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MPC-inspired neural network method for cooperative control of vehicle platoons

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Abstract

A model predictive control (MPC) inspired neural network (NN) method is proposed to solve the cooperative problems of vehicle platoon in this paper. The controller design is approximate to a quadratic programming (QP) solver for MPC problems. However, the method proposed in this paper is based on data-driven MPC rather than being strictly model-based. Meanwhile, compared to QP solver, the computational efficiency is significantly improved. To ensure asymptotic convergence of the vehicle platoons, terminal penalty matrix and terminal set are taken into the optimization problem, and a supervised learning based feedforward neural network is trained to approximate control inputs. Compared to traditional neural network controllers, this method has the similar performance of ensuring asymptotic stability as model predictive controller. To validate the effectiveness of the proposed controller, the information from the leading vehicle utilizes real-world driving data from commercial trucks, which more accurately reflects the dynamic behavior of the vehicle under actual driving conditions. Based on the real truck platform, the experimental results show that when the leading vehicle accelerates or decelerates, the following vehicles in the platoon can make real-time responses while exhibiting excellent dynamic performance. In addition, joint simulations based on MATLAB and Trucksim in the curved road scenario show that the performance of lane keeping can also be guaranteed.

Keywords

Vehicle platoon, feedforward neural network, model predictive control, supervised learning, real truck platform

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Introduction

Emerging transportation technologies, represented by autonomous driving, have a profound impact on public travel, road transportation, and urban development.[1] The industry generally believes that autonomous driving technology, represented by connected autonomous trucks (CATs), can bring disruptive changes in the transportation field.[2] As one of the auxiliary driving technologies, cooperative control of vehicle platoons plays an important role in reducing driving burden and improving traffic efficiency,[3] which has received extensive attention in recent years.

Vehicle platoon can be seen as a strongly nonlinear and high-dimensional system. Due to the robustness and ability of constraints handling, model predictive controller has been widely used in the field of vehicle platoon control. To further enhance the performances, distributed model predictive control (DMPC) is used to solve the coordination problem of high-speed vehicle platoons.[4–6] A DMPC algorithm is developed to ensure the asymptotic consistency of mixed traffic flows.[7] A model predictive controller considering the bounded sensor measurement range and actuator time lag is proposed.[8] Combined with the safety potential field model (SPF), model predictive control (MPC) can further improve the traffic capacity.[9] A path coupling extended prediction method is introduced to improve the safety and tracking capability of vehicle platoons.[10]

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However, in actual scenarios, considering uncertainties and complex nonlinear motion characteristics, the computation burden of MPC will be greatly increased. Due to the excellent fitting properties and high solving efficiency, neural networks (NNs) have been widely used. A tracking control strategy of vehicle platoons is proposed based on adaptive neural network for reducing the measurement and communication burden between vehicles.[11] To enhance the convergence efficiency compared with traditional reinforcement learning (RL) algorithms, a guided deep deterministic policy gradient algorithm (GuidDDPG) is proposed.[12] However, even well-trained neural network models face limitations in interpretability and performance guarantees, which can be critical issues for practical applications. Many existing works combine MPC with learning algorithms, but these efforts mainly focus on improving learning efficiency. Challenges still remain in balancing the solution of optimal control strategies with real-time responsiveness.

In this paper, a MPC-inspired neural network method is proposed. Compared with traditional NNs, this method can ensure convergence by considering MPC terminal constraints, while significantly enhancing both generalization capability and system stability. Compared with traditional MPC controller, the proposed method alleviates the dependence on the system model, and can significantly improve computational efficiency. Together with the vehicle platoon model, the effectiveness of the method has been verified by real truck data experiments and joint simulations based on Matlab and Trucksim.

The structure of this paper is as follows: Section "Problem setup" is the problem setup, including longitudinal and lateral dynamics of the vehicle platoon; Section "Longitudinal and lateral platoon controller design" introduces optimization problem description and the designing process of MPC-inspired neural network controller; Section "Experimental results" presents the experimental results based on real truck platform and joint simulation by MATLAB and Trucksim; Section "Conclusion" concludes the whole paper.

Problem setup

This section will introduce the longitudinal and lateral vehicle dynamics, construct the vehicle platoon model, and clarify the control objectives based on the communication topology structure.

Vehicle dynamics

Consider a vehicle platoon consisting of N homogeneous vehicles, as shown in Figure 1. For the i th vehicle in platoon, the longitudinal dynamics model is[13]:

$$\begin{cases} \dot{s}_{x,i} = v_{x,i} \\ \dot{v}_{x,i} = a_i \\ \dot{a}_i = f_i(v_{x,i}, a_i) + g_i(v_{x,i})\eta_i \end{cases} \tag{1}$$

where $s_{x,i}$ is the longitudinal position of the i th vehicle($i \geqslant 2$), N the total number of vehicles in platoon including the leader and following vehicles, $v_{x,i}$ and a_i respectively the velocity and acceleration, $f_i(\cdot)$ and $g_i(\cdot)$ can be respectively expressed as:

$$\begin{aligned} f_i(v_{x,i}, a_i) &= \frac{-2C_{d,i}}{m_i} v_{x,i} a_i - \frac{1}{\tau_i(v_{x,i})} \\ &\quad \left(a_i + \frac{C_{d,i}}{m_i} v_{x,i}^2 + \frac{d_{m,i}}{m_i}\right) \\ g_i(v_{x,i}) &= \frac{1}{m_i \tau_i(v_{x,i})} \end{aligned} \tag{2}$$

where $C_{d,i}$ is the aerodynamic coefficient, m_i the vehicle mass, τ_i the time constant, and $d_{m,i}$ the mechanical drag.

The engine input η_i can be expressed as:

$$\eta_i = m_i u_i + C_{d,i} v_{x,i}^2 + d_{m,i} + 2\tau_i C_{d,i} v_{x,i} a_i \tag{3}$$

Then the nonlinear system (1) can be transformed into the equivalent linear system:

$$\begin{cases} \dot{s}_{x,i} = v_{x,i} \\ \dot{v}_{x,i} = a_i \\ \dot{a}_i = -\tau_i^{-1} a_i + \tau_i^{-1} u_i \end{cases} \tag{4}$$

where u_i is the expected acceleration of the i th vehicle.

Assuming that the longitudinal speed $v_{x,i}$ is known, then the lateral vehicle dynamics model is[14]:

$$\begin{cases} \left(m_i \dot{v}_{y,i} + m_i \dot{v}_{x,i} \dot{\psi}_i\right) = F_i^{yf} + F_i^{yr} \\ I_{z,i} \ddot{\psi}_i = l_{f,i} F_i^{yf} - l_{r,i} F_i^{yr} \end{cases} \tag{5}$$

where $v_{y,i}$ is the lateral velocity, $\dot{\psi}_i$ the yaw rate, $\ddot{\psi}_i$ the yaw acceleration, $I_{z,i}$ the moment of inertia, F_i^{yf} and F_i^{yr} the lateral forces on the front and rear tires, $l_{f,i}$ and $l_{r,i}$ the distance from the center of mass to the front and rear axles.

