Research Article

Model-Predictive Optimization for Pure Electric Vehicle during a Vehicle-Following Process

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In this paper, a pure electric vehicle (PEV) equipped with adaptive cruise control (ACC) system is studied for a vehicle-following process. And a multiobjective optimization algorithm for ACC system is proposed in a model-predictive control (MPC) framework for optimizing safety, tracking capability, driving comfortability and energy consumption. The longitudinal dynamics of the ACC system are modeled, which not only considers the vehicle spacing and speed, but also introduces the acceleration and the change rate of acceleration (jerk) for the host vehicle and fully considers the influence of the acceleration of the leading vehicle. The improvement of driving comfortability and the reduction of energy consumption are achieved mainly by optimizing the acceleration and jerk of host vehicle. Some optimized reference trajectories are introduced to MPC for improving driving comfortability of host vehicle. The performances of the multiobjective upper level algorithm combined with the PEV model are evaluated for three representative scenarios. The results demonstrate the effectiveness of the proposed algorithm.

1. Introduction

Environment pollution and energy shortage have become more and more serious, which makes the vehicle technology enter the field of energy saving and environmental protection [1], wherein pure electric vehicles (PEVs) are regarded as the promising vehicle type because of their environment-friendly and zero operational emission features [2]. Because PEVs are driven by motors and powered by batteries [3, 4], the characteristics of vehicle dynamic and limitations of energy consumption for a PEV are completely different compared with traditional vehicles. PEV could introduce intelligent driving to enhance the safety and convenience for drivers [5]. Advanced driver assistant system (ADAS) is gradually being used in passenger vehicles, which includes adaptive cruise control (ACC), lane-change assistance, and automatic parking [6, 7]. With a combination of these two vehicular technologies, vehicles can get good performances in terms of safety, dynamic process, driving comfortability, and energy conservation. Therefore, in this paper, a PEV equipped with ACC system is studied for a vehicle-following

process in order to optimize driving comfortability and energy consumption besides safety and tracking capability.

Many scholars have paid enough attention to the ACC controller design of traditional vehicle, and different control algorithms, such as PID control, sliding mode control, fuzzy control, machine learning, and model-predictive control (MPC), have been studied in ACC researches [8–11]. Among various methods, MPC is thought of as the most common method to realize ACC, because MPC can make a prediction of the future state for ACC system and achieve receding horizon optimization for multiple objectives under constrained conditions. In [11], future states of the leading vehicle were predicted and the optimal vehicle control input was computed based on MPC. And the fuel consumption was minimized by optimizing the velocity with the driving torque constraint. In [12], MPC was employed to design mode-switching ACC algorithm, in which controllers can shift between speed control mode and distance control mode. By applying the error of vehicle spacing and relative speed, the cost function was established. And the acceleration was considered as a constraint. In [13], driver desired response,

tracking capability, and fuel economy were considered in the cost function of the MPC algorithm for ACC system. The feasible region was enlarged by using constraint-softening method. Corona et al. [14] designed an ACC controller for a smart car and different MPC methods have been applied in ACC system. Nonlinearities were considered and the compromise between the complexity and accuracy of the solution was made. In [15], an MPC algorithm was applied to a fuel economy-oriented ACC system and inequality constraints in the prediction horizon were relaxed to speed up the calculation.

At present, the researches on ACC system of PEV are relatively few. Zhang et al. [16] designed an ACC controller by involving modeling mechanical partially. The objective was to reduce energy consumption for four-wheel independent drive PEV. In [17], a control algorithm combining with regenerative braking function for ACC system is presented. Some variables like state of charge (SOC) for battery were considered in modeling. In [18], the energy management and driving strategy (EMDS) are combined with terrain information and actuator efficiency for the purpose of maximizing the travel distance of PEV with four-wheel independent drive. In [19], a controller was designed for a smart and green autonomous vehicle (SAGA), which is an eco-ACC in order to minimize energy consumption and maximize energy recovery of PEV. Mechanics of PEV and SOC for battery were both considered in modeling. In [20], a speed controller based on a fast model-predictive framework was proposed to minimize SOC consumption of PEV. Through the above analysis, in the existing studies, the performances of ACC system are usually optimized by modeling the mechanics and the state of charge (SOC) for battery in a MPC framework. The complexity of modeling and calculations for these methods is improved when multiple objectives need to be optimized. Besides, PEVs are driven by motors, which leads to the different acceleration and deceleration characteristics compared with traditional vehicles. These differences make acceleration-related variables extremely important in the study of ACC for PEV. But the importance of acceleration-related variables is ignored in existing researches of ACC. In existing researches, jerk has not been fully considered in the longitudinal dynamics model.

Therefore, a new multiobjective optimization algorithm in an MPC framework for ACC system is presented. The contributions of this paper are as follows: firstly, the longitudinal dynamics model of the ACC system is established, which not only considers the vehicle spacing and speed, but also introduces the acceleration and jerk of the host vehicle and fully considers the influence of the acceleration for the leading vehicle. Compared with the traditional model, the new longitudinal dynamics model improves the control precision and can reflect the mutual longitudinal dynamics of the host vehicle and leading vehicle more realistically. Moreover, it is beneficial for the multiobjective control design. Secondly, the improvement of driving comfortability and the reduction of energy consumption are achieved mainly by optimizing acceleration and jerk in an MPC framework, rather than the mechanics and SOC, which reduces the complexity of modeling and calculations for MPC. Thirdly, several optimal

TABLE 1: Main parameters in vehicle model.

