Indirect adaptive fuzzy sliding mode control for uncertain longitudinal brake system of hybrid electric bus

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Abstract: - In this paper, an indirect adaptive fuzzy sliding mode control scheme is designed for hybrid electric bus. The trajectory tracking control for stopping the bus in a bus station is proposed. The control strategies of regenerative braking in the hybrid electric bus add the control difficulty of the longitudinal braking system. Its nonlinearities are estimated by adaptive fuzzy method and projection method. The stability and convergence properties of the longitudinal brake control system are analytically proved by using Lyapunov stability theory and Barbalat's lemma. The simulation results demonstrate that the proposed controller shows a good performance of tracking the pre-designed profile even the brake system has the regenerative braking or has different initial state from the velocity profile.

Key-Words: - Hybrid electric bus; Longitudinal brake control; Regenerative braking; Adaptive control; Fuzzy logic; Sliding mode control

1 Introduction

With rising public concern about fuel economy and emission requirements in automobiles, interest in hybrid electric vehicles has never been greater. In the present hybrid power train systems, the brake action of a vehicle is generally achieved by hydraulic/pneumatic brake system and regenerative braking system [1, 2]. When hybrid electric vehicles, such as series-parallel hybrid electric buses, are driving with a stop-and-go pattern in urban areas, effective regenerative braking can significantly improve the fuel economy. However, the regenerative braking directly affects modeling and control design, which adds some complexity to the brake control design. It's recognized that longitudinal control problems in hybrid electric vehicles are quite from those encountered in the control design for general vehicles [3, 4]. The capacity of regenerative braking changes with varying factors, such as the battery SOC (state-of-charge), vehicle speed and brake pedal position [5].

The main current brake controls are focused on regenerative braking with minimized stopping distance, regenerative braking with optimal energy recovery, and the cooperation between the hydraulic/pneumatic braking system and the regenerative braking system. In [6], a control strategy of motor regenerative braking for a mild hybrid vehicle is established, but its control strategy doesn't consider the disturbance of road conditions and the nonlinear characteristic of hydraulic dynamic processes. [7] introduced a new anti-skid re-adhesion control considering the air brake, which carries out the cooperation control of regenerative braking and pneumatic brake system. In [8], a computational procedure to maximize the regenerated brake energy during braking is presented and the relationship between the regenerated brake energy and the power train components are surveyed.

As for the longitudinal braking control for heavy duty vehicles, such as a city bus, the large mass of a hybrid electric bus demand large braking force during deceleration and the regenerative braking torque cannot be made as much as possible to provide all the required braking torque. The model mismatch, measurement noise, actuator time delay and external disturbances can affect the brake control system design. The sliding mode control techniques and fuzzy control have applied to longitudinal braking control, but thee accurate motion control cannot be achieved. To remedy this problem, various control approaches are applied to adjust the actuator pressure to force the vehicle to stop in a desired manner [9, 10]. Generally, the control objectives of these control method is to make the vehicle track a desired velocity within the safety distance. Vehicles equipped with advanced brake systems which can make the drivers more comfortable would dominate the markets; therefore, smooth braking trajectory control would be inevitable in the future automotive engineering [11].

In this paper a sliding mode controller incorporating the fuzzy adaptive concept will be developed to control a hybrid electric bus to stop at a bus station. Due to imperfect knowledge of vehicle system and road conditions, a stable adaptive fuzzy inference system was embedded in boundary layer to cope with the uncertainties and disturbances that can arise during the braking process. The close-loop dynamics is proved to be asymptotically stable by using Lyapunov stability theory and Barbalat's lemma. Some computer simulation results are also presented in order to verify the proposed controller.

2 Model Formulation

2.1. Powertrain configuration

For the powertrain model of the hybrid electric bus [12], seen in Fig.1, there are three different sources of torque, namely ICE, integrated starter-generator (ISG) and traction motor (TM) in this series-parallel powertrain configuration. They work together with clutch and transmission to form different driving modes. Moreover, the high-voltage battery is the energy storage device for the bus. A separate controller, called energy management system (EMS), is used to coordinate the energy distribution among those controllers of ICE, ISG, TM and high-voltage battery. The regenerative braking is achieved by the TM and its brake torque can be sent by the EMS via CAN (Control Area Network) bus system.