Assuming that the slip angles of both the front and rear tires are within a limited range, and the tire model is linear. Then the lateral tire forces of the front and rear wheels can be calculated as follows[15]:

$$\begin{aligned} F_i^{yf} &= C_i^{cf}\left(\delta_i - \frac{v_{y,i} + l_{f,i}\dot{\psi}_i}{v_{x,i}}\right) \\ F_i^{yr} &= C_i^{cr}\left(\frac{l_{r,i}\dot{\psi}_i - v_{y,i}}{v_{x,i}}\right) \end{aligned} \tag{6}$$

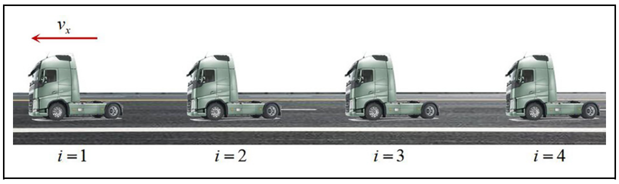

Figure 1. Basic structure of vehicle platoon.

where δ_i represents the front wheel steering angle, C_i^{cf} and C_i^{cr} respectively represent the lateral stiffness of the front and rear wheels.

Substituting (6) into (5), then the lateral dynamics model can be written as:

$$\begin{aligned} \dot{v}_{y,i} &= -v_{x,i}\dot{\psi}_i + \frac{1}{m_i}\left(-\frac{\left(C_i^{cf}+C_i^{cr}\right)v_{y,i}}{v_{x,i}} - \frac{\left(C_i^{cf}l_{f,i}-C_i^{cr}l_{r,i}\right)\dot{\psi}_i}{v_{x,i}} + C_i^{cf}\delta_i\right) \\ \ddot{\psi}_i &= \frac{1}{I_{z,i}}\left(-\frac{\left(C_i^{cf}l_{f,i}-C_i^{cr}l_{r,i}\right)v_{y,i}}{v_{x,i}} - \frac{\left(C_i^{cf}l_{f,i}^2+C_i^{cr}l_{r,i}^2\right)\dot{\psi}_i}{v_{x,i}} + C_i^{cf}l_{f,i}\delta_i\right) \end{aligned} \tag{7}$$

Communication topology

V2V communication system is a short-range communication technology that enables vehicles to share information.[16] Common V2V communication topologies include predecessor-following (PF) and predecessor-leader-following (PLF) structures.[17] In the PF structure, each vehicles only receives information from the preceding one, and the PLF structure enables the vehicles to receive the information from both the leader and the preceding one (Figure 2).

Different vehicle platoon strategies are determined by the specific communication topologies employed.[18] The PF communication topology structure is adopted in this paper, that is, the following vehicle can only receive information from the preceding one. In the subsequent research of this paper, it is assumed that all vehicles share a synchronized clock, and communication delays and noise interference between vehicles in the convoy are neglected.

Vehicle platoon model for control

To achieve longitudinal and lateral control objectives, this subsection introduces the process of establishing the longitudinal and lateral vehicle platoon error model based on longitudinal single-vehicle model (4) and lateral single-vehicle model (7).

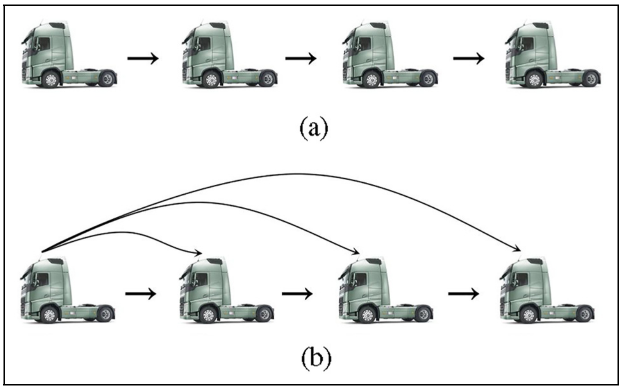

Figure 2. Schematic diagram of communication topology structure: (a) PF communication topology structure and (b) PLF communication topology structure.

In longitudinal platoon control, it is essential to maintain a safe and appropriate distance between vehicles.[19] In this paper, the chosen spacing policy combines fixed spacing with headway, that is, the expected vehicle spacing is defined as follows:

$$d_{i,des} = d_0 + h_i v_i \tag{8}$$

where $d_{i,des}$ is the expected vehicle spacing, d_0 the fixed spacing, h_i the time headway, and v_i the speed of the i th vehicle in platoon.

Define the longitudinal spacing error e_i^x and speed error e_i^v as:

$$\begin{cases} e_i^x = s_{x,i-1} - s_{x,i} - d_{i,des} \\ e_i^v = v_{x,i-1} - v_{x,i} \end{cases} \tag{9}$$

Denote $x_i = [e_i^x e_i^v a_i]^T$, then the state-space representation of longitudinal platoon model can be written as:

$$\dot{x}_i(t) = \bar{A}_i x_i(t) + \bar{B}_{1,i}u_i(t) + \bar{B}_{2,i}a_{i-1}(t) \tag{10}$$

with $\bar{A}_i = \begin{bmatrix} 0 & 1 & -h_i \\ 0 & 0 & -1 \\ 0 & 0 & -\tau^{-1} \end{bmatrix}, \bar{B}_{1,i} = \begin{bmatrix} 0 \\ 0 \\ \tau^{-1} \end{bmatrix}, \bar{B}_{2,i} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$

Define T_s as the sampling time, then the discrete state-space representation of the longitudinal vehicle platoon model (10) based on Euler discretization method is:

$$x_i(k+1) = A_i x_i(k) + B_{1,i}u_i(k) + B_{2,i}a_{i-1}(k) \tag{11}$$

where

$$A_i = \begin{bmatrix} 1 & T_s & -T_s h_i \\ 0 & 1 & -T_s \\ 0 & 0 & 1-\frac{T_s}{\tau} \end{bmatrix}, B_{1,i} = \begin{bmatrix} 0 \\ 0 \\ \frac{T_s}{\tau} \end{bmatrix}, B_{2,i} = \begin{bmatrix} 0 \\ T_s \\ 0 \end{bmatrix}$$

For the lateral control, the heading angle error of the i th vehicle in platoon e_i^{ψ} is:

$$e_i^{\psi} = \psi_i - \varphi_i \tag{12}$$

where ψ_i is the heading angle, φ_i the heading angle of reference path.

The lateral position error with respect to the reference path can be described as:

$$\dot{e}_i^{y} = v_{x,i}\sin\left(e_i^{\psi}\right) + v_{y,i}\cos\left(e_i^{\psi}\right) \tag{13}$$

where e_i^{ψ} is an extremely small number, that is, $\sin\left(e_i^{\psi}\right) \approx e_i^{\psi}$ and $\cos\left(e_i^{\psi}\right) \approx 1$, then (13) can be transformed into:

$$\dot{e}_i^{y} = v_{x,i} \cdot e_i^{\psi} + v_{y,i} \tag{14}$$

Combining (7), (12), and (14), the lateral vehicle platoon model is obtained:

$$\begin{aligned}
\ddot{e}_i^{y} = & -\frac{\left(C_i^{cf} + C_i^{cr}\right)}{m_i v_{x,i}}\dot{e}_i^{y} + \frac{\left(C_i^{cf} + C_i^{cr}\right)}{m_i}e_i^{\psi} - \\
& \frac{\left(C_i^{cf} l_{f,i} - C_i^{cr} l_{r,i}\right)}{m_i v_{x,i}}\dot{e}_i^{\psi} + \left(-\frac{\left(C_i^{cf} l_{f,i} - C_i^{cr} l_{r,i}\right)}{m_i v_{x,i}} - v_{x,i}\right) \\
& \varphi_i + \frac{C_i^{cf}}{m_i}\delta_i \\
\ddot{e}_i^{\psi} = & -\frac{\left(C_i^{cf} l_{f,i} - C_i^{cr} l_{r,i}\right)}{I_{z,i} v_{x,i}}\dot{e}_i^{y} + \frac{\left(C_i^{cf} l_{f,i} - C_i^{cr} l_{r,i}\right)}{I_{z,i}}e_i^{\psi} \\
& -\frac{\left(C_i^{cf} l_{f,i}^2 + C_i^{cr} l_{r,i}^2\right)}{I_{z,i} v_{x,i}}\dot{e}_i^{\psi} - \frac{\left(C_i^{cf} l_{f,i}^2 + C_i^{cr} l_{r,i}^2\right)}{I_{z,i} v_{x,i}} \\
& \varphi_i + \frac{C_i^{cf} l_{f,i}}{I_{z,i}}\delta_i
\end{aligned} \tag{15}$$

