) speed; c) acceleration; d) jerk; e) distance; f) following distance error.



(a) (b) (c)

Fig. 5 – Distribution of jerk and distance error for different control strategies: a) acceleration distributions; b) jerk distributions; c) distance error distributions.

As shown in Figs. 4e, 4f and Fig. 5c, The MPC controller achieves superior tracking precision, with over 90% of errors concentrated within ± 0.5 m (centered at zero) and maximum deviations consistently below 1 m. The Lyapunov-optimization controller achieves satisfactory accuracy with approximately 80% of errors within ± 1 m, though its distribution displays broader tails and occasional 2 m spikes in the error-time curve. The PID controller maintains errors primarily within ± 1.5 m but suffers from occasional exceedances beyond 3 m. The H∞ controller shows greater dispersion, with 70% of errors within ± 2 m and isolated peaks exceeding 4 m. Most notably, the fuzzy controller exhibits the poorest performance, characterized by a broad error distribution (± 5 m) containing extreme outliers (>10 m) and persistent oscillatory behavior (mean error: 3 m; peak error: 12 m), rendering it unsuitable for precision control applications. The controllers exhibit significant computational efficiency variations: PID (0.08 s) and H∞ (0.10 s) controllers demonstrate the fastest execution, while fuzzy (87.53 s) and Lyapunov-optimization (102.28 s) controllers show moderate computational demands. The MPC controller (164.85 s), despite its superior control performance, requires the highest computational resources.

As shown in Figs. 6a, 6b, 6c, 6d and 6e, car6's trajectory consistently overlapped with car1's, indicating that five control algorithms effectively eliminated cumulative position errors in the simulated environment. While all algorithms successfully stabilized Car6's velocity near the target, the H∞ controller demonstrated the most accurate average velocity tracking (0 m/s deviation), despite showing marginally larger steady-state oscillations (± 1.0 m/s) compared to fuzzy, Lyapunov-optimization, and MPC controllers (± 0.5 m/s). The PID controller exhibited the largest average velocity deviation and greater oscillations. The H∞ controller achieved superior ride comfort, with minimal steady-state acceleration oscillations (± 0.1 m/s²) and negligible jerk (± 0.05 m/s³). The Lyapunov-optimization controller also performed well (± 0.3 m/s², ± 0.4 m/s³), while the PID controller exhibited the highest oscillations (± 0.8 m/s², ± 0.7 m/s³), indicating the lowest comfort level. The H∞ controller achieved the most precise inter-vehicle spacing, with a steady-state distance error oscillation of only ± 0.05 m, demonstrating superior robustness and accuracy. In comparison, the PID controller exhibited larger oscillations of ± 0.2 m.