Symbol	Values	Symbol	Values
M_v	1550kg	ρ_{air}	1.206kg/m ³
A	2.8m ²	$P_{M,max}$	65KW
C_w	0.3	SOC_{ini}	0.6
f_r	0.015	Q_{bat}	93Ah

reference trajectories are introduced to improve driving comfortability.

The rest of this paper is organized as follows. The PEV model is provided in Section 2. The longitudinal dynamic model, control objectives, and constraints are provided in Section 3. In Section 4, a multiobjective optimization algorithm for ACC system of PEV is designed in an MPC framework. The simulation experiment and discussion of the proposed algorithm are provided in Section 5. Some conclusions are drawn in Section 6.

2. Pure Electric Vehicle Model

2.1. Pure Electric Vehicle. The front-wheel drive pure electric vehicle equipped with ACC system is the modeling objective for host vehicle in this paper. As shown in Figure 1, the structure of the PEV is presented. The position and speed of the leading vehicle can be measured from millimeter wave radar. The ACC controller determines the acceleration command of the host vehicle based on the sensing information of the millimeter wave radar and the vehicle state information of the vehicle controller VCU. The VCU generates the signals of motor torque and brake pressure according to acceleration command. The driving system of vehicle includes a motor, a two-speed transmission, and a final drive. The torque generated by the motor is transmitted to the front wheel through the gearbox, the final drive, and the half shaft. The brake system generates brake pressure through the ESP and uses the pedal simulator to simulate the pedal feel of a conventional vehicle. The main parameters in vehicle model are shown in Table 1, wherein M_v is the mass of host vehicle, A is the front area, C_w is the drag coefficient, f_r is the coefficient of rolling resistance, ρ_{air} is the air density, $P_{M,max}$ is the maximum motor power, SOC_{ini} is the initial SOC, and Q_{bat} is the total battery capacity.

2.2. Battery Model. Lithium battery is selected as the power source. The battery model can be simplified to the internal resistance model [21] as shown in Figure 2, wherein R_{int} is the internal resistance of the battery and V_{oc} is the open circuit voltage. And I_c and U_c are the current and voltage of the external load, respectively. The internal resistance is related to battery SOC. The higher the internal resistance of battery is, the lower the discharging efficiency becomes.

2.3. Motor Model. The permanent magnet synchronous motor is chosen for the paper. The efficiency for motor is considered in this paper, which is related to the torque and

FIGURE 1: The structure of pure electric vehicle.

speed of motor [22]. The motor torque-speed curves are presented in Figure 3. The maximum driving torque T_{M_max} is defined in (1), wherein ω_{ini} is the minimum speed of constant torque control, ω_b is the base speed of the motor, ω_{end} is the highest speed, and $f_m(\omega_m)$ is the correction value of driving torque determined by motor efficiency. When the motor speed is less than the base speed, the motor adopts constant torque control. And when the motor speed is greater than the base speed, the motor adopts constant power control.

$$T_{M_max} = \begin{cases} \frac{9550P_{M_max}}{\omega_m} f_m(\omega_m) & (0 \leq \omega_m \leq \omega_{ini}) \\ \frac{9550P_{M_max}}{\omega_b} & (0 \leq \omega_m \leq \omega_b) \\ \frac{9550P_{M_max}}{\omega_m} & (\omega_b \leq \omega_m \leq \omega_{end}) \end{cases} \quad (1)$$

The motor model of this paper is designed based on the above torque-speed characteristics and considers battery and voltage state and adds the power limit component.

3. Modeling, Controlling Objectives and Constraints

Generally, an ACC controller usually adopts hierarchical control structure. And it contains a lower level controller and an upper level controller [23]. Acceleration command from the upper level controller is used as the input of lower level

FIGURE 2: Internal resistance model for battery.

controller. The drive and brake for tracking the acceleration command is determined in the lower level controller. The longitudinal dynamics, constraints, and requirements are considered in an upper level controller. When the upper controller is designed, the lower controller is simplified approximately as a first-order system [12, 24, 25]. The first-order system for the lower level controller is approximated as

$$\tau \frac{da(t)}{dt} + a(t) = u(t) \quad (2)$$

where τ is the time lag corresponding to the finite bandwidth for the lower level controller, u is the value of control command coming from the upper level controller, and a is the acceleration of the host vehicle.

FIGURE 3: Motor torque-speed characteristics.

By applying a method of difference approximation, the discretization of (2) is obtained

$$a(k+1) = \left(1 - \frac{T_s}{\tau}\right) a(k) + \frac{T_s}{\tau} u(k) \quad (3)$$

where T_s is the sampling period and $a(k)$ and $u(k)$ are the acceleration and the control command for host vehicle at the sampling instant k , respectively.

The constant time headway (CTH) strategy is defined:

$$\Delta s_{des}(k) = d_0 + t_h \cdot v(k) \quad (4)$$

where $\Delta s_{des}(k)$ is the expected vehicle spacing and velocity at sampling instant k , $v(k)$ is the velocity at sampling instant k , d_0 is a fixed safe spacing as the vehicle speed reaches zero or low, and t_h is the expected time headway.