Define the state $\bar{x}_i$ and the front wheel steering angle $\tilde{u}_i$ of the lateral vehicle platoon model as:

$$\begin{aligned}
\bar{x}_i &= \begin{bmatrix} e_i^{y} & \dot{e}_i^{y} & e_i^{\psi} & \dot{e}_i^{\psi} \end{bmatrix}^T \\
\tilde{u}_i &= \delta_i
\end{aligned}$$

Then the state-space equation of lateral vehicle platoon is:

$$\dot{\bar{x}}_i(t) = \widehat{\bar{A}}_i \bar{x}_i(t) + \widehat{\bar{B}}_i \tilde{u}_i(t) + \widehat{\bar{E}}_i \dot{\varphi}_i(t) \tag{16}$$

where

$$\widehat{\bar{A}}_i = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & -\frac{\left(C_i^{cf} + C_i^{cr}\right)}{m_i v_{x,i}(t)} & 0 & -\frac{\left(C_i^{cf} l_{f,i} - C_i^{cr} l_{r,i}\right)}{I_{z,i} v_{x,i}(t)} \\ 0 & \frac{\left(C_i^{cf} + C_i^{cr}\right)}{m_i} & 0 & \frac{\left(C_i^{c} l_{f,i} - C_i^{c} l_{r,i}\right)}{I_{z,i}} \\ 0 & -\frac{\left(C_i^{c} l_{f,i} - C_i^{cr} l_{r,i}\right)}{m_i v_{x,i}(t)} & 1 & -\frac{\left(C_i^{cf} l_{f,i}^2 + C_i^{cr} l_{r,i}^2\right)}{I_{z,i} v_{x,i}(t)} \end{bmatrix}^T$$

$$\widehat{\bar{B}}_i = \begin{bmatrix} 0 & \frac{C_i^{cf}}{m_i} & 0 & \frac{C_i^{cf} l_{f,i}}{I_{z,i}} \end{bmatrix}^T$$

$$\widehat{\bar{E}}_i = \begin{bmatrix} 0 & -\frac{\left(C_i^{cf} + C_i^{c}\right)}{m_i v_{x,i}(t)} - v_{x,i}(t) & 0 & -\frac{\left(C_i^{cc} l_{f,i}^2 + C_i^{cr} l_{r,i}^2\right)}{I_{z,i} v_{x,i}(t)} \end{bmatrix}^T$$

The discrete state-space representation of the lateral vehicle platoon model based on Euler discretization method is written as:

$$\tilde{x}_i(k+1) = \hat{A}_i \tilde{x}_i(t) + \hat{B}_i \tilde{u}_i(t) + \hat{E}_i \dot{\varphi}_i(t) \tag{17}$$

where $\hat{A}_i$, $\hat{B}_i$, and $\hat{E}_i$ are the discretized coefficient matrix.

Control objective

For the vehicle platoon, the control objectives for the following vehicles are to maintain longitudinal tracking of the leading vehicle while also achieving effective lane-keeping control. Additionally, state and control constraints need to be considered.

The longitudinal control objective of the vehicle platoon is to track the longitudinal velocity of the leader vehicle, that is,

$$\begin{cases} \lim\limits_{k \to \infty} \parallel v_{x,i}(k) - v_{x,i-1}(k) \parallel \ = 0 \\ \lim\limits_{k \to \infty} \parallel s_{x,i-1}(k) - s_{x,i}(k) - d_{i,des} \parallel \ = 0 \end{cases} \quad i \geqslant 2, k \geqslant 0 \tag{18}$$

The position error e_i^x and speed error e_i^v between two adjacent vehicles should be maintained at a desired value, that is,

$$\begin{cases} e_{i,min}^x \leqslant e_i^x(k) \leqslant e_{i,max}^x \\ e_{i,min}^v \leqslant e_i^v(k) \leqslant e_{i,max}^v \end{cases} \quad i \geqslant 2, k \geqslant 0 \tag{19}$$

where $e_{i,min}^x$ and $e_{i,max}^x$ are the allowed minimum and maximum permissible spacing errors, $e_{i,min}^v$ and $e_{i,max}^v$ the minimum and maximum speed error.

The lateral control objective of the vehicle platoon is to track the lane markings, that is,

$$\begin{cases} \lim\limits_{k \to \infty} \parallel e_i^y(k) - 0 \parallel \ = 0 \\ \lim\limits_{k \to \infty} \parallel e_i^{\psi}(k) - 0 \parallel \ = 0 \end{cases} \quad i \geqslant 2, k \geqslant 0 \tag{20}$$

Furthermore, to ensure that vehicles in the platoon remain within the road boundaries, the following constraints are imposed:

$$\begin{cases} e^{\psi}_{i,min} \leqslant e^{\psi}_{i}(k) \leqslant e^{\psi}_{i,max} \\ e^{y}_{i,min} \leqslant e^{y}_{i}(k) \leqslant e^{y}_{i,max} \end{cases} \quad i \geqslant 2, k \geqslant 0 \tag{21}$$

where $e^{\psi}_{i,min}$ and $e^{\psi}_{i,max}$ are the allowed minimum and maximum heading errors of the i th vehicle relative to the lane, $e^{y}_{i,min}$ and $e^{y}_{i,max}$ correspond to the minimum and maximum lateral position errors relative to the lane.

Longitudinal and lateral platoon controller design

In this section, a MPC-inspired neural network method is proposed for vehicle platoon control, where each vehicle in the platoon sequentially solves its local optimization problem and communicates information with its neighbors.

Distributed model predictive controller

Under DMPC framework, a global optimization problem is converted into local optimization problems, where each subsequent vehicle solves its own problem synchronously.

For the i th vehicle in platoon, define the sequence of the inputs $\mathbb{U}_i(:|k)$ at moment k as:

$$\mathbb{U}_i(:|k) = \left\{U_i(k|k), U_i(k+1|k), ..., U_i\left(k + N_{i,p} - 1|k\right)\right\} \tag{22}$$

where $N_{i,p}$ is the prediction horizon length, $U_i(:|k)$ the predictive control input. Accordingly, the sequence of the states $\mathbb{X}_i(:|k)$ at moment k is:

$$\mathbb{X}_i(:|k) = \left\{X_i(k|k), X_i(k+1|k), ..., X_i\left(k + N_{i,p} - 1|k\right)\right\} \tag{23}$$

where $X_i(:|k)$ the predictive state, and $X_i(k) = \mathbb{X}_i(k|k)$, $U_i(k) = \mathbb{U}_i(k|k)$.

