V2X Based Cooperative Motion Control and Energy Management for Electronic Vehicles

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Abstract—V2X communication is a key technology for intelligent transportation system to improve traffic safety and efficiency. Electric vehicles can reduce greenhouse gas emissions and fossil fuel dependence, but they face challenges such as limited driving range, high battery cost, and long charging time. This paper proposes a V2X communication assisted hierarchical cooperative control strategy for EVs that aims at improving driving performance and energy efficiency. The upper layer uses improved model predictive control (MPC) method for cooperative motion control. A mechanism is designed for V2X communication loss in the algorithm. The lower layer employs a hybrid energy storage system for powertrain management. The algorithm in the lower layer uses the predictive information from the upper layer to enhance the powertrain efficiency and prolong the battery life. The proposed strategy is simulated using a Prescan-Carsim simulation platform. The results demonstrate that the proposed method can improve the battery lifetime over 13% compared with baseline method.

Index Terms—Electric vehicle, model predictive control, hierarchical strategy, vehicle-to-everything communication.

I. INTRODUCTION

Vehicle-to-Everything (V2X) communication can provide information that is not detected by on-board sensors, such as the position, speed of other vehicles and road conditions, etc. V2X communication can also facilitate coordination and cooperation among vehicles to achieve safer and more efficient driving. Electric vehicles (EVs) can mitigate greenhouse gas emissions and fossil fuel dependence in transportation, but they face challenges such as limited range, high battery cost, and long charging time. Thus, EVs need to cooperate with each other and the environment to optimize their energy consumption and driving performance through V2X communication.

Several studies have proposed V2X communication based cooperative driving methods for different scenarios and objectives. [1] proposed a cooperative adaptive cruise control (CACC) system that uses V2X communication to achieve string stability for vehicle platoons. [2], [3] proposed cooperative lane change (CLC) algorithm that uses vehicle communication information to negotiate with neighboring vehicles and find a suitable gap for lane change. Most of these methods assume ideal or reliable V2X communication, which may not be realistic in practical scenarios. In reality, V2X communication may suffer from packet loss, delay, noise, interference, or malicious attacks, which can degrade the performance or even jeopardize the safety of cooperative driving. Therefore, it is important to design robust and resilient cooperative driving methods that can cope with V2X communication failures. Considering the communication resources, event-trigger mechanism have been introduced into controller design [4], [5]. Nonetheless, these methods implies the necessity of maintaining constant availability of network resources, which is unfavorable for scheduling shared network resources. The vehicle control problem is often regarded as a multi-objective optimization problem. A hierarchical cooperative control strategy is a common approach to deal with complex control problems that involve multiple objectives or constraints. [6] proposed a hierarchical energy management system (EMS) for hybrid electric vehicles (HEVs) that consists of two levels: the upper level determines the optimal power split ratio between the engine and the motor based on the driving cycle, while the lower level regulates the battery state of charge (SOC) and the motor torque based on the power split ratio. [7]–[9] proposed hierarchical control strategies for electric vehicle cooperative driving that optimize the vehicle speed and acceleration based on the road grade or traffic information. Moreover, most of these methods do not consider the coupling relationship between electric vehicle power system regulation and motion system control, or only consider it in a static or deterministic way. Therefore, it is challenging to design a V2X communication assisted hierarchical cooperative control strategy that can dynamically coordinate electric vehicle powertrain system regulation and motion system control under uncertain or stochastic driving conditions.

This paper proposes a novel V2X communication assisted hierarchical cooperative control strategy for EVs to improve their driving performance and energy efficiency. The strategy addresses two fundamental and coupled challenges: the energy management of the internal powertrain and the vehicle motion control. The powertrain output affects the vehicle motion control, or only consider it in a static or deterministic way. Therefore, it is challenging to design a V2X communication assisted hierarchical cooperative control strategy that can dynamically coordinate electric vehicle powertrain system regulation and motion system control under uncertain or stochastic driving conditions.
problem between the ego vehicle and the preceding vehicle using an improved MPC algorithm that handles communication loss; the lower layer employs a hybrid powertrain of a battery pack and supercapacitor to reduce the battery stress and uses the predictive information from the upper layer to enhance the power source efficiency and prolong the battery life.