The vehicle spacing $\Delta s(k)$, error of vehicle spacing δ , and the relative velocity v_e are defined as

$$\begin{aligned} \Delta s(k) &= \Delta s(k-1) \\ &+ \left(v_l(k-1) \cdot T_s + \frac{1}{2} a_l(k-1) \cdot T_s^2 \right) \\ &- \left(v(k-1) \cdot T_s + \frac{1}{2} a(k-1) \cdot T_s^2 \right) \end{aligned} \quad (5)$$

$$\delta(k) = \Delta s(k) - \Delta s_{des}(k) \quad (6)$$

$$v_e(k) = v_l(k) - v(k) \quad (7)$$

where $\Delta s(k)$ is the actual vehicle spacing between leading vehicle and host vehicle at the sampling instant k and $v_l(k)$ is the velocity of the leading vehicle at the sampling instant k .

Jerk $j(k)$ is the change rate of vehicle acceleration and defined as

$$j(k) = \frac{a(k) - a(k-1)}{T_s} \quad (8)$$

Combining (3) and (8), it can get

$$\begin{aligned} j(k+1) &= \frac{1}{T_s} \left[\left(1 - \frac{T_s}{\tau}\right) \cdot a(k) \right] + \frac{1}{\tau} u(k) - \frac{1}{T_s} \\ &\cdot a(k) = -\frac{1}{\tau} a(k) + \frac{1}{\tau} u(k) \end{aligned} \quad (9)$$

where $j(k+1)$ is the jerk value at sampling instant $k+1$.

The state of the vehicle dynamics is composed of vehicle spacing, velocity, relative velocity, acceleration, and jerk. The performance output includes error of vehicle spacing, relative velocity, acceleration, and jerk. The acceleration $a_l(k)$ for the leading vehicle is considered as the system disturbance $w(k)$. The state, output, and disturbance could be written as follows:

$$x(k) = [\Delta s(k), v(k), v_e(k), a(k), j(k)] \quad (10a)$$

$$y(k) = [\delta(k), v_e(k), a(k), j(k)] \quad (10b)$$

$$w(k) = a_l(k) \quad (10c)$$

Then the state-space dynamics of the host vehicle and leading vehicle are provided:

$$x(k+1) = Ax(k) + Bu(k) + Gw(k) \quad (11a)$$

$$y(k) = Cx(k) - Z \quad (11b)$$

where

$$\begin{aligned} A &= \begin{bmatrix} 1 & 0 & T_s & -\frac{1}{2}T_s^2 & 0 \\ 0 & 1 & 0 & T_s & 0 \\ 0 & 0 & 1 & -T_s & 0 \\ 0 & 0 & 0 & 1 - \frac{T_s}{\tau} & 0 \\ 0 & 0 & 0 & -\frac{1}{\tau} & 0 \end{bmatrix} \\ B &= \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{T_s}{\tau} \\ \frac{1}{\tau} \end{bmatrix} \\ G &= \begin{bmatrix} \frac{1}{2}T_s^2 \\ 0 \\ T_s \\ 0 \\ 0 \end{bmatrix} \end{aligned}$$

$$C = \begin{bmatrix} 1 & -t_h & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$Z = \begin{bmatrix} d_0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (12)$$

The upper level controller is designed to perform a vehicle-following process in a safe, tracked, comfortable, and economic manner.

To achieve the objective of tracking capability, two requirements are necessarily satisfied. First, the ACC system adjusts host vehicles speed to approach the velocity of leading vehicle. Second, ACC system keeps the vehicle spacing approach the expected value:

$$\begin{aligned} \text{Objectives : } \delta(k) &\longrightarrow 0, \\ v_e(k) &\longrightarrow 0, \\ \text{as } k &\longrightarrow \infty. \end{aligned} \quad (13)$$

As for the driving comfortability of drivers, the smaller the absolute values for acceleration and jerk of host vehicle, the better the driving comfortability:

$$\text{Objectives : } \begin{cases} \min |a(k)| \\ \min |j(k)| \end{cases} \quad (14)$$

In order to improve driving comfortability, smooth responses are preferred. Hence, some smooth curves that gradually converged to the expected values are also introduced and they are called the reference trajectories. Instead of minimizing the performance variables to zero directly, it makes them move along the references trajectories. In this paper, the exponential attenuation function which approaches the expected value gradually is chosen as the form of reference trajectory. The reference trajectory of acceleration is taken as an example. It is defined as

$$a_r(k+i) = a(k) + [0 - a(k)] \left[1 - e^{-iT_s/\alpha_a} \right] = \rho_a^i a(k) \quad (15)$$

where T_s is the sampling period of reference trajectory, α is time constant of reference trajectory, and $\rho_a = e^{-T_s/\alpha_a}$ ($0 < \rho_a < 1$) is the designed parameter. A larger value of ρ_a in the scope of definition can make the response characteristics better and improve the robust for ACC system. Similarly, the definition of other variables in the reference trajectories, such as ρ_δ, ρ_v and ρ_j , can be obtained.