For the longitudinal control of the i th vehicle in platoon, the optimization problem can be described as follows:

Problem 1.

$$minimize\ J_i(x_i(k), u_i(k)) = \sum_{j=0}^{N_{i,p}-1} q_i(x_i, u_i) + p_i(x_i) \tag{24}$$

s.t.

$$\begin{aligned} & p_i(x_i) = \| x_i\left(k + N_{i,p} - 1|k\right) \|^2_{P_i}, \\ & q_i(x_i, u_i) = \| x_i(k+j|k) \|^2_{Q_i} + \| u_i(k+j|k) \|^2_{R_i}, \\ & x\left(k + N_{i,p} - 1|k\right) \in \Omega_i, \\ & v^x_{i,min} \leqslant v^x_i(k+j|k) \leqslant v^x_{i,max}, \\ & a_{i,min} \leqslant a_i \leqslant a_{i,max}, \\ & e^x_{i,min} \leqslant e^x_i \leqslant e^x_{i,max}, \\ & e^v_{i,min} \leqslant e^v_i \leqslant e^v_{i,max} \end{aligned}$$

where Q_i and R_i are the weight matrices, P_i the terminal penalty matrix, Ω_i the terminal constraint set.

The definitions of the terminal penalty matrix P_i and terminal constraint set Ω_i are used to ensure the asymptotic consensus of the platoon. The terminal penalty matrix P_i is calculated by solving the following discrete Riccati equation:

$$A_i^T\left(P_i - P_iB_i\left(R_i + B_i^TP_iB_i\right)^{-1}B_i^TP_i\right)A_i - P_i + Q_i = 0 \tag{25}$$

The terminal constraint set Ω_i should satisfy that:

$$\Omega_i := \{x_i \in \mathbb{R}^m \mid x_i^TP_ix_i \leqslant \alpha_i\} \tag{26}$$

where α_i is a positive constant around the equilibrium point of the system.

If Problem 1 is feasible at the initial time instant, the feasibility of Problem 1 can be guaranteed with the terminal penalty matrix P_i and terminal set Ω_i, that is, the asymptotic consensus of the vehicle platoon is guaranteed.

Definition 1. (Asymptotic consensus[20]): At time instant k, if the state of the leading vehicle changes, all the errors of following vehicles in the platoon can asymptotically converge to zero.

At time instant k, only the first element of the input sequence is applied to the i th vehicle. At the next time instant, the entire process will be repeated with updated measurements and information exchange, that is,

$$x_i(k+1) = f\left(x_i(k), u_{mpc}(x_i(k))\right)k \geqslant 0 \tag{27}$$

where

$$u_i(x_i(k)) = u_{mpc}(x_i(k)) = \mathbb{U}_i(0 \mid k) \tag{28}$$

Define $J_i(x_i(k), u_i(k))$ as the cumulative cost, and denote $J_i^*(x_i(k), u_i(k))$ as the optimal cumulative cost associated with the optimal input $u_i^*(x(k))$. By utilizing the Lyapunov stability theorem, a sufficient condition for asymptotic consensus can be derived.

Accordingly, for lateral control of the i th vehicle in platoon, the optimization problem can be described as follows:

Problem 2.

$$minimize\ \tilde{J}_i(\tilde{x}_i(k), \tilde{u}_i(k)) = \sum_{j=0}^{\tilde{N}_{i,p}-1} \tilde{q}_i(\tilde{x}_i, \tilde{u}_i) + \tilde{p}_i(\tilde{x}_i) \tag{29}$$

s.t.

$$\begin{aligned}
&\tilde{p}_i(\tilde{x}_i) = \| \tilde{x}_i(k + \tilde{N}_{i,p} - 1|k) \|^2_{\tilde{P}_i},\\
&\tilde{q}_i(\tilde{x}_i, \tilde{u}_i) = \| \tilde{x}_i(k + j|k) \|^2_{\tilde{Q}_i} + \| \tilde{u}_i(k + j|k) \|^2_{\tilde{R}_i},\\
&\tilde{x}(k + \tilde{N}_{i,p} - 1|k) \in \tilde{\Omega}_i,\\
&v^y_{i,min} \leqslant v^y_i(k + j|k) \leqslant v^y_{i,max},\\
&\psi_{i,min} \leqslant \psi_i \leqslant \psi_{i,max},\\
&\delta_{i,min} \leqslant \delta_i \leqslant \delta_{i,max},\\
&e^{\psi}_{i,min} \leqslant e^{\psi}_i \leqslant e^{\psi}_{i,max},\\
&e^y_{i,min} \leqslant e^y_i \leqslant e^y_{i,max}
\end{aligned}$$

where $\tilde{Q}_i$ and $\tilde{R}_i$ are the weight matrices, $\tilde{P}_i$ the terminal penalty matrix, $\tilde{\Omega}_i$ the terminal constraint set.

A vehicle platoon problem is studied in this paper that considers the decoupled longitudinal and lateral vehicle dynamics, while model predictive controller may lead to significant computational burdens. In practical applications, insufficient computing power can result in controller failure. To address this issue, next subsection will introduce a MPC-inspired neural network method.

MPC-inspired neural network controller

Neural networks can address computational efficiency issues through offline training. However, the training data sources for traditional NN controllers are often unknown, and their internal structures are typically opaque. Therefore, in this subsection, a MPC-inspired neural network controller is proposed by combining MPC with feedforward neural networks (FNNs). This method not only ensures the interpretability of data sources but also enhances the dynamic performance of the NNs. The overall control block diagram is shown in Figure 3.

The dataset required for training and testing the neural network includes information on states and control inputs. By randomizing initial conditions and applying to the MPC law, multiple data sequences can be generated. The dataset $\mathcal{D}$ is defined as:

$$\mathcal{D} = \{x_i, u_{mpc}(x_i)\}^N_{\xi=1} \tag{30}$$

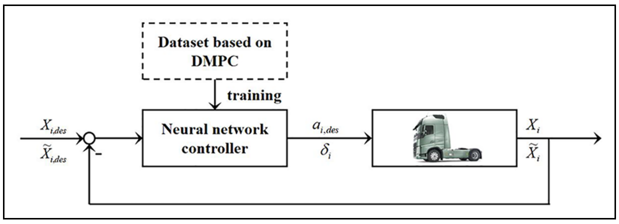

Figure 3. The structure of MPC-inspired NN controller.

where ξ is the number of training trajectories, and N the total number of data trajectories, including the training dataset N_{train} and the testing dataset N_{test}.

Feedforward neural networks are adapted to approximate the control law of MPC. The transmission expression for the l-th layer of the single neuron is defined as:

$$\begin{aligned}
&z^{(l)} = W^{(l)} \cdot a^{(l-1)} + b^{(l)},\\
&a^{(l)} = f_l(z^{(l)}).
\end{aligned} \tag{31}$$

where l represents the number of layers, $f_l(\cdot)$ the activation function of the l th neurons, $W^{(l)}$ the weight matrix from layer $l-1$ to l, $b^{(l)}$ the bias from layer $l-1$ to l, $z^{(l)}$ the input of the l th neurons, and $a^{(l)}$ the output of the l th neurons.

In the imitation phase, supervised learning is employed for NN training with the goal of minimizing the following mean squared error (MSE):

$$\theta = \arg\min_{\theta} \frac{1}{N_{train}} \sum_{\xi=1}^{N_{train}} \| u_{nn} - u_{mpc} \|^2_2 \tag{32}$$

where θ represents the NN parameter, u_{nn} the control input approximated by NNs.

Remark 1. During the training process, the NNs can be further fine-tuned using a reinforcement learning algorithm, which may help reduce instability under extreme conditions.