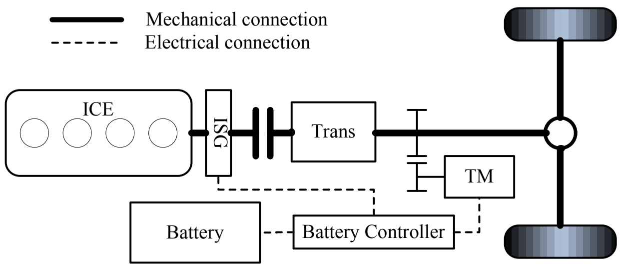

Fig.1 Configuration of series-parallel powertrain for a hybrid electric bus

2.2 Vehicle Model

The dynamic equation for a vehicle model is obtained for a straight-line braking event. An F=ma force balance for the vehicle is described by the following equation:

$$M\frac{dv}{dt} = F_{xf} + F_{xr} - F_d \tag{1}$$

where

M Vehicle mass including wheels;
v Vehicle longitudinal velocity;
F_{xf} Road force on the front wheels;
F_{xr} Road force on the rear wheels;
F_d Drag forces due to wind and grade.

2.3 Wheel model

With moment balances, the dynamic equations for the driving wheels (rear wheels) and the driven wheels (front wheels) are:

$$\begin{cases} J_{wf}\dot{\omega}_{wf} = -rF_{xf} - M_f - T_{bf} \\ J_r\dot{\omega}_r = T_e - rF_{xr} - M_r - T_{br} - T_{regb} \end{cases} \tag{2}$$

where

J_{wf} , J_r Inertia of front wheels and axle;
$\dot{\omega}_{wf}$, $\dot{\omega}_r$ Angular acceleration of wheels;
F_{xf} , F_{xr} Road forces on wheels;
M_f , M_r Rolling resistance of wheels;
T_{bf} , T_{br} Brake torques on wheels;
T_{regb} Regenerative brake torque;
T_e Axle shaft torque;
r Wheel radius.

2.4 Longitudinal dynamics model

At low levels of deceleration, wheel slip is quite small [13]. It's fundamentally same for a bus driving into a bus station in that the pneumatic brake and regenerative brake are used to generate moderate longitudinal resistance effort. For a smooth stopping, the bus braking is usually kept smooth to ensure the passengers' comfort. Therefore, the wheel slip λ can be assumed to be negligible, then the kinematic rolling condition has $\dot{\omega}_{wf} = \dot{\omega}_r = \dot{v}/r$, and the dynamic equations of (1) and (2) are solved as:

$$\begin{aligned} &[T_e - T_{bf} - T_{br} - M_r - M_f - T_{regb}]/r - F_d \\ &= (m + (J_r + J_{wf})/r^2)a \end{aligned} \tag{3}$$

Let T_b be the total pneumatic brake torque and M_{lr} be the lumped rolling resistance, and substitute the $J_r = J_{wr} + J_e$ for the lumped rear wheels/power train inertia, (3) can be rewritten as follows:

$$\begin{aligned} &T_e - T_b - M_{lr} - T_{regb} - F_d r \\ &= (J_e + (mr^2 + J_{wr} + J_{wf})R_{dr}^2)a / r / R_{dr}^2 \end{aligned} \tag{4}$$

where R_{dr} is the ratio of the wheel rotational speed to the engine rotational speed, $M_{lr} = C_r \cdot m \cdot g \cdot r$ and $F_d = C_a \cdot v^2$. By defining

$$M_L = \frac{1}{rR_{dr}^2}(J_e + R_{dr}^2(mr^2 + J_{wr} + J_{wf})) \tag{5}$$

We obtain

$$T_e - T_b - M_{lr} - T_{regb} - F_d r = M_L a \tag{6}$$

In the particular case of stopping a hybrid electric bus at a bus station, the torque from ICE described in Fig.1 is cut off by the clutch. Let x_1 be the longitudinal displacement of brake and x_2 be the vehicle speed during the longitudinal motion. Considering the disturbance d caused by road conditions, so (6) can be described by:

$$\begin{cases} \dot{x}_1 = x_2 \\ M_L \cdot \dot{x}_2 + M_{lr} + C_a \cdot r \cdot x_2{}^2 + d = u \end{cases} \tag{7}$$

Where u is the composite input brake torque of the regenerative braking and pneumatic braking. With respect to the uncertainties of the longitudinal dynamic model, the following physically motivated assumptions can be made:

Assumption 1. The parameter M_L is time varying and unknown caused by the varying number of passengers, but it is positive and bounded, i.e. $0 < M_{L\_\min} < M_L < M_{L\_\max}$.

Assumption 2. The parameter C_a is unknown but positive and bounded, i.e. $0 < C_{a\_\min} < C_a < C_{a\_\max}$.

Assumption 3. The parameter C_r is known and constant. The disturbance due to variations of road is included in d, which is unknown but bounded, i.e. $|d| < \delta$.