The acceleration command is chosen as the performance index for energy consumption [26]. And the acceleration command is also the expected acceleration. To reduce the

energy consumption, the absolute value of expected acceleration should be minimized.

$$\text{Objectives : } \min |u(k)| \quad (16)$$

To ensure safety during the vehicle-following process, the vehicle spacing between the host vehicle and leading vehicle should be larger than minimum safe value d_c for vehicle spacing:

$$\text{Hard constraint : } \Delta s(k) \geq d_c. \quad (17)$$

Because any collision cannot be allowed, this constraint should be regarded as a hard constraint.

In addition, considering the capacity limitation of the PEV itself, the following constraints should be applied to the speed, acceleration, acceleration command, and jerk of the PEV. Because the PEV capabilities associated with velocity, acceleration, control command, and jerk are standardized in ACC systems, these constraints are also regarded as hard constraint in this paper.

$$\text{Hard constraint : } v_{\min} \leq v(k) \leq v_{\max} \quad (18a)$$

$$\text{Hard constraint : } a_{\min} \leq a(k) \leq a_{\max} \quad (18b)$$

$$\text{Hard constraint : } u_{\min} \leq u(k) \leq u_{\max} \quad (18c)$$

$$\text{Hard constraint : } j_{\min} \leq j(k) \leq j_{\max} \quad (18d)$$

Through the above analysis, safety, tracking capability, driving comfortability, and energy consumption of ACC system and vehicle capacity limitations are analyzed; they are transformed into corresponding optimization objectives and system constraints. Then, the upper control strategy could be designed in an MPC framework.

4. Model-Predictive Control

In this section, multiobjective optimization for ACC system is designed in an MPC framework. The basic principle of MPC is summarized as follows: at each time of system sampling, the future behavior is predicted according to the predictive model, the performance index of the future time is optimized, and the predictive model is revised according to the output of the measured object. Finally, the design of control strategy is transformed into an online optimization process. By solving the corresponding optimization problem, the control sequence is obtained. The first value in control sequence is used for control system. Next the process is repeated after the horizon moves forward a step. Because it adopts the control ideas of multistep prediction, feedback correction, and receding horizon optimization, it has the advantages of good control effect and strong robustness [27–29]. Moreover, it can give better consideration to multiple control objectives and system constraints and maintain the stability and performance optimization of the system, so it is very suitable for the design of multiobjective upper control strategy of ACC [23]. Using the longitudinal dynamic model

of ACC as the prediction model, the future behavior of the system is predicted as follows.

$$\begin{aligned}\widehat{X}_p(k+p|k) &= \overline{A}x(k) + \overline{B}U(k+m) \\ &\quad + \overline{G}W(k+p)\end{aligned}\quad (19a)$$

$$\begin{aligned}\widehat{Y}_p(k+p|k) &= \overline{C}x(k) + \overline{D}U(k+m) \\ &\quad + \overline{E}W(k+p) - \overline{Z}\end{aligned}\quad (19b)$$

where

$$\widehat{X}_p(k+p|k) = \begin{bmatrix} \widehat{x}_p(k+1|k) \\ \widehat{x}_p(k+2|k) \\ \vdots \\ \widehat{x}_p(k+p|k) \end{bmatrix},$$

$$\widehat{Y}_p(k+p|k) = \begin{bmatrix} \widehat{y}_p(k+1|k) \\ \widehat{y}_p(k+2|k) \\ \vdots \\ \widehat{y}_p(k+p|k) \end{bmatrix}$$

$$U(k+m) = \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+m-1) \end{bmatrix},$$

$$W(k+p) = \begin{bmatrix} w(k) \\ w(k+1) \\ \vdots \\ w(k+p-1) \end{bmatrix}$$

$$\overline{A} = \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^p \end{bmatrix}$$

$$\overline{B} = \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \ddots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{p-1}B & A^{p-2}B & \cdots & A^{p-m}B \end{bmatrix}$$

$$\overline{G} = \begin{bmatrix} G & 0 & \cdots & 0 \\ AG & G & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ A^{p-1}G & A^{p-2}G & \cdots & G \end{bmatrix}$$

$$\overline{C} = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^p \end{bmatrix}$$

$$\overline{D} = \begin{bmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & \ddots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{p-1}B & CA^{p-2}B & \cdots & CA^{p-m}B \end{bmatrix}$$

$$\overline{E} = \begin{bmatrix} CG & 0 & \cdots & 0 \\ CAG & CG & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ CA^{p-1}G & CA^{p-2}G & \cdots & CG \end{bmatrix}$$

$$\overline{Z} = \begin{bmatrix} Z \\ Z \\ \vdots \\ Z \end{bmatrix}$$

(20)

where m is the control horizon, p is predicted horizon, $u(k)$, $u(k+1)$, $u(k+2)$, $\dots$, $u(k+m-1)$ are the control sequence that need to be solved, and $x(k)$ is the measured state at the sampling instant k .

In actual use, $W(k+p)$ is the disturbance vector for ACC system. It can be modeled in the following manner.

The disturbance $w(k)$ is the acceleration of the leading vehicle at the sampling instant k . It is difficult to obtain current disturbance directly, but it can be obtained approximately by the value of disturbance at the sampling instant $k-1$, which can be got by using the measurement of relative velocity and acceleration for the ACC system:

$$w(k) = \widehat{w}(k-1|k) \quad (21)$$

$$\widehat{w}(k-1|k) = \frac{v_e(k) - v_e(k-1)}{T_s} + a(k-1) \quad (22)$$

where $\widehat{w}(k-1|k)$ is the disturbance at previous sampling time and it is estimated at the current sampling time.