This paper is structured as follows. Section II presents the system description and problem formulation. Section III describes the design of the hierarchical control algorithm in detail. Section IV evaluates the performance of the proposed method. Section V summarizes the paper and draws conclusions of our work.

II. SYSTEM DESCRIPTION AND PROBLEM STATEMENT

As depicted in Fig. 1, this paper proposes a V2X-assisted hierarchical strategy that improve the driving performance of electric vehicle. The details of the system architecture are elaborated as follows:

The purpose of the upper-layer cooperative motion layer is to provide optimal control inputs for the vehicle, so that the vehicle can stably track the preceding vehicle. The upper layer receives the state information of the preceding vehicle through V2V communication, and receives real-time geographic information including road slope, wind resistance coefficient, etc. through V2I communication. Due to the complex electromagnetic environment in actual traffic scenarios, the communication state is difficult to guarantee. To deal with the communication packet loss problem, upper layer designs an improved MPC controller to ensure the robustness of control. At the same time, the decisions made by the cooperative motion controller provide future estimated information for the powertrain management of vehicle itself.

The lower-layer powertrain system consists of a hybrid energy storage system (HESS) composed of batteries and supercapacitors. Two DC/DC converters regulate the output/input status of the HESS modules under the control of electronic control unit (ECU). The motor is connected to the powertrain through a motor driver and can operate in both motor and generator modes. The motor torque is transmitted to the wheels through a gearbox, which drives the vehicle. The lower-level energy management method can effectively alleviate the battery stress and reasonably allocate the energy sources by using the predictive results from the upper-level motion planning. This can improve the energy efficiency and extend the battery life.

A. Vehicle Longitudinal Dynamics Model

The present study utilizes a first-order inertial system to describe the relationship between desired acceleration and actual acceleration. By combining it with the vehicle’s kinematic relationships, the following discrete equations can be established for the longitudinal dynamics model of the vehicle:

\[
\begin{align*}
 s(k+1) &= s(k) + v(k)\Delta t, \\
v(k+1) &= v(k) + a(k)\Delta t, \\
a(k+1) &= a(k) + \frac{\Delta t}{\tau} \left[u(k) - a(k)\right],
\end{align*}
\]

where \( s(k), v(k), \) and \( a(k) \) are the position, velocity, and acceleration of the ego vehicle, respectively. \( \tau \) is the time constant with \( \tau = 0.5s \), \( u(k) \) is the upper layer control input, and \( \Delta t \) is the system sampling time with \( \Delta t = 0.05s \). The vehicle state \( x(k) \) is defined as \( [s(k), v(k), a(k)]^T \), and the discrete state-space equation for the longitudinal inter-vehicle kinematic model is derived from equation (1):

\[
x(k+1) = Ax(k) + Bu(k),
\]

where \( A = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 - \frac{\Delta t}{\tau} \end{bmatrix}, B = \begin{bmatrix} 0 \\ 0 \\ \frac{\Delta t}{\tau} \end{bmatrix} \).

B. Electric Vehicle Powertrain System

The powertrain system of the electric vehicle considered in this study composed of batteries and supercapacitors. The power balance equation is expressed as follows:

\[
\eta_{b}(k)P_{b}(k) + \eta_{ac}(k)P_{ac}(k) = P_{d}(k),
\]

where \( P_{b}(k), P_{ac}(k), \) and \( P_{d}(k) \) are the output powers of the battery pack, the capacitor pack, and the vehicle propulsion, respectively. The parameters \( \eta_{b}(k) \) and \( \eta_{ac}(k) \) are the efficiency coefficients of the DC/DC converters connected to the battery and the supercapacitor. The vehicle propulsion power \( P_{d}(k) \) is a crucial state that links the lower and upper layers, and it is given by:

\[
P_{d}(k) = \frac{1}{2\rho_{air}C_{r}Av(k)^{3} + m\nu(k)[a(k) + a_{m}(k)]},
\]