3 Adaptive fuzzy sliding mode controller design

3.1 Feedback linearizable continuous time nonlinear system

The inversion of nonlinear system in this paper uses the control algorithm for nonlinear systems in [14, 15]. The control method assumes that the system has well-defined relative degree r= (r1, r2, ..., rq) at the equilibrium point zero, under which assumption, the system can be partially linearized. Based on this linearization, a coordinate-change for system equations is made and computations of the input can be converted to the solution of a function of the output, its derivatives and the trajectories of the zero dynamics. The following is a review of inversion method in [14]. Consider the nonlinear system

$$\dot{x} = f(x(t)) + g(x(t))u(t) \tag{8}$$

$$y(t) = h(x(t)) \tag{9}$$

defined on a neighborhood X of the origin of R^n with input $u(\cdot) \in R^q$ and output $y(\cdot) \in R^q$. The functions $f(x)$, $g_i(x)$ (the ith column of $g(x)$) i = 1, 2, …, q are smooth vector fields, and $h_i(x)$ for i = 1, 2 , … , q are smooth functions on X with $f(0) = 0$ and $g(0) = 0$. Given a smooth reference output trajectory, such as tracking a drive circle within tracking limits, the problem is to solve the input $u_d(t)$ and possibly also the states $x_d(t)$ in the following system:

$$\dot{x}_d = f(x_d(t)) + g(x_d(t))u_d(t) \tag{10}$$

$$y_d(t) = h(x_d(t)) \tag{11}$$

$x_d(\cdot)$ is the desired state trajectory and $u_d(\cdot)$ is the nominal control input. It is also assumed that all functions are smooth, which means that the function is continuously differentiable, so that their necessary derivatives exist and equivalent computation are also available. According to the nonlinear theory listed in [15], the standard notation for Lie derivatives are:

$$L_f h(x) = \sum_i f_i(x) \frac{\partial}{\partial x_i} h(x) \tag{12}$$

$$L_f^r h(x) = L_f(L_f^{r-1} h(x)) \tag{13}$$

Since the relative degree r= (r1, r2, …. , rq) is assumed at the equilibrium point zero, for all $1 \le i, j \le q$,for all $k < r_i - 1$, and for all x in a neighborhood of the origin:

$$L_{gj} L_f^k h_i(x) = 0 \tag{14}$$

and the $q \times q$ matrix

$$\bar{\beta} = \begin{pmatrix} L_{g1} L_f^{r1-1} h_1(x) \cdots L_{gq} L_f^{r1-1} h_1(x) \\ L_{g1} L_f^{r2-1} h_2(x) \cdots L_{gq} L_f^{r2-1} h_2(x) \\ \cdots\cdots\cdots\cdots\ddots\cdots\cdots\cdots\cdots \\ L_{g1} L_f^{rq-1} h_q(x) \cdots L_{gq} L_f^{rq-1} h_q(x) \end{pmatrix} \tag{15}$$

is non-singular in a neighborhood of the origin, then the outputs can be differentiated for at least one input $u_j(\cdot)$ to appear explicitly, which will happen at exactly the r_{th} derivative of $y_i(\cdot)$ due to (14).

In summary, in order to solve the control problem of a series-parallel hybrid bus, first we have to find the relative degree r of the power train system. According to Fig.1 and(7), the powertrain system can be represented with

$$\begin{cases} \dot{x}_1 = x_2 + x_0 \\ \dot{x}_2 = \dfrac{1}{M_L}(-C_r \cdot m \cdot g \cdot r - C_a \cdot r \cdot x_2^{\,2} + C_{hev} \cdot x_3) \\ \dot{x}_3 = -\dfrac{1}{\tau} \cdot x_3 + \dfrac{1}{\tau} \cdot u_p \\ y = x_1 \end{cases} \tag{16}$$

Where x_0 is the initial speed of the bus, x_3 is the brake torque at the wheel, u_p is the input to the treadle (foot) valve from the driver, C_{hev} is the brake torque factor affected by HEV control strategies and τ is the brake time-delay factor.

First, we will determine the relative degree of the plant model. To do this, we simply take derivatives of the y until the input appears and for this case,

$$L_g h(x) = L_g L_f h(x) = 0 \tag{17}$$

And

$$L_g L_f^2 h(x) = -\frac{1}{\tau} \cdot \frac{b}{M_L} \neq 0 \tag{18}$$

So that the relative degree is d=n=3 and if we let $y^{(d)}$ denote the d^{th} derivative of y may be rewritten as

$$y^{(d)} = (\alpha(x) + \alpha_k(x)) + (\beta(x) + \beta_k(x)) \cdot u_p \tag{19}$$

We assume that $\alpha_k(x)$ and $\beta_k(x)$ are known components of the dynamics of the plant, which may depend on the state or known exogenous time-dependent signals, and that $\alpha(x)$ and $\beta(x)$ represent nonlinear dynamics of the plant that are unknown. It is also assumed that if the state x is a bounded vector, then $\alpha_k(x)$, $\beta_k(x)$, $\alpha(x)$, and $\beta(x)$ are bounded signals. In the following analysis, both $\alpha_k(x)$ and $\beta_k(x)$ are set to be zero.