In this paper, the sampling time is very short, so the disturbance for ACC system is assumed to keep unchanged

in a single sampling time approximately. Therefore, the disturbance is assumed unchanged in predictive horizon corresponding to the single sampling time. There are some inaccuracies for this approximation method, but it can get some compensation by updating the disturbance data in the next predictive horizon. The method for updating data in different predictive horizon reflects the receding horizon optimization of MPC:

$$w(k+i) = w(k), \quad i = 1, 2, \dots, p-1. \quad (23)$$

Next, the disturbance vector for ACC system is defined:

$$W(k+p) = \begin{bmatrix} \hat{w}(k-1|k) \\ \hat{w}(k-1|k) \\ \vdots \\ \hat{w}(k-1|k) \end{bmatrix} \quad (24)$$

It is an advantage of MPC to make a compensation for the inaccuracies of modeling the disturbance vector by using the receding horizon optimization [30, 31].

Then the objectives of tracking capability, driving comfortability, and energy consumption are integrated into an objective function of MPC by weighted sum:

$$J = \sum_{i=1}^p \left[\hat{y}_p \left(k + \frac{i}{k} \right) - y_r(k+i) \right]^T \cdot Q \left[\hat{y}_p \left(k + \frac{i}{k} \right) - y_r(k+i) \right] + \sum_{i=0}^{m-1} u(k+i)^T \cdot Ru(k+i) \quad (25)$$

where $y_r(k+i)$ is the reference trajectory for the performance vector, Q is the weighting matrices of objectives, and R is the weighting matrices of control.

The objectives of safety and the capabilities limit of PEV are considered as constraints of MPC:

$$s.t. \begin{cases} \Delta x(k) \geq d_c \\ v_{\min} \leq v(k) \leq v_{\max} \\ a_{\min} \leq a(k) \leq a_{\max} \\ j_{\min} \leq j(k) \leq j_{\max} \\ u_{\min} \leq u(k) \leq u_{\max} \end{cases} \quad (26)$$

The multiple objectives are integrated into an MPC framework, which enlarges the scope of design requirements of later work. For example, by using the method of modeling, the vehicle stability and mechanical stress can also be studied.

Substituting (19b) into (25), the performance criteria adopted the matrix form is obtained:

$$J = V^T \bar{Q} V + U(k+m)^T \bar{R} U(k+m) \quad (27)$$

where

$$\begin{aligned} V &= \bar{C}x(k) + \bar{D}U(k+m) + \bar{E}W(k+p) - \bar{Z} \\ &\quad - \bar{\Phi}Cx(k) + \bar{\Phi}Z \\ \bar{Q} &= \begin{bmatrix} Q & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & Q \end{bmatrix}, \\ \bar{R} &= \begin{bmatrix} R & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R \end{bmatrix} \\ \bar{\Phi} &= \begin{bmatrix} \Psi_1 \\ \Psi_2 \\ \vdots \\ \Psi_p \end{bmatrix}, \\ \Psi_i &= \begin{bmatrix} \rho_\delta^i & 0 & 0 & 0 \\ 0 & \rho_v^i & 0 & 0 \\ 0 & 0 & \rho_a^i & 0 \\ 0 & 0 & 0 & \rho_j^i \end{bmatrix} \end{aligned} \quad (28)$$

where $\rho_\delta, \rho_v, \rho_a$, and ρ_j are the parameters of reference trajectories corresponding to spacing error, relative velocity, acceleration, and jerk, respectively.

Expanding (27) and omitting the independent terms with the control output, then the following is obtained:

$$\begin{aligned} J &= U(k+m)^T \left(\bar{R} + \bar{D}^T \bar{Q} \bar{D} \right) U(k+m) \\ &\quad + 2 \left\{ x(k)^T \left[\bar{C}^T - \bar{C}^T \bar{\Phi}^T \right] \bar{Q} \bar{D} \right. \\ &\quad \left. + W(k+p)^T \bar{E}^T \bar{Q} \bar{D} - \left(\bar{Z}^T - \bar{Z}^T \bar{\Phi}^T \right) \bar{Q} \bar{D} \right\} U(k \\ &\quad + m) \end{aligned} \quad (29)$$

The constraint inequalities of (26) can be transformed into the matrix inequality form:

$$s.t. \begin{cases} \bar{M} \leq \bar{L} \hat{X}_p(k+p) \leq \bar{N} \\ U(k+m) \leq U_{\max} \\ -U(k+m) \leq -U_{\min} \end{cases} \quad (30)$$

where

$$\begin{aligned}
 M &= \begin{bmatrix} d_c \\ v_{\min} \\ a_{\min} \\ j_{\min} \end{bmatrix}, \\
 N &= \begin{bmatrix} Inf \\ v_{\max} \\ a_{\max} \\ j_{\max} \end{bmatrix} \\
 L &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \\
 \bar{L} &= \begin{bmatrix} L \\ L \\ \vdots \\ L \end{bmatrix}, \\
 \bar{M} &= \begin{bmatrix} M \\ M \\ \vdots \\ M \end{bmatrix}, \\
 \bar{N} &= \begin{bmatrix} N \\ N \\ \vdots \\ N \end{bmatrix} \\
 U_{\max} &= \begin{bmatrix} u_{\max} \\ \vdots \\ u_{\max} \end{bmatrix}, \\
 U_{\min} &= \begin{bmatrix} u_{\min} \\ \vdots \\ u_{\min} \end{bmatrix}
 \end{aligned} \tag{31}$$

where Inf is a real positive infinite value, showing that there is not an upper bound for the vehicle spacing.