where \( a_{m}(k) = g \sin(\theta(k)) + c_{r}g \cos(\theta(k)) \) is the map-related term that accounts for the road gradient effects on the powertrain output, which can be obtained by V2I communication. \( c_{r} \) is rolling resistance coefficient, \( \rho_{air}, C_{r}, \) and \( A \) respectively represent the air density, air drag coefficient, and windward area of the vehicle during driving. We use the T-S fuzzy modeling approach to derive the dynamic models of the battery and supercapacitor state of charge (SoC):

\[
x^{-}(k+1) = A(k)x^{-}(k) + B(k)u^{-}(k) + E(k),
\]

where \( x^{-}(k) = [SoC_{b}(k), SoC_{ac}(k)]^T \) and \( u^{-}(k) = [P_{b}(k), P_{ac}(k)]^T \) are the SoC and output power vectors for
the battery and supercapacitor, respectively. The time-varying system model parameter matrices \( A(k) \), \( B(k) \), and \( E(k) \) are detailed in [10].

III. V2X ASSISTED HIERARCHICAL STRATEGY DESIGN

In this section, we design a V2X assisted hierarchical strategy, which consists of cooperative motion control in the upper layer and powertrain management in the lower layer. We also explain how to integrate the upper and lower layers and handle the communication packet loss problem.

A. Cooperative Motion Control in Upper Layer

Model Predictive Control (MPC) is a popular technique for vehicle control problems. It predicts the future system outputs based on historical data and future inputs, and computes the optimal current control decisions. MPC can generate and estimate the optimal control sequence and system states over a given time horizon. This makes MPC suitable for upper layer cooperative control. MPC can also provide the predicted velocity trajectory and the future power demand for lower-level powertrain optimization. The optimization problem for a controlled vehicle is:

\[
\begin{align}
\min_u & \quad L(k) = \sum_{\tau=0}^{N_p-1} l(\tau; k), \\
\text{s.t.} & \quad x(\tau + 1; k) = f_e(x(\tau; k), u(\tau; k)), \\
& \quad G(x(N_p; k) - x_p^*(N_p; k)) = \delta(N_p; k), \\
& \quad x(0; k) = x(k), u(\tau; k) \in U, \\
\end{align}
\]  

(6)

where \( x(\tau; k) \) and \( u(\tau; k) \) are the predicted state and control sequences of the vehicle at time \( k \), respectively. \( f_e(\cdot) \) is the vehicle state equation (2) for predicting the future driving state. \( x(k) \) and \( u(k) \) are the measured state and control input at the current time \( k \). \( U \) is the control variable constraint set, which depends on the road segment and vehicle type. The terminal constraint (6d) ensures that the vehicle can follow its preceding vehicle stably at the end of the prediction horizon. \( x_p^*(\tau; k) \) is the sequence of preceding vehicle state information obtained through V2V communication. \( G = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \) is the terminal constraint coefficient. The variable \( \delta(\tau; k) \) is defined as \( \delta(\tau; k) = [d_0 + h \cdot v(\tau; k), \ 0]^T \), where \( d_0 \) is the desired inter-vehicle distance when the vehicle is stationary, \( h > 0 \) is the headway time. The objective function (6a) considers the tracking error and driving comfort as follows:

\[
l(\tau; k) = ||u(\tau; k)||_R^2 + ||x(\tau; k) - x^*(\tau; k)||_P^2 + ||G(x(\tau; k) - x_p^*(\tau; k)) - \delta(\tau; k)||_Q^2,
\]

(7)

where \( R, P \) and \( Q \) are symmetric weight matrices. The cost function (7) has three terms. The first term \( R \) penalizes the deviation of the control input from the constant speed input, to achieve smooth driving. The second term \( P \) ensures that the vehicle follows its estimated trajectory \( x^*(\tau; k) \), which is important for the internal energy management in the lower layer. The cost term \( Q \) aims to adjust the vehicle’s driving state to track the driving state of the preceding vehicle.