In this case, we want the output y and its derivatives $\dot{y}(t),...,y^{(d)}(t)$ to track a "reference trajectory" $y_m(t)$ and its derivatives $\dot{y}_m(t),...,y_m^{(d)}(t)$ respectively for better brake comfort. So we assume both the "reference trajectory" and its derivatives are bounded. If we can approximate the $\alpha(x)$ and $\beta(x)$ of the actual system as following:

$$\begin{cases} \hat{a}(x) = \theta_\alpha^T(t)\phi_\alpha(x) \\ \hat{\beta}(x) = \theta_\beta^T(t)\phi_\beta(x) \end{cases} \tag{20}$$

by adjusting $\theta_\alpha(t)$ and $\theta_\beta(t)$ online, where $\theta_\alpha(t) \in \Omega_\alpha$ and $\theta_\beta(t) \in \Omega_\beta$, then:

$$\begin{cases} a(x) = \theta_\alpha^{*T}(t)\phi_\alpha(x) + w_\alpha(x) \\ \beta(x) = \theta_\beta^{*T}(t)\phi_\beta(x) + w_\beta(x) \end{cases} \tag{21}$$

where

$$\begin{cases} \theta_\alpha^{*T} = \underset{\theta_\alpha(t)\in\Omega_\alpha}{\arg\min}\left(\left|\hat{a}(x) - a(x)\right|\right) \\ \theta_\beta^{*T} = \underset{\theta_\beta(t)\in\Omega_\beta}{\arg\min}\left(\left|\hat{\beta}(x) - \beta(x)\right|\right) \end{cases} \tag{22}$$

and $w_\alpha(x)$, $w_\beta(x)$ are approximation errors caused by finite size approximates of $\alpha(x)$ and $\beta(x)$. We assume that these approximation errors are bounded in $W_\alpha(x)$ and $W_\beta(x)$ respectively.

The indirect adaptive control law can be:

$$u_p = u_{ce} + u_{si} \tag{23}$$

where the control term u_{ce} is the "certainty equivalence" term and u_{si} is the "sliding mode" control term.

3.2 Certainty Equivalence Control Term

Let the tracking error of the deceleration profile be:

$$e(t) = x_1(t) - x_{1d}(t) \tag{24}$$

Let

$$\Lambda = [\lambda_0, \lambda_1, \cdots, \lambda_{rd-2}, 1]^{\mathrm{T}} \tag{25}$$

be a vector of design parameters and

$$\begin{aligned} e_s(t) = e^{(rd-1)}(t) + \lambda_{d\text{-}2} e^{(rd-2)}(t) + \cdots \\ + \lambda_1 \dot{e}(t) + \lambda_0 e(t) \end{aligned} \tag{26}$$

Where *rd* is the relative degree of the dynamic system. If we define:

$$\overline{e}_s(t) = \lambda_{d\text{-}2} e^{(rd-1)}(t) + \cdots + \lambda_0 \dot{e}(t) \tag{27}$$

Then

$$\overline{e}_s(t) = \dot{e}_s(t) - e^{(d)}(t) \tag{28}$$

Let

$$L(s) = s^{rd-1} + \lambda_{rd-2} s^{rd-2} + \cdots + \lambda_1 s + \lambda_0 \tag{29}$$

and assume that the design parameters in (25) are chosen so that $L(s)$ has its roots in the left half plane.

Notice that $e_s(t)$ is a measurement of the tracking error. Considering the model (7) where *rd* =2 so $\Lambda = [\lambda_0, 1]^{\mathrm{T}}$ and

$$e_s(t) = \dot{e}(t) + \lambda_0 e(t) \tag{30}$$

For $L(s)$ to have its rood in the left half plane, λ_0 is selected to be a strictly positive constant.

Regarding the development of the control law, the following assumptions are made:

Assumption 4. The states x_1 and x_2 are available.

Assumption 5. The desired trajectory x_{1d}, x_{2d} and $\dot{x}_{2d}$ are available and bounded.