Substituting (19a) into (30), the constraints are transformed as

$$\Omega U(k+m) \leq T \tag{32}$$

where

$$\begin{aligned}
 \Omega &= [\bar{L}\bar{B} \quad -\bar{L}\bar{B} \quad I \quad -I]^T \\
 T &= \begin{bmatrix} \bar{N} - \bar{L}\bar{G}W(k+p) - \bar{L}\bar{A}x(k) \\ -\bar{M} + \bar{L}\bar{G}W(k+p) + \bar{L}\bar{A}x(k) \\ U_{\max} \\ -U_{\min} \end{bmatrix}
 \end{aligned} \tag{33}$$

Through the above analysis, the multiobjective optimization problem for ACC system of PEV by using MPC theory can be written in the form

$$\begin{aligned}
 \min \quad & \{U(k+m)^T KU(k+m) + 2SU(k+m)\} \\
 \text{s.t.} \quad & \Omega U(k+m) \leq T
 \end{aligned} \tag{34}$$

Then the above problem is transformed into a quadratic programming (QP) problem that can be solved online by using a standard mathematical programming algorithm.

At each sampling time, the current measurement of vehicle spacing, relative velocity, velocity, acceleration, and jerk are obtained from ACC system. Solving a QP problem by combining these measurements, the control sequence is obtained. The first value of control sequence is used to control system. At the next sampling time, the process is repeated.

5. Simulation Experiments and Discussion

5.1. Methods. The setup is proposed to evaluate the performance of the multiobjective optimization algorithm for ACC system of PEV. Two different algorithms are employed and compared. They are the multiobjective optimization algorithm that considers driving comfortability, energy consumption, safety and tracking capability (MULTI_OBJ), and the dual-objective optimization algorithm that only considers safety and tracking capability (DUAL_OBJ). The differences for setting between two algorithms are threefold. Firstly, the values of Q and R in (25) are different. In DUAL_OBJ, the values of Q and R are set as $\text{diag}\{1, 10, 0, 0\}$ and 0 , respectively. Secondly, the upper bound and lower bound for the constraint of jerk are set as Inf and $-Inf$ in DUAL_OBJ. Thirdly, in DUAL_OBJ, there are no optimization reference trajectories for performance vector in objective function and the performance variables are minimized to zero directly.

Whether the vehicle spacing between the host vehicle and leading vehicle is larger than a minimum value (5m) for safe vehicle spacing is considered as the criterion of safety. The tracking capability is evaluated by the behaviors of adjusting the vehicle spacing and velocity to the expected values. Driving comfortability is evaluated by using the peak values of jerk [32]. The ratio of the change in the SOC and the distance s during the simulation process is used to measure the energy consumption.

The main parameters in the simulation process are listed in Table 2. The value of τ is obtained from the identification of PEV model; other parameters in Table 2 are chosen according to [12, 24, 33]. Three representative traffic scenarios

TABLE 2: Main parameters in the simulation process.

Symbol	Values	Symbol	Values
T_s	0.2s	j_{min}	-3m/s ³
τ	0.15 s	j_{max}	3m/s ³
d_0	7m	$\rho_\delta, \rho_v, \rho_a, \rho_j$	0.94
d_c	5m	Q	diag{1, 10, 1, 1}
v_{min}	0 m/s	R	1
v_{max}	36m/s	p	10
a_{min}	-5.5m/s ²	m	5
a_{max}	2.5m/s ²	road slope	0
u_{min}	-5.5m/s ²	T	50s

TABLE 3: Data for Scenario 1.

	DUAL_OBJ	MULTI_OBJ	Improvement
max jerk	12.66m/s ³	1.65m/s ³	+86.97%
$\Delta SOC / s$	0.0056km ⁻¹	0.0036km ⁻¹	+35.99%

in simulation are as follows: (1) following a leading vehicle with constant speed, (2) following a leading vehicle with varying speed, and (3) hard stop. Control algorithms in this paper are designed in MATLAB/Simulink and verified in the cosimulation of Carsim and MATLAB/Simulink.

5.2. Discussion. (1) In the scenario of following a leading vehicle with constant speed, the leading vehicle is running at a constant speed and the host vehicle approaches the leading vehicle from a distance. When the vehicle spacing is decreased continuously, the host vehicle brakes to avoid collision effectively. In this simulation process, the initial value of vehicle spacing is 50m and the initial velocities of leading vehicle and host vehicle are 15 m/s and 10m/s, respectively. The simulation results of the two algorithms are presented as in Figure 4. The data for the driving comfortability and energy consumption is listed in Table 3. Compared with the DUAL_OBJ, the improvements of driving comfortability and energy consumption for the MULTI_OBJ are also included in Table 3.