Fig. 2 illustrates the mechanism of the proposed algorithm and the process of constructing the estimated state. At each instant, ego vehicle solves the optimization problem (6) to obtain the optimal control sequence \( u^*(\cdot; k) \) and optimal state trajectory \( x^*(\cdot; k) \). Then, it applies the first control element \( u^*(0; k) \) (the yellow circle in Fig.2) to adjust its actual state. It uses the optimal state sequence \( x^*(\cdot; k) \) to construct the estimated future state sequence \( x^*(\tau; k) \) for the next instant as follows:

\[
x^*(\tau; k + 1) = \begin{cases} x^*(\tau + 1; k), & \tau = 0, \ldots, N_p - 1, \\
D \cdot x^*(N_p; k), & \tau = N_p,
\end{cases}
\]

(8)

where \( D = [1, \Delta t, 0; 0, 1, 0; 0, 0, 1] \). In Fig. 2, the green circle represents the estimated future state constructed using the predictive model. Real-world traffic scenarios involve complex traffic conditions and communication environments, which may cause packet loss and delays in V2V communication. Maintaining a perfect communication state is challenging in practice. If a vehicle experiences packet loss or significant delays at time \( k \), we consider it as a communication failure (denoted as \( \gamma(\tau) = 1 \)) and discard that information to ensure data quality. Based on these considerations, we redefine the iterative update method for the estimated state sequence as follows:

\[
x^*(\tau; k + 1) = \begin{cases} x^*(\tau + \kappa_t; t_e), & \tau = 0, \ldots, N_k, \\
D^{\tau - N_k} \cdot x^*(N_p; t_e), & \tau = N_k + 1, \ldots, N_p,
\end{cases}
\]

(9)

where \( N_k = N_p - \kappa_t \), \( t_e \) is the time of the most recent successful transmission before the current time \( k \). Thus, \( t_e \leq k \) and \( t_e \in \{0, 1, \ldots, N_T\} \), \( \kappa_t = k - t_{e-1} \) is the number of sampling intervals between \( k \) and \( t_e \), which indicates the consecutive communication failures.

B. Powertrain Management in Lower Layer

The lower layer aims to control the charging and discharging power of the battery and supercapacitor, denoted as \( u^*(k) \) at each sampling instant based on the upper layer motion control decisions. The objectives are to: 1) ensure sufficient power output without compromising driving performance; 2) minimize battery life degradation by reducing discharge rates and suppressing power fluctuations; and 3) ensure the operational efficiency of the supercapacitor. The cost function
for the energy management problem is:

\[
J(k) = \alpha_1 (P_d(k))^2 + \alpha_{2,1} (\Delta P_d(k))^2 + \alpha_{2,2} (\Delta P_{sc}(k))^2 + \alpha_3 \text{dist}(\text{SoC}_{sc}(k) \mid S),
\]

(10)

where \( \alpha_1, \alpha_{2,1}, \alpha_{2,2}, \alpha_3 > 0 \) are weighting coefficients. \( \Delta P_d(k) = P_d(k) - \bar{P}_d(k-1) \), and \( \Delta P_{sc}(k) = P_{sc}(k) - \bar{P}_{sc}(k-1) \) are the power changes of the battery and the supercapacitor, respectively. Moreover, \( \text{dist}(x \mid S) = \inf_{x_d \in S} \frac{1}{2} ||x - x_d||^2 \) is the norm distance between \( x \) and the set \( S \), where \( S = \{x_d \mid \bar{x_d} \leq x_d \leq \bar{x_d}\} \) is the ideal energy range for the supercapacitor’s operational efficiency. We formulate the real-time energy management problem for the vehicle powertrain management as a rolling optimization problem: :

\[
\begin{align}
\min_{x_{-1}} & \sum_{\tau=0}^{N_p-1} J(x^-(\tau + 1; k), u^-(\tau; k)) \\
\text{s.t.} & \ x^-(\tau + 1; k) = f_{soc}(x^-(\tau; k), u^-(\tau; k)), \\
& [\theta, \eta_{soc}] \cdot u^-(\tau; k) = P_d(\tau; k), \\
& x^-(0; k) = x^-(k), u^-(1; k) = u^-(k - 1), \\
& x^-(\tau + 1; k) \in \mathcal{X}, u^-(\tau; k) \in \mathcal{U}.
\end{align}
\]