Then the certainty equivalence control term is defined as

$$u_{ce} = \frac{1}{\hat{\beta}(x)}(-\hat{\alpha}(x) + \nu(t)) \tag{31}$$

Where

$$\nu(t) = y_m^{rd} + \gamma \cdot e_s + \overline{e}_s \tag{32}$$

and $\gamma > 0$ is a design parameter. The 3rd derivative of the output error is $e^{(3)} = y_m^{(3)} - y^{(3)}$, substituted by (19) and (23), we get

$$\begin{aligned} e^{(3)} &= (\hat{\alpha}(x) - \alpha(x)) + (\hat{\beta}(x) - \beta(x)) \cdot u_{ce} \\ &- \gamma \cdot e_s - \overline{e}_s - \beta(x) \cdot u_{si} \end{aligned} \tag{33}$$

With (28), we can arrive

$$\begin{aligned} \gamma \cdot e_s + \dot{e}_s &= (\hat{\alpha}(x) - \alpha(x)) + (\hat{\beta}(x) \\ &- \beta(x)) \cdot u_{ces} - \beta(x) \cdot u_{si} \end{aligned} \tag{34}$$

3.3 Sliding Mode Control Term

We define the sliding mode control term as $u_{si} = -\eta \cdot \operatorname{sgn}(e_s)$, where η is the control gain and

$$\operatorname{sgn}(e_s) = \begin{cases} 1 & \text{if } e_s > 0 \\ 0 & \text{if } e_s = 0 \\ -1 & \text{if } e_s < 0 \end{cases} \tag{35}$$

With η being properly chosen, the sliding condition is

$$u_{si} = -\eta \cdot \operatorname{sgn}(e_s) \tag{36}$$

3.4 Parameter Adaptation Law

Let $\hat{\theta}_{\alpha,\beta}$ denote the estimates of $\theta_{\alpha,\beta}$ and $\tilde{\theta}_{\alpha,\beta}$ represent the estimation error ($\tilde{\theta}_{\alpha,\beta} = \hat{\theta}_{\alpha,\beta} - \theta_{\alpha,\beta}$). In order to obtain an approximation to the $\alpha(x)$, the estimate $\hat{\alpha}(x)$ will be computed by fuzzy adaptive algorithm. The basic configuration of a fuzzy logic system consists of a fuzzifier, some fuzzy If-Then rules, a fuzzy inference engine and a defuzzifier.

The adopted fuzzy inference engine is the zero order Takagi-Sugeno-Kang, which uses the If-Then rules to perform a mapping from an input $e_s(t)$ to an output of $\hat{d}_f(t)$. The i_{th} fuzzy rule is written as:

Rule(i): if s is Si then $\hat{d}_{fi} = \hat{D}_i$;

Where Si is fuzzy set and its membership function could be properly selected; $\hat{D}_i$ is the fuzzy singleton for the output in each once of the N fuzzy rules. By using the singleton fuzzifier, product inference and weighted mean defuzzifier, the output of the fuzzy system can be expressed as follows:

$$\hat{d}_f(e_s) = \frac{\sum_{i=1}^{N} \omega_i \cdot \hat{d}_{fi}}{\sum_{i=1}^{N} \omega_i} = \theta_\alpha^{\mathrm{T}} \cdot \Phi(e_s) \tag{37}$$

Where N is the number of fuzzy rules, $\theta_\alpha = [\ \hat{D}_1, \hat{D}_2, \cdots, \hat{D}_N\ ]^{\mathrm{T}}$ is the adjustable parameter vector (composed of consequent parameters), and $\Phi(e_s) = [\phi_1(e_s), \phi_2(e_s), \cdots, \phi_N(e_s)]^{\mathrm{T}}$,where

$$\phi_i(e_s) = \omega_i / \sum_{i=1}^{N} \omega_i \tag{38}$$

is the fuzzy basis function (FBF) and ω_i is the firing strength of each rule.

Considering the system(7) with the feedback controller(23), let the adaptation law of the adjustable parameter vector be

$$\dot{\hat{\theta}}_\alpha = -\eta_\alpha \cdot e_s \cdot \Phi(e_s) \tag{39}$$

Where η_α is a strictly positive constant and determines the convergence rate of $\hat{\theta}_\alpha$.