From Figures 4(a) and 4(b), it is shown that host vehicle accelerates to catch up with the leading vehicle during the initial stage. When the vehicle spacing is adjusted to a proper value, continuous acceleration operation will result in collision with the leading vehicle. Therefore, the host vehicle decelerates to guarantee the safety of the driving process. The vehicle spacings are larger than minimum value (5m) for the safe vehicle spacing, so the safety is guaranteed in two algorithms. As for the tracking capability of desired vehicle spacing, the DUAL_OBJ is better. As for the tracking capability of speed for leading vehicle, two algorithms are closer. And in the early stage of speed tracking, the overshoot of DUAL_OBJ is greater than MULTI_OBJ. And in the later stage of speed tracking, the DUAL_OBJ tracks the speed better. This is because there is no limitation on the jerk amplitude in DUAL_OBJ; the host vehicle can accelerate and decelerate more aggressively when the speed of leading vehicle changes. It is a tradeoff for the optimization of

TABLE 4: Data for Scenario 2.

	DUAL_OBJ	MULTI_OBJ	Improvement
max jerk	18.66m/s ³	1.99m/s ³	+89.34%
$\Delta SOC / s$	0.0078km ⁻¹	0.0053km ⁻¹	+31.74%

different performances including tracking capability, driving comfortability, and energy consumption.

In this process, the response of vehicle spacing for the MULTI_OBJ and DUAL_OBJ is roughly similar, and the trends of speed and acceleration are the same, but the dynamic performances of the response curve and the driving comfortability and energy consumption in the driving process are obviously different. From Table 3, it can be seen that the peak values for the absolute values of jerk are 12.66m/s³. The corresponding peak value is bigger than MULTI_OBJ and 12.66m/s³ is out of the perception limitation (3m/s³) of passengers [33]. However, in the MULTI_OBJ, the variable speed behavior of host vehicle is effectively balanced, a smoother acceleration and jerk response are adopted, and the absolute value of peak value for the jerk is always in the range of 3m/s³. Therefore, the driving comfortability in MULTI_OBJ is better. In Table 3, it can be seen that the ratio for measuring the energy consumption in MULTI_OBJ is lower than DUAL_OBJ, so the energy consumption is reduced. This is because the performance index for energy consumption is included in the objective function.

From above analysis, in this scenario, better performances of driving comfortability and energy consumption are provided in the MULTI_OBJ compared with the DUAL_OBJ. With the effect of the exponential attenuation function and limitation of the constraints for jerk, the dynamic responses in the driving process are smoothed and constrained. The driving comfortability and energy consumption are optimized, which is better for improving the driver's satisfaction with the ACC system and improving the utilization rate of the ACC system.

(2) The scenario of following a leading vehicle with varying speed is the most common traffic scenario in real life. In this scenario, spacing adjustment, speed tracking capability and dynamic response of acceleration and jerk for the host vehicle are mainly studied when the speed of leading vehicle changes frequently. In this simulation process, the initial value of vehicle spacing is 50 m, the initial velocity for leading vehicle is 15m/s, and the initial velocity for host vehicle is 10 m/s (the relative velocity is 5m/s). The amplitude of acceleration for leading vehicle is 2 m/s². The simulation results of the two algorithms are shown in Figure 5. The data for the driving comfortability and energy consumption is listed in Table 4. Compared with the DUAL_OBJ, the improvements of driving comfortability and energy consumption for the MULTI_OBJ are also included in Table 4.

From Figures 5(a) and 5(b), it is shown that there is no collision between the host vehicle and the leading vehicle in MULTI_OBJ and DUAL_OBJ during the process of driving, which ensures the safety of the driving process. When the

FIGURE 4: Following a leading vehicle with constant speed.

FIGURE 5: Following a leading vehicle with varying speed.

speed of leading vehicle changes continuously, the host vehicle adjusts continuously to accommodate the changes of the leading vehicle in MULTI.OBJ and DUAL.OBJ. Without the constraint of jerk in DUAL.OBJ algorithm, it enables a wider range of changes for speed, thus achieving better tracking of the desired spacing. As for the tracking of the velocity, the two algorithms are closer. It is a tradeoff among tracking capability, driving comfortability, and energy consumption. For the MULTI.OBJ, the detailed speed response is provided. During the period of $0-t_1$, the host vehicle accelerates to catch up with the speed of the leading vehicle, and the vehicle spacing between the two vehicles gradually increases to maximum value. During the period of t_1-t_2 , because of the large vehicle spacing between the two vehicles, the host vehicle continues to accelerate in order to reduce the vehicle spacing between the two vehicles after catching up with the speed of the leading vehicle. Because of the continuous changes of acceleration for the leading vehicle, the effect of speed tracking is not very good. Speed tracking is better when the acceleration trends of the two vehicles are consistent. During the period of t_2-t_3 , the leading vehicle starts to decelerate, and the vehicle spacing between the two vehicles begins to shrink. However, in order to make the speed of host vehicle approach the speed of the leading vehicle and the vehicle spacing approaches to the expected value, the host vehicle also starts to decelerate, so that the vehicle spacing is kept within the safe distance. During the period of t_3-t_4 , the leading vehicle accelerates and the host vehicle starts to accelerate; thus host vehicle catches up with the speed of the leading vehicle. During the period of t_4-t_5 , the leading vehicle decelerates and the host vehicle also decelerates. During the period of t_5-t_6 , the speed of leading vehicle is constant, and the host vehicle gradually adjusts the speed to approach the leading vehicle. When the changes of acceleration for leading vehicle are very little, the speed tracking is better. However, when the changes of acceleration for leading vehicle are great, the speed tracking is poor.