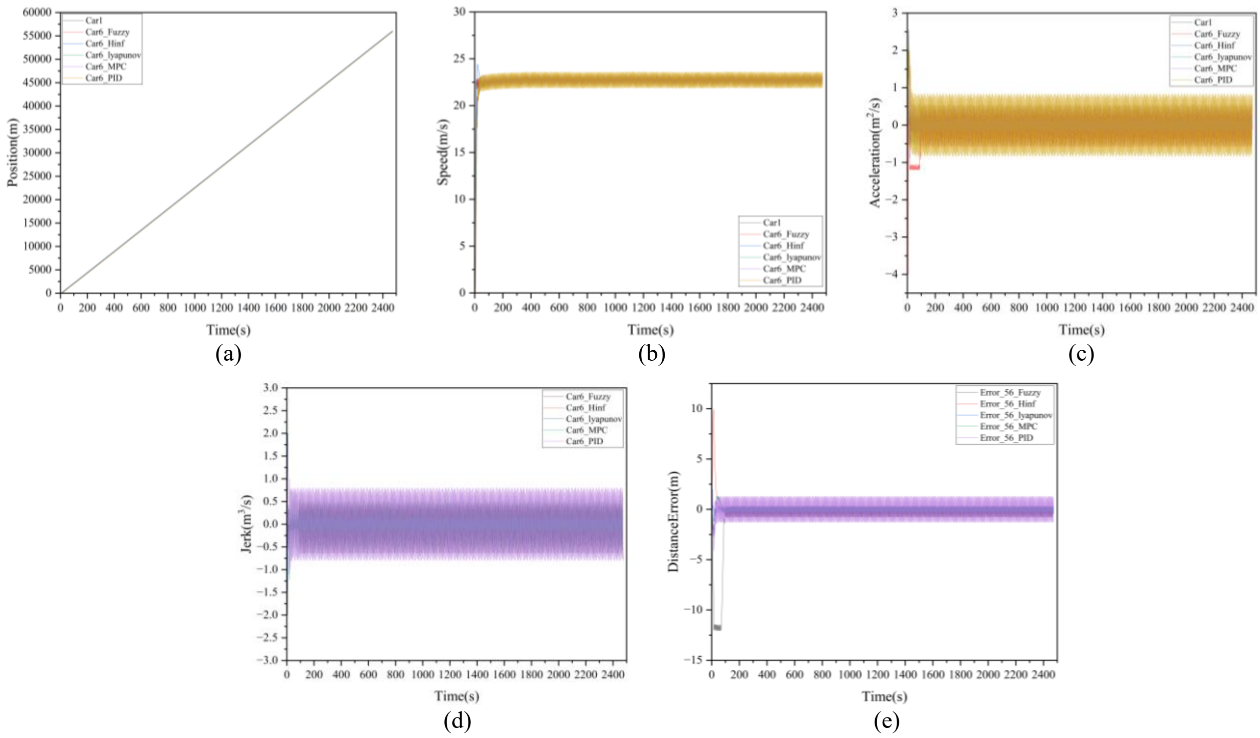


Fig. 6 – Comparative analysis of vehicle following control algorithms under steady-state conditions: (a) position, (b) speed, (c) acceleration, (d) jerk, (e) distance error.

The five controllers exhibit distinct performance trade-offs. The Lyapunov-optimization controller offers balanced performance in tracking, stability, and disturbance rejection. MPC controller achieves the highest precision and stability but with high computational cost. PID and fuzzy controllers provide fast response but suffer from poor accuracy, larger oscillations, and steady-state errors. In contrast, the H∞ controller excels in speed tracking, ride comfort, and spacing control, demonstrating superior oscillation suppression. Controller selection should thus be guided by specific requirements on accuracy, stability, and computational constraints.

5. CONCLUSION

An optimal ACC and SP method for a networked logistics platoon during the following process is proposed. By leveraging V2V and V2I communication, real-time position and speed data of the preceding vehicle are obtained. A SQP-based algorithm computes the optimal platoon speed in real time, balancing driving comfort and energy efficiency, while an adaptive cruise controller ensures accurate tracking of the desired inter-vehicle spacing.

Simulation results show speed planning times of 30.47 s for periodic slopes and 29.25 s for random slopes. Compared to PID controller, the Lyapunov-optimization controller reduces jerk by 42.9% (from ± 0.7 to ± 0.4 m/s³), improves speed tracking accuracy by 40% (0.3 *vs* 0.5 m/s average error), and enhances spacing precision by 75% (± 0.05 *vs* ± 0.2 m), with 80% of position errors within ±1 m. Relative to the fuzzy controller, it reduces maximum jerk by 86.7% (from ± 3 to ± 0.4 m/s³), eliminates a 5% steady-state speed error, and maintains comparable computational efficiency (102.28 vs 87.53 s). Compared to H∞ controller, it achieves more consistent performance (speed error variation < 0.2 *vs* 0.5 m/s), avoids bimodal jerk distribution, and handles sudden speed changes without overshoot, albeit with higher computation time (102.28 *vs* 0.10 s). While MPC controller achieves higher tracking precision (90% of errors within ±0.5 m *vs* ± 1 m) and greater jerk reduction (72.5% *vs* 42.9%), the Lyapunov-optimization controller offers a favorable trade-off with 38% faster computation (102.28 *vs* 164.85 s), more symmetric error distribution, and better compatibility with existing vehicle control architectures.

The method proposed in this paper aims to achieve multi-objective optimization during the platoon following process. Given the growing demand for eco-friendly intelligent transportation, further optimization of ACC and SP for logistics platoons is needed. Future work will focus on hardware-in-the-loop simulations and real-vehicle tests.

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