The proposed MPC-inspired NN controller not only ensures the stability of the NN controller but also inherits the excellent performance while addressing the issue of excessive computation time associated with traditional MPC. The approximate control quantity $\widehat{u}_i(x_i(k))$ is defined as:

$$\widehat{u}_i(x_i(k)) = u_{nn}(x_i(k)) \tag{33}$$

where $\widehat{u}_i : \mathbb{R}^m \to \mathbb{R}^n$, m the dimension of input quantity and n the dimension of output quantity.

Table 1. Parameters of longitudinal controller.

Parameters	Value	Parameters	Value
T_s	0.1 s	$N_{i,p}$	8
Q_i	$diag(30\ 30\ 10)$	R_i	10
$x_{i,max}$	$[10\ 2\ 2]$	$x_{i,min}$	$[-10-2-2]$
N_{hidden}	3	n_{hidden}	[20 10 20]
N_{input}	3	N_{output}	1

Table 2. Parameters of lateral controller.

Parameters	Value	Parameters	Value
T_s	0.1 s	$\tilde{N}_{i,p}$	8
$\tilde{Q}_i$	$diag(20\ 20\ 20\ 20)$	$\tilde{R}_i$	10
$\tilde{x}_{i,max}$	$[0.7\ 0.7\ 0.7\ 0.7]$	$\tilde{x}_{i,min}$	$[-0.7-0.7-0.7-0.7]$
$\tilde{N}_{hidden}$	3	$\tilde{n}_{hidden}$	[20 10 20]
$\tilde{N}_{input}$	4	$\tilde{N}_{output}$	1

Experimental results

This section will introduce the experimental results of dataset generation, and verify the effectiveness of the proposed controller based on actual truck driving data, and MATLAB/Trucksim joint simulation.

Neural network training and testing

For the longitudinal control of platoon, the parameters of the MPC-inspired NN controller are shown in Table 1.

where N_{hidden} is the number of hidden layers, n_{hidden} the number of hidden layer neurons, N_{input} and N_{output} the number of input and output layers. Accordingly, the parameters for the lateral controller are shown in the following Table 2.

According to the process of data generation (30), the longitudinal and lateral dataset for training is shown in Figure 4, where Figure 4(a) represents the relationship between longitudinal position error e_i^x, longitudinal velocity deviation e_i^v and acceleration a_i, (b) represents the lateral position error e_i^y, the heading angle deviation e_i^ψ and lateral velocity deviation $\dot{e}_i^y$, respectively.

To test the approximation effect, correlation coefficients R_{train}, R_{test} are defined to quantify the relationship between the approximate values and expected values:

$$R_{train} = \frac{\sum_{i=1}^{N_{train}} (u_i - \bar{u}_i)(\hat{u}_i - \bar{\hat{u}}_i)}{\sqrt{\sum_{i=1}^{N} (u_i - \bar{u}_i)^2 \sum_{i=1}^{N_{train}} (\hat{u}_i - \bar{\hat{u}}_i)^2}}$$
$$R_{test} = \frac{\sum_{i=1}^{N_{test}} (u_i - \bar{u}_i)(\hat{u}_i - \bar{\hat{u}}_i)}{\sqrt{\sum_{i=1}^{N} (u_i - \bar{u}_i)^2 \sum_{i=1}^{N_{test}} (\hat{u}_i - \bar{\hat{u}}_i)^2}} \tag{34}$$

where $\bar{u}_i$ is the average of actual values and $\bar{\hat{u}}_i$ the average of approximate values, $u_i = u_{mpc}(x_i(k))$ and $\bar{u}_i = u_{nn}(x_i(k))$.

If R_{train} and R_{test} are close to 1, it indicates that the NNs exhibit strong approximation capabilities. From Figure 5, it can be seen that all deviations are below 0.01, indicating that the MPC-inspired neural network exhibits excellent approximation performance.

Real vehicle numerical verification

In order to better verify the effectiveness of the proposed controller, this subsection selects real driving data as the test condition to assess the performance of the NN controller. During the real truck experiment, two domestic heavy-duty trucks were selected as the experimental vehicles. The following truck obtains status information of the leading truck through the perception module, and achieves data fusion through the CANFD device. Based on these information, the following truck needs to plan the driving path and calculate the control inputs to achieve good performance. The real vehicle data collection is shown in Figure 6.

Representative test data needs to be selected from extensive data. The entire validation process should include various driving conditions such as acceleration, deceleration, and constant speed. The extracted speed and acceleration data of the truck were applied to verify the effectiveness of the NN controller proposed in this paper. The verification results are shown in Figure 7.

Figure 7(a) and (b) represent the spacing error e_{1-2}^x and longitudinal velocity error e_{1-2}^v, respectively. By comparison, it can be seen that two curves align closely, indicating that the NN controller has excellent approximation performance. Figure 7(c) and (d) represent the acceleration a_i and speed v_i of two trucks. It indicates that the following truck successfully follows the leading truck and has good performances.