From Figures 5(c) and 5(d), the acceleration and jerk of host vehicle are changed drastically to follow the leading vehicle in DUAL.OBJ, when leading vehicles speed is changed frequently. From Table 4, the peak values for the absolute values of jerk are 18.66 m/s^3 , which are bigger than MULTI.OBJ and the 18.66 m/s^3 exceeds maximum value (3 m/s^3) that ordinary passengers can accept. This will result in obvious discomfort for passengers. In MULTI.OBJ, the smoother responses of acceleration and jerk are always adopted for host vehicle. The corresponding jerk is always less than 3 m/s^3 during vehicle-following process. These guarantee driving comfortability. From Table 4, it can be seen that the ratio for measuring the energy consumption in MULTI.OBJ is lower than DUAL.OBJ, so the energy consumption is reduced. This is because the optimization for energy consumption is included in the objective function.

In summary, in the scenario of following a leading vehicle with varying speed, the performance of MULTI.OBJ is superior to the DUAL.OBJ in terms of driving comfortability and energy consumption. In MULTI.OBJ, with the effect of exponential attenuation function and limitation of the constraints

TABLE 5: Data for Scenario 3.

	DUAL.OBJ	MULTI.OBJ	Improvement
$\max jerk $	13.25 m/s^3	2.51 m/s^3	+81.61%
$\Delta \text{SOC} / s$	0.0039 km^{-1}	0.0026 km^{-1}	+33.16%

for jerk, the systems responses are smoothed effectively. In MULTI.OBJ, driving comfortability is improved and energy consumption is reduced on the basis of ensuring safety and tracking capability.

(3) In the scenario of hard stop, the leading vehicle brakes suddenly when the two vehicles are close to each other. Effective measurements are taken to avoid collision for host vehicle and other driving purposes, such as driving comfortability and energy consumption, are also ensured as far as possible. In this simulation process, initial velocity of leading vehicle and host vehicle both are 20 m/s during the vehicle-following process. The initial vehicle spacing is 50 m . After twenty seconds, the leading vehicle performs a hard stop. The simulation results of the two algorithms are shown in Figure 6. The data for the driving comfortability and energy consumption is listed in Table 5. Compared with the DUAL.OBJ, the improvements of driving comfortability and energy consumption for the MULTI.OBJ are also included in Table 5.

From Figures 6(a) and 6(b), the host vehicle brakes urgently to avoid collision with the leading vehicle both in MULTI.OBJ and DUAL.OBJ, because safety is the most basic and important control object for the ACC system during driving process. The vehicle spacings are bigger than the minimum value (5 m) for the safe distance in the two algorithms which ensured the safety of driving. Emergency braking makes speed of host vehicle decrease to zero rapidly in MULTI.OBJ and DUAL.OBJ. Without the limitation of the jerk in DUAL.OBJ, it enables a wider range of changes for speed. As for the tracking capability of desired vehicle spacing, the DUAL.OBJ is better. As for the tracking of speed of the leading vehicle, the two algorithms are closer. It is a tradeoff among the tracking capability, driving comfortability, and energy consumption.

In Figure 6(c), both algorithms decelerate intensely to stop quickly, so that the fluctuations for acceleration response curve both are big. This is because in such a dangerous situation, the safety is greatly threatened. In MULTI.OBJ, the host vehicle brakes drastically to ensure the safety of driving, while ignoring the optimization of other performance for the time being. From Figure 6(d), the absolute value of peak value for jerk corresponding to MULTI.OBJ is within the 3 m/s^3 , while the jerk is greater than 3 m/s^3 and there are serious fluctuations for jerk response curve in DUAL.OBJ. So the driving comfortability in MULTI.OBJ is better. The optimization of energy consumption is considered in the objective function and the ratio for measuring the energy consumption for the MULTI.OBJ is lower compared with DUAL.OBJ, so the energy consumption is reduced.

From the above analysis, in the scenario of hard stop, safety is the primary goal; other performances are ignored for the time being. The performance of driving comfortability

FIGURE 6: Hard stop.

and energy consumption in MULTI.OBJ is better than the DUAL.OBJ. In the MULTI.OBJ, with the effect of the exponential attenuation function and limitation of the constraints for jerk, the systems responses are smoothed effectively. In MULTI.OBJ, driving comfortability is improved and energy consumption is reduced on the basis of ensuring safety and tracking capability.

6. Conclusion

In this paper, a new ACC algorithm for PEV is proposed for the purpose of optimizing multiple objectives, which are safety, tracking capability, driving comfortability, and energy consumption, wherein multiple objectives are optimized based on a new longitudinal control model. Driving comfortability is improved and energy consumption is reduced mainly by optimizing the acceleration and jerk. The performances of the multiobjective optimization algorithm for ACC system combined with the PEV model are evaluated in three representative traffic scenarios. The simulation results showed that safety and tracking capability requirements are ensured. Driving comfortability is improved with limitation of the constraints for jerk and the effect of the exponential attenuation function. Energy consumption is reduced with the minimization of absolute value for acceleration command. It can be expected that the proposed multiobjective optimization algorithm of ACC will possibly promote the application of ACC by improving driving comfortability for passengers and reducing energy consumption to vehicle owners.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no competing financial interests.

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