(11a)

Constraint (11b) is the state equation of the vehicle powertrain management system based on the T-S fuzzy modeling in equation (5). (11c) is the power balance equation for the powertrain system. \( x^-(k) \) is the measured value of the current battery state, \( u^-(k - 1) \) denotes the previous charging and discharging decision. \( P_d(\tau; k) \) is the future \( N_p \)-step driving power demand sequence, which is calculated from the estimated state sequence \( x^*(\tau; k) \). The upper layer estimated information integrates the states of the ego vehicle and the preceding vehicle, and provides future power demand information for lower layer energy management. This enables smoother power allocation for the powertrain, reducing the battery peak discharge frequency. This maximizes battery health protection and lifetime.

IV. PERFORMANCE EVALUATION

To evaluate the performance of the proposed strategy, we use Matlab-Prescan-Carsim co-simulation with real vehicle parameters. The powertrain is modified based on ADVISOR to implement the proposed energy management system and show the real-time energy consumption of the vehicle. Fig. 3 illustrates the simulation platform used in the experiment.

A. Simulation Setup

In the simulation, we consider the preceding vehicle driving according to the Urban Dynamometer Driving Schedule (UDDS) to simulate urban conditions. We test the control performance under acceleration, cruising, deceleration, and stop scenarios. In the inter-vehicle distance strategy, we set \( d_0 = 10 \) and \( h = 10 \). Moreover, in practical V2X communication, we assume a packet loss rate of 10% following a Bernoulli distribution.

B. Results and Analysis

Fig.4 shows the time-domain simulation results of the vehicle motion state and powertrain operation based on the proposed hierarchical strategy. The vehicle velocity trajectory shows that the vehicle can stabilize its speed and position tracking errors to the equilibrium point despite the disturbances from the preceding vehicle. The tracking error curve shows that the controlled vehicle can maintain a reasonable following distance even when the preceding vehicle changes its speed drastically. We compare our method with the conventional ACC method and find that the conventional ACC has frequent jitter in the tracking error when the preceding vehicle changes its speed sharply, which reduces the comfort and increases the unnecessary energy consumption. In addition,
The comparison methods rely on ACC algorithms. These schemes use an ACC algorithm based on instantaneous optimization for the upper level, which only considers the current vehicle motion state and looks ahead one step at each time instant. The lower layer powertrain management system uses a single battery or rule-based or instantaneous optimization methods. We use UDDS driving conditions for testing and compare several methods in terms of battery lifetime (BLT) estimation. The simulation results are shown in Table 1, which indicate that our proposed method can minimize battery loss and improve it by 13.63% compared with baseline method. The comparison methods rely on ACC algorithm to follow the preceding vehicle speed changes, which requires fast adjustment of driving state for platoon stability. This leads to lower driving smoothness and frequent acceleration and deceleration operations, which cause significant battery loss. Our proposed method benefits from upper layer control to provide short-term future information. The comparison methods have limited information for regulating powertrain, and battery bears most of peak discharge pressure. The supercapacitor’s capability is not fully utilized and only recovers braking energy.

V. CONCLUSION

This paper considers the inherent coupling relationship between electric vehicle power system regulation and motion system control, and studies the electric vehicle cooperative motion control problem with V2X assistance. We propose a hierarchical control strategy: the upper layer focuses on vehicle cooperative motion control using an improved MPC method, and discusses the packet loss problem in V2X communication; the lower layer power source management uses a rolling optimization method, which utilizes the predictive information provided by the upper layer and the power source effectively. We use a real-time vehicle simulation tool to verify the algorithm performance.

VI. ACKNOWLEDGMENT

This work was supported by National Natural Science Foundation of China under the grant No. 61731012 and No. 62025305.

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