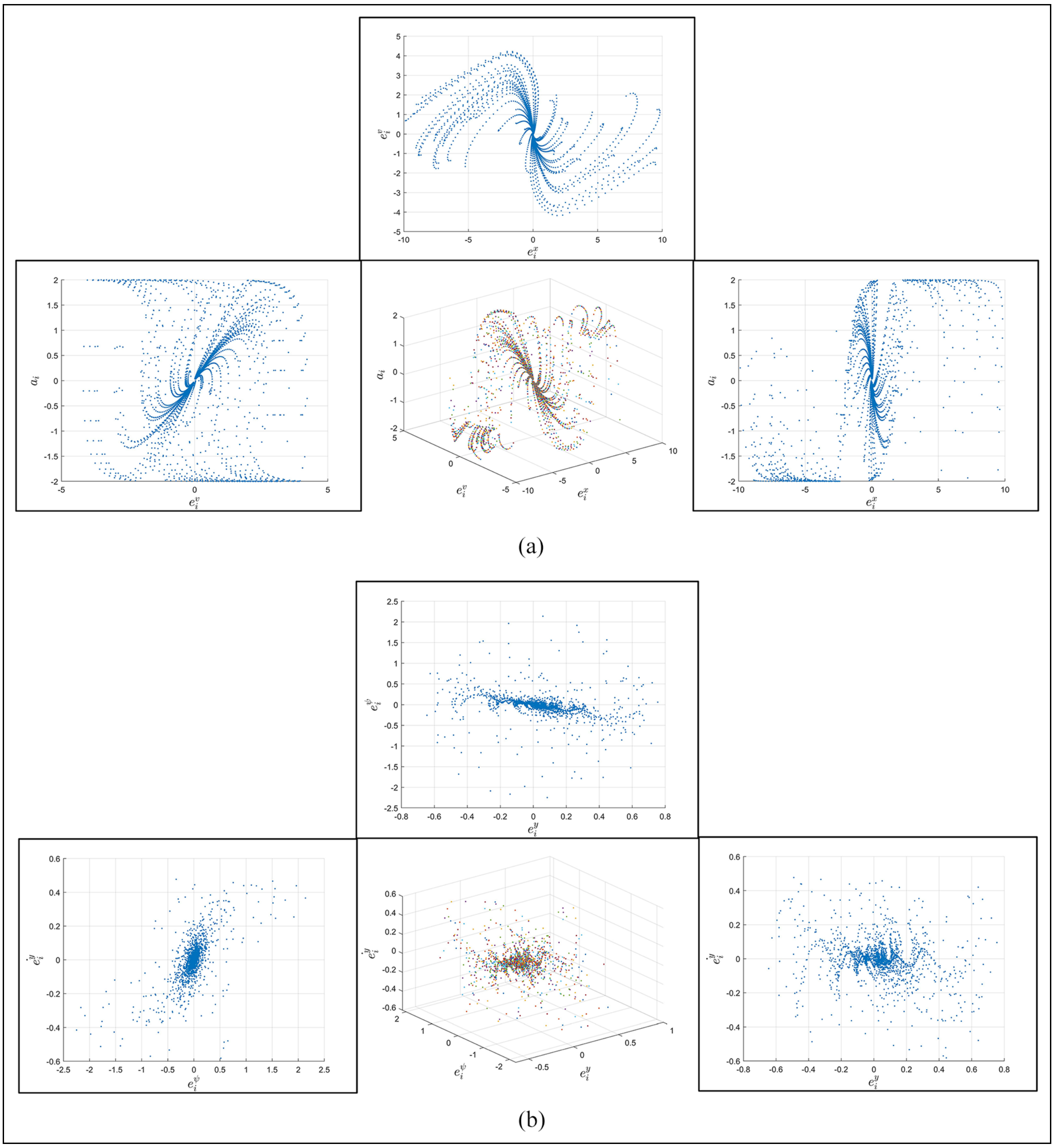

Figure 4. Dataset for training: (a) dataset for longitudinal controller designing and (b) dataset for lateral controller designing.

Simulation results

Consider a homogeneous commercial vehicle platoon consisting of one leading vehicle and three following vehicles, all of which are fully loaded. Build an union simulation platform based on MATLAB and Trucksim. The vehicle parameters are shown in Table 3.

The computer configuration is 12th Gen Intel (R) Core (TM) i7-12700 2.10GHz and NVIDIA GeForce GT 1030. To verify the effectiveness of the controller, two simulation conditions are designed as follows based on Chinese road design standards.

Driving condition 1. In this driving condition, four vehicles drive at a constant speed of 20 m/s. The leading vehicle then decelerates, and enters a curve with a turning radius of 200 m before exiting. The simulation results are shown in Figure 8.

Driving condition 2. In this driving condition, four vehicles drive at a constant speed of 20 m/s, the leading vehicle then accelerates, and enters a curve with a turning radius of 400 m before exiting. The simulation results are shown in Figure 9.

From the results, it can be seen that the MPC-inspired NN controller proposed in this paper can achieve real-time optimization of strategies while ensuring that the following vehicles maintains good dynamic performance. When the leading vehicle turns, the

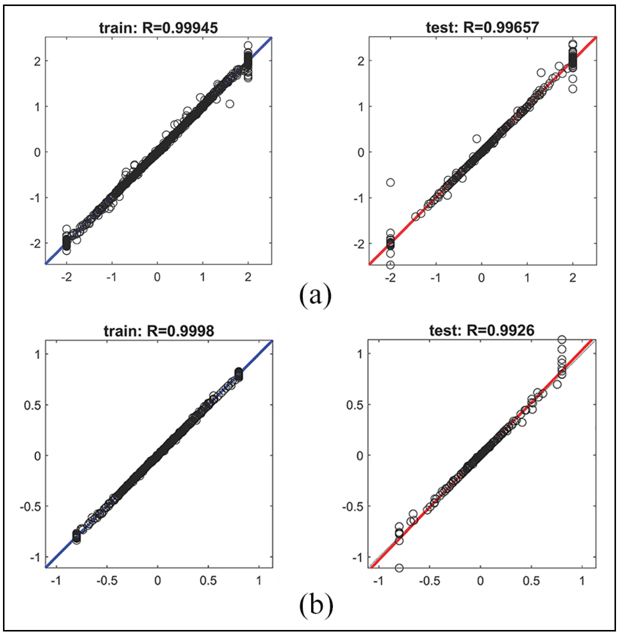

Figure 5. Approximate effect verification (The horizontal axis represents the actual value, and the vertical axis represents the approximate value. The black circles represent the data points, and the solid line represents the mapping relationship.): (a) longitudinal controller verification and (b) lateral controller verification.

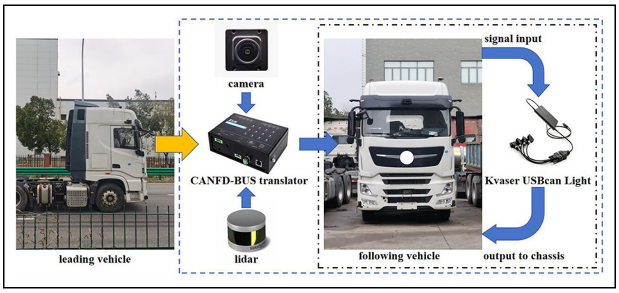

Figure 6. Real vehicle data collection.

following vehicle quickly adapts, maintaining all errors within allowable ranges. This ensures that the platoon maintains strong tracking performances.

In the two driving conditions described, the MPC-inspired NN controller has an average computational time of 3.04×10^{-2} ms, while MPC takes 2.61×10^{-1} ms on average. Note that the values are obtained after the computer's performance is stable. Compared to MPC, the computational efficiency of the MPC-inspired NN controller is improved by more than 80%, achieving the expected control objectives.

Remark 2. String stability is a common evaluation metrics for vehicle platoons, referring to the situation

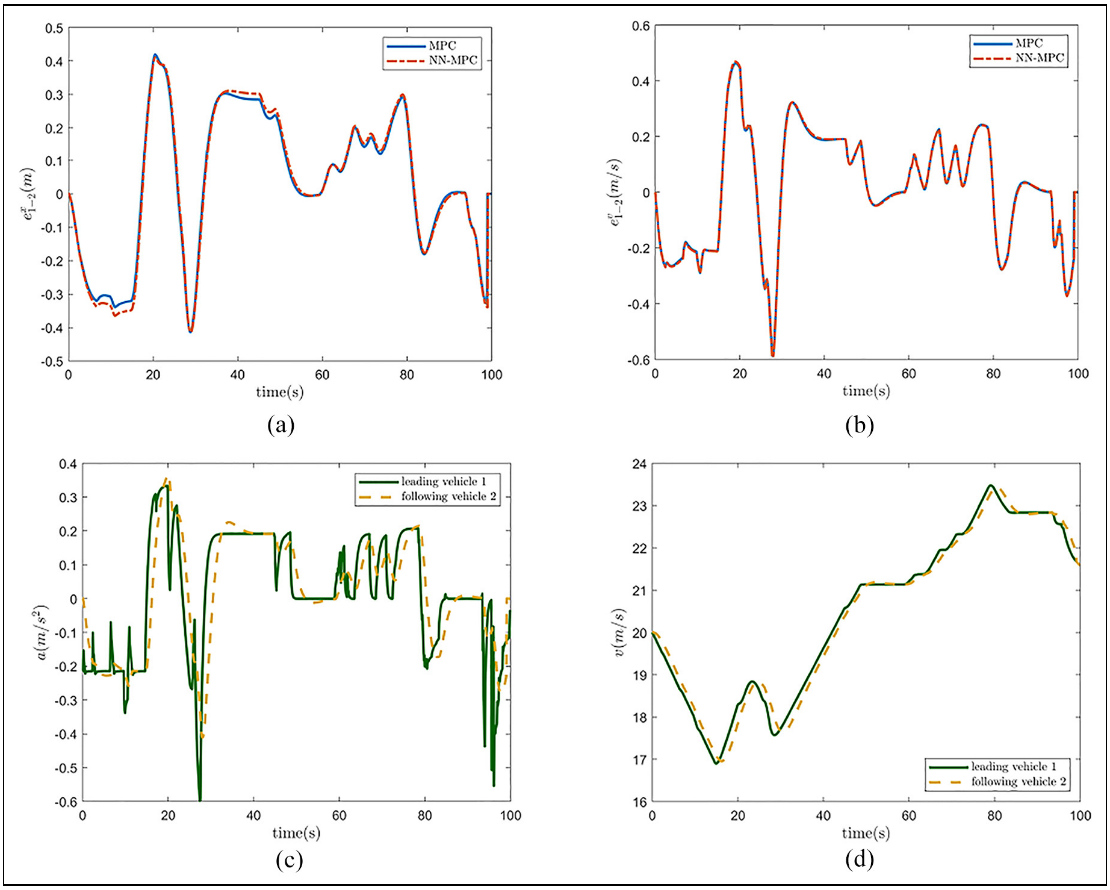

Figure 7. Verification results based on real vehicle data (The blue solid line and red dotted line represent the performance of MPC, and MPC-inspired NN respectively.): (a) longitudinal position error, (b) longitudinal speed error, (c) longitudinal acceleration, and (d) longitudinal speed.