The unknown parameter vector θ_β is within a known bounded convex set Ω_θ, that is

$$\theta_\beta \in \Omega_{\theta_\beta} \triangleq \{\theta_\beta : \theta_{\beta\min} < \theta_\beta < \theta_{\beta\max}\} \tag{40}$$

where $\theta_{\beta\min}$ and $\theta_{\beta\max}$ are some known constants. Then a simple discontinuous projection $\dot{\hat{\theta}}_\beta = \operatorname{Proj}_{\hat{\theta}_\beta}(\theta_\beta^{ud})$ can be defined as:

$$\operatorname{Proj}_{\hat{\theta}_\beta}(\theta_\beta^{ud}) = \begin{cases} 0, & \text{if } \hat{\theta}_\beta \geq \theta_{\beta\max} \text{ and } \theta_\beta^{ud} \geq 0 \\ 0, & \text{if } \hat{\theta}_\beta \leq \theta_{\beta\min} \text{ and } \theta_\beta^{ud} \leq 0 \\ \theta_\beta^{ud} = -\eta_\beta \cdot \phi_\beta \cdot e_s \cdot u_{ce}, & \text{otherwise} \end{cases} \tag{41}$$

Theorem 1. Consider the longitudinal dynamic system represented by(16) . Then, for any conditions that subject to Assumption 1-5, the controller (23) can ensure the asymptotic tracking and the convergence of the states with defuzzifier (37) and adaptation laws of (39) and (41).

Proof. We employ the Lyapunov function

$$V = \frac{1}{2}e_s^2 + \frac{1}{2\eta_\alpha}\tilde{\theta}_\alpha^T\tilde{\theta}_\alpha + \frac{1}{2\eta_\beta}\tilde{\theta}_\beta^T\tilde{\theta}_\beta \tag{42}$$

Therefore, by differentiating along the trajectories of the system, we have

$$\begin{aligned}\dot{V} &= e_s\dot{e}_s + \frac{1}{\eta_\alpha}\tilde{\theta}_\alpha^T\dot{\tilde{\theta}}_\alpha + \frac{1}{\eta_\beta}\tilde{\theta}_\beta^T\dot{\tilde{\theta}}_\beta \\ &= e_s((\hat{\alpha}(x)-\alpha(x)) + (\hat{\beta}(x)-\beta(x))\cdot u_{ces} \\ &\quad -\beta(x)\cdot u_{si} - \gamma\cdot e_s) + \frac{1}{\eta_\alpha}\tilde{\theta}_\alpha^T\dot{\tilde{\theta}}_\alpha + \frac{1}{\eta_\beta}\tilde{\theta}_\beta^T\dot{\tilde{\theta}}_\beta\end{aligned} \tag{43}$$

Notice that $\hat{\alpha}(x)-\alpha(x) = \tilde{\theta}_\alpha^T(t)\phi_\alpha(x) - w_\alpha(x)$ and $\hat{\beta}(x)-\beta(x) = \tilde{\theta}_\beta^T(t)\phi_\beta(x) - w_\beta(x)$.

Then,

$$\begin{aligned}\dot{V} = &-\gamma\cdot e_s^2 + \tilde{\theta}_\alpha^T(\phi_\alpha(x)e_s + \frac{1}{\eta_\alpha}\dot{\tilde{\theta}}_\alpha) \\ &+\tilde{\theta}_\beta^T(\ \phi_\beta(x)e_s u_{ce} + \frac{1}{\eta_\beta}\dot{\tilde{\theta}}_\beta\ ) \\ &-(w_\alpha(x) + w_\beta(x)u_{ce} + \beta(x)u_{si})e_s\end{aligned} \tag{44}$$

Note that the adaptation law (39) and (41) is represented by the following vector form $\dot{\tilde{\theta}} = \dot{\hat{\theta}}$.Substituting (39) and (41) into(44), hence

$$\dot{V} = -\gamma\cdot e_s^2 - (w_\alpha(x) + w_\beta(x)u_{ce} + \beta(x)u_{si})e_s \tag{45}$$

By applying the adaptation law of (36) to (45),

$$\dot{V} = -\gamma\cdot e_s^2 - (w_\alpha(x) + w_\beta(x)u_{ce} + \beta(x)\cdot\eta\cdot\mathrm{sgn}(e_s))\cdot e_s \tag{46}$$

To ensure that (46) is less than or equal to zero, the η is chosen as

$$\eta = -\frac{(W_\alpha(x) + W_\beta(x)|u_{ce}|)}{\beta_0} \tag{47}$$

where β_0 is a known constant and satisfy $0 < \beta_0 \le \beta(x)$.