Table 3. The parameters of the vehicle.

Parameters	Value	Parameters	Value
h_i	1	d_0	10 m
$C_{d,i}$	0.3	τ_i	0.25
m_i	18,000 kg	$I_{z,i}$	130,235.8 $kg \cdot m^2$
$l_{f,i}$	3.5 m	$l_{r,i}$	1.5 m
C_i^{cf}	271,127.22 N/rad	C_i^{cr}	533,145.17 N/rad

where the error between vehicles gradually decreases as the number of following vehicles increases.[21] This paper focuses more on approximating MPC based on terminal constraints using supervised learning to ensure that the system exhibits performance and convergence nearly identical to that of the MPC, without considering the string stability constraints at this stage. Test results show that under different traffic conditions, the errors between vehicles are consistently much smaller

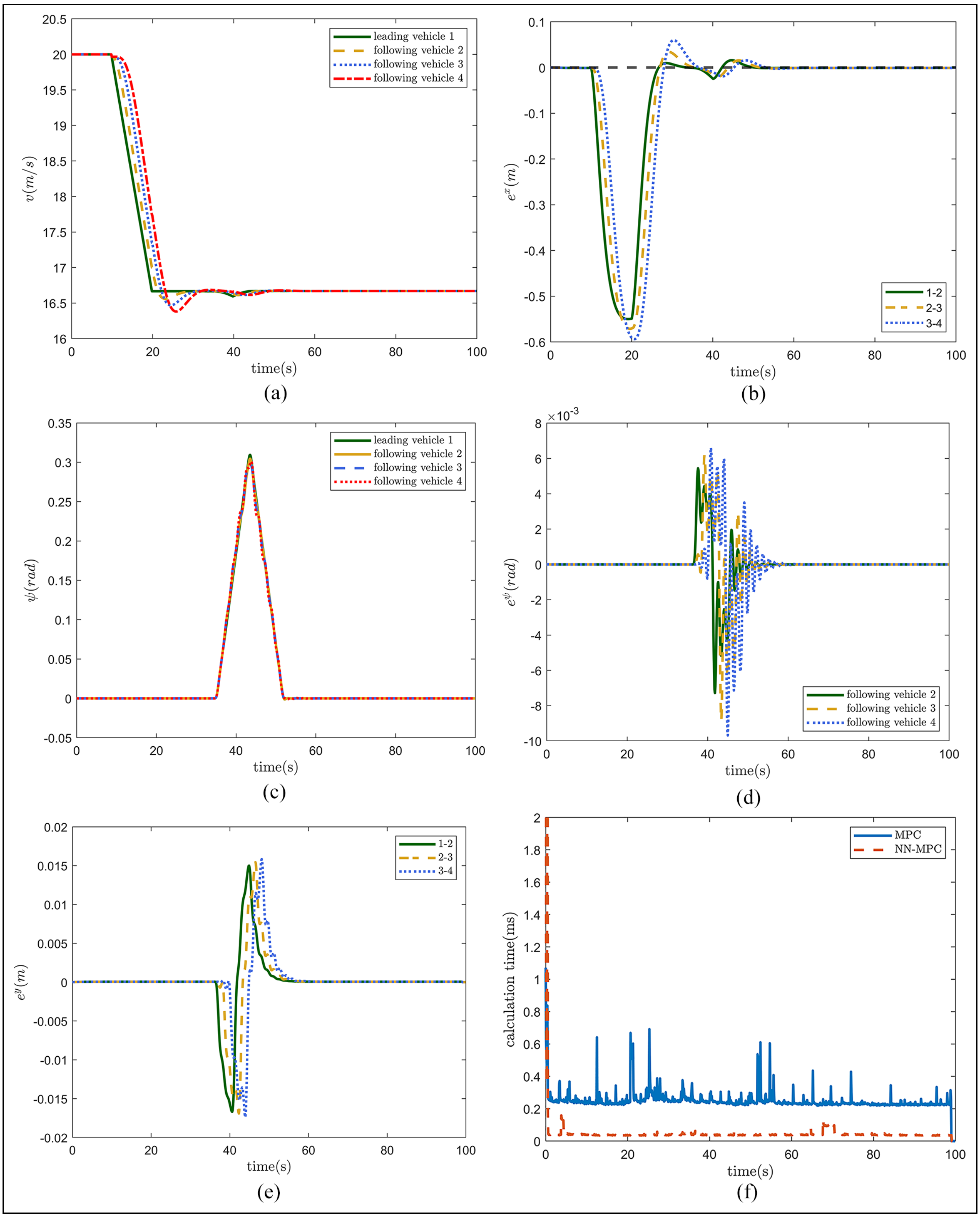

Figure 8. Driving condition 1: (a) longitudinal speed, (b) longitudinal position error, (c) heading angle, (d) heading angle error, (e) lateral position error, and (f) computational time.

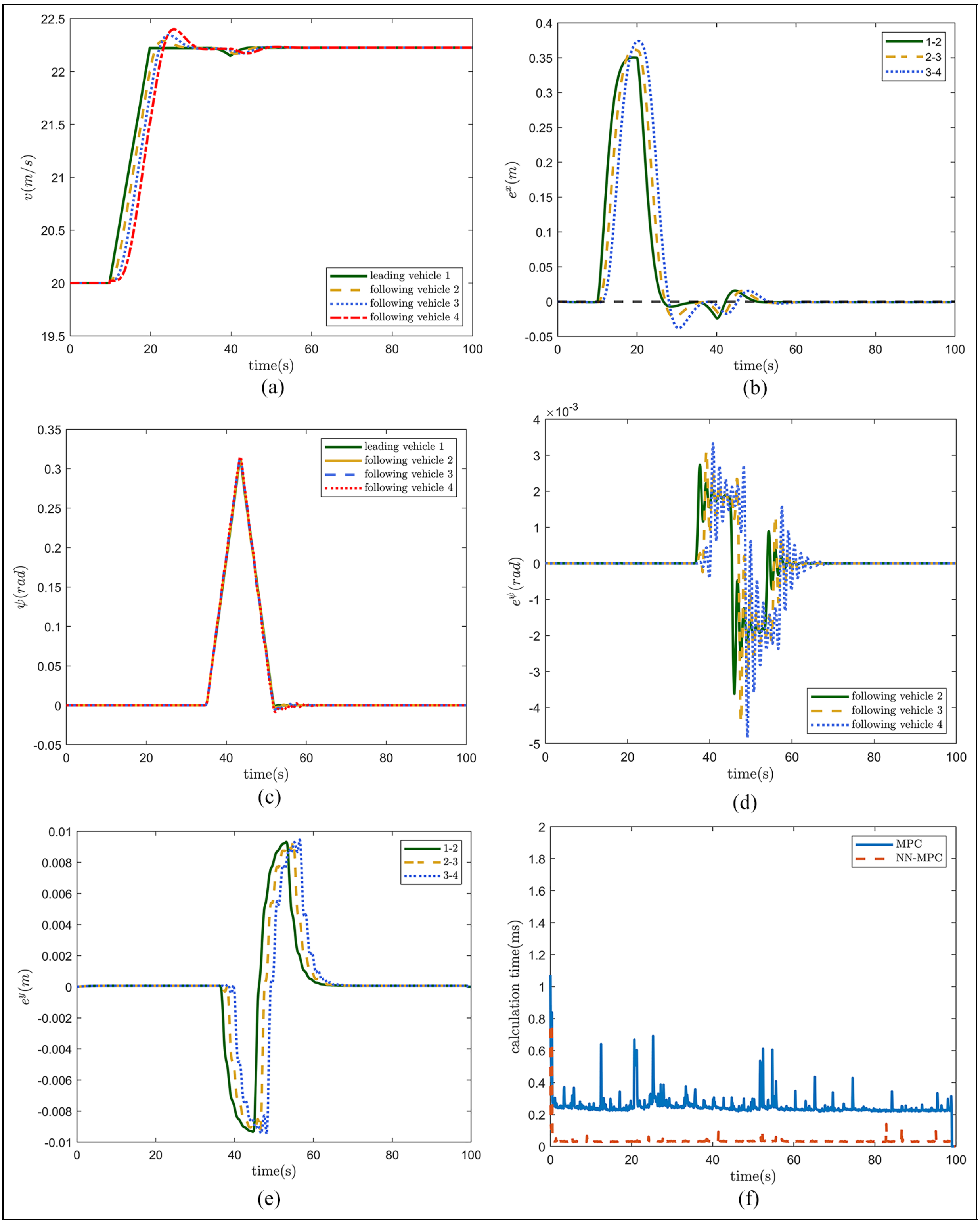

Figure 9. Driving condition 2: (a) longitudinal speed, (b) longitudinal position error, (c) heading angle, (d) heading angle error, (e) lateral position error, and (f) computational time.

than the allowable values, with minimal differences among the error values, meeting practical application requirements. String stability constraints will be considered in future to further enhance the completeness of the theory.

Conclusion

In this paper, a MPC-inspired NN controller was proposed for cooperative control of vehicle platoons. This method combined the advantages of MPC and NNs, which ensured asymptotic consensus of vehicle platoons, and greatly improved the computational efficiency. Through the driving data collection platform of trucks and joint simulation platform based on MATLAB and Trucksim, the proposed MPC-inspired NN controller demonstrated its ability to meet the expected control objectives, proving its effectiveness in real-world applications. This method presented a new concept for the current autonomous vehicle platoon controller, which enhanced the safety and intelligence of autonomous vehicles to some extent. But this approach also has certain limitations, including the disregard for string stability and the effects of lateral-longitudinal coupling. Future research will focus on optimizing this method further and incorporating more complex traffic conditions to bridge the gap between theoretical models and real-world scenarios.

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References

1. Hui F, Chengqian J, Zhangzhe N, et al. A review on planning and control of connected autonomous truck platooning. *Ind Eng J* 2024; 27(1): 25.
2. Hummer J. *Driverless America: SAE International* , 2020, pp.i–xi.
3. Zhu B, Jiang Y, Zhao J, et al. A car-following control algorithm based on deed reinforcement learning. *China J Highway Trans* 2019; 32(6): 53–60.
4. Liu P, Kurt A and Ozguner U. Distributed model predictive control for cooperative and flexible vehicle platooning. *IEEE Trans Control Syst Technol* 2018; 27(3): 1115–1128.
5. Min H, Yang Y, Fang Y, et al. Constrained optimization and distributed model predictive control-based merging strategies for adjacent connected autonomous vehicle platoons. *IEEE Access* 2019; 7: 163085–163096.
6. Qiang Z, Dai L, Chen B, et al. Distributed model predictive control for heterogeneous vehicle platoon with inter-vehicular spacing constraints. *IEEE Trans Intell Transp Syst* 2022; 24(3): 3339–3351.
7. Gong S and Du L. Cooperative platoon control for a mixed traffic flow including human drive vehicles and connected and autonomous vehicles. *Transp Res B Methodol* 2018; 116: 25–61.
8. Yu SM, Wu SN, Zhao YB, et al. Delayed feedback MPC algorithms of vehicle platoons subject to constraints on measurement range and driving behaviors. *Asian J Control* 2018; 20(6): 2260–2270.
9. Li L, Gan J, Qu X, et al. A dynamic control method for CAVS platoon based on the MPC framework and safety potential field model. *KSCE J Civ Eng* 2021; 25(5): 1874–1886.
10. Zuo Z, Yang K, Wang H, et al. Distributed MPC for automated vehicle platoon: a path-coupled extended look-ahead approach. *IEEE Trans Intell Veh*. Epub ahead of print 18 March 2024. DOI: 10.1109/TIV.2024.3376797.
11. Huang C, Shi Q, Ding W, et al. A robust MPC approach for platooning control of automated vehicles with constraints on acceleration. *Control Eng Pract* 2023; 139: 105648.
12. Chen J, Wu X, Lv Z, et al. Collaborative control of vehicle platoon based on deep reinforcement learning. *IEEE Trans Veh Technol* 2024; 73(10): 14399–14414.
13. He H, Han M, Liu W, et al. MPC-based longitudinal control strategy considering energy consumption for a dual-motor electric vehicle. *Energy* 2022; 253: 124004.
14. Chen X, Zhou B and Wu X. Autonomous vehicle path tracking control considering the stability under lane change. *Proc IMechE, Part I: J Systems and Control Engineering* 2021; 235(8): 1388–1402.
15. Yang Y, Ma F, Wang J, et al. Cooperative ecological cruising using hierarchical control strategy with optimal sustainable performance for connected automated vehicles on varying road conditions. *J Clean Prod* 2020; 275: 123056.
16. Wang CX, Cheng X and Laurenson DI. Vehicle-to-vehicle channel modeling and measurements: recent advances and future challenges. *IEEE Commun Mag* 2009; 47(11): 96–103.
17. Dhand R, Lee G and Cole G. Communication delay modelling and its impact on real-time distributed control systems. In: *Proc. 4th International Conference on Advanced Engineering Computing and Applications in Science*, Florence, Italy, 25–30 October, 2010, pp.39–46, IARIA, Venice, Italy.
18. Li SE, Qin X, Li K, et al. Robustness analysis and controller synthesis of homogeneous vehicular platoons with bounded parameter uncertainty. *IEEE ASME Trans Mechatron* 2017; 22(2): 1014–1025.
19. Yu S, Chen H, Feng Y, et al. Nash optimality based distributed model predictive control for vehicle platoon. *IFAC Pap OnLine* 2020; 53(2): 6610–6615.
20. He D, Qiu T and Luo R. Fuel efficiency-oriented platooning control of connected nonlinear vehicles: a distributed economic MPC approach. *Asian J Control* 2020; 22(4): 1628–1638.
21. Feng Y, Yu S, Sheng E, et al. Distributed MPC of vehicle platoons considering longitudinal and lateral coupling. *IEEE Trans Intell Transp Syst* 2023; 25(3): 2293–2310.