Note that

$$\begin{cases} -(w_\alpha(x) + w_\beta(x)u_{ce})e_s \le (|w_\alpha(x)| + |w_\beta(x)u_{ce}|)|e_s| \\ \dfrac{\beta(x)}{\beta_0} \ge 1 \end{cases} \tag{48}$$

Hence

$$\begin{aligned}\dot{V} \le &-\gamma\cdot e_s^2 + (|w_\alpha(x)| + |w_\beta(x)u_{ce}|)|e_s| \\ &-\beta(x)\cdot\frac{(W_\alpha(x) + W_\beta(x)|u_{ce}|)}{\beta_0}\cdot\mathrm{sgn}(e_s)\cdot e_s\end{aligned} \tag{49}$$

Recall that $|w_\alpha(x)| \le W_\alpha(x)$ and $|w_\beta(x)| \le W_\beta(x)$, so

$$\dot{V} \le -\gamma\cdot e_s^2 \tag{50}$$

Therefore, it follows by Barbalat's lemma that $e_s \to 0$ as $t \to \infty$, which ensures the stability in the sense of Lyapunov, i.e., the desired trajectory tracking can be achieved. This ensures the global stability of the closed-loop system and completes the proof.

4 Simulation results

The simulation studies are performed to show the effectiveness of the proposed adaptive fuzzy sliding model control scheme. Both wheel velocity and vehicle velocity are assumed available. The symmetric Gaussian membership functions are adopted for the parameter adaption law, with the central values defined as -10,0, and 10.The spread values all equal to 10 and using all possible combinations of rules so we get *i*=9 rules. This means that we will tune 36 parameters for the approximate. The initial values for the vector of adjustable parameters were $\hat{\theta}_{\alpha,\beta} = 0$, and are updated at each iteration step according to the adaptation law of (39) and (41) . The simulations are done in 2 different cases for different initial velocity and abrupt regenerative braking torque. Considering the driver and passengers' comfort, the displacement trajectory and velocity trajectory in Fig.2 and Fig.3 are selected. The initial velocity of bus as the controller brake torque is applied is set to be 30km/h.The obtained results are presented from Fig.4 to Fig.15.

In the first case, the following values were chosen $M_L = 6200\text{kg}$, $C_a = 2.9436$, $C_r = 0.01$, $\lambda_0 = 100$, $\lambda_1 = 20$, $T_{regb} = 0\text{N}\cdot\text{m}$, $\eta_\alpha = 10$, $\eta_\beta = 250$. Take $\tau = 0.03$ and $b = 1$. We only take these as constant nominal values that we do not know. However, we know that $\tau \in [0.02, 0.05]$ and $b \in [0.8, 1.2]$. We choose $W_\alpha = 50$ and $W_\beta = 30$. The regenerative braking torque happens at t=1.5s and the initial speed is 8.34m/s.

The parameters that are used in the approximates are shown in Fig.4 and Fig.5. As observed from

Fig.6, there is a large fluctuation at t=1.5, which is caused by the regenerative braking torque. Fig.6 shows the actuator output of the brake pedal. From Fig.7 to Fig.9, the results show good profile tracking quality and fast tracking ability.

In the second case, the initial speed is set to 9m/s and the regenerative braking is shut off during the braking process. For the other parameters keep the previously adopted values. The parameters for approximates and the desired trajectory are presented from Fig.10 to 15.

It can be seen from Fig.10 and Fig.11 that the parameters for the approximates are much smaller compared with the firs case. This is caused by the shut off of the regenerative braking, i.e., the smaller uncertainty. Though the initial velocity is larger than that of the velocity profile, it can be observed from Fig.12 that the designed controller can still brake the bus at the desired position. Good tracking performance can still be achieved from the results in Fig.13 to Fig.15.

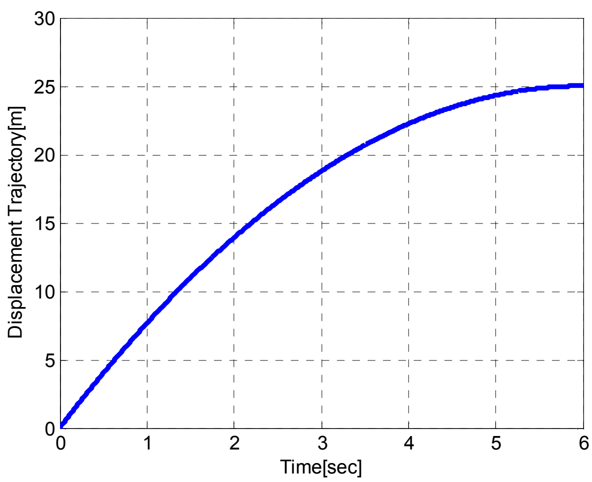

Fig.2 Displacement profile

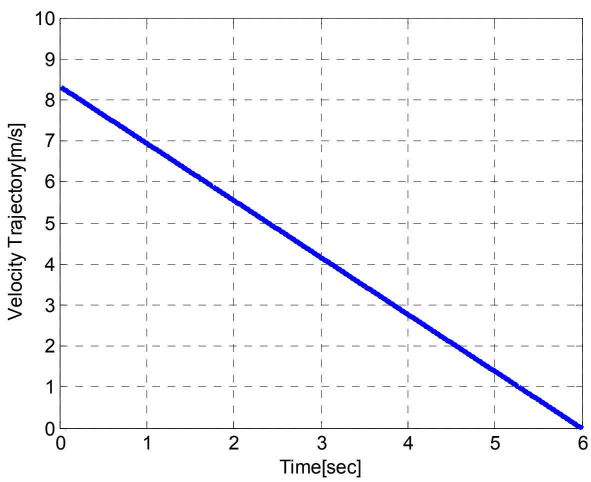

Fig.3 Velocity profile

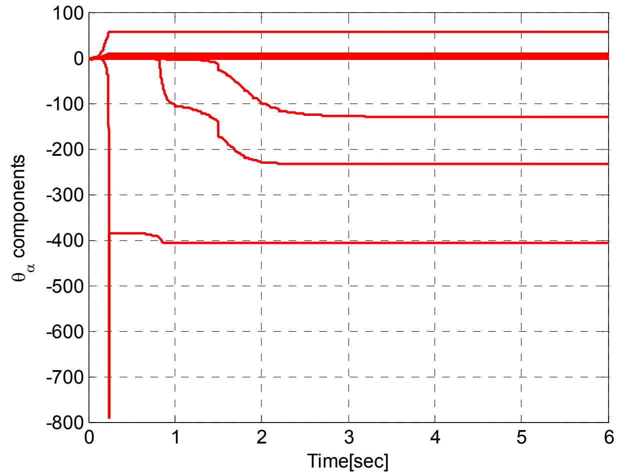

Fig.4 Components of θ_α with regenerative braking

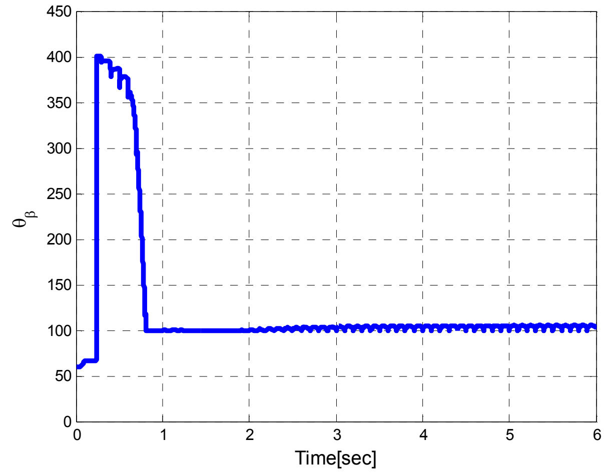

Fig.5 θ_β with regenerative braking

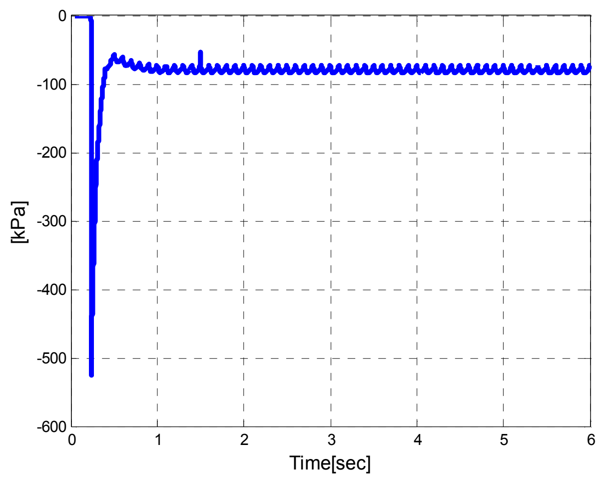

Fig.6 Actuator output with regenerative braking

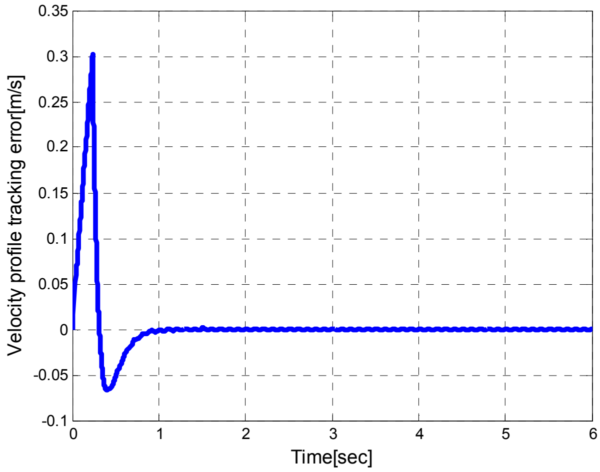

Fig.7 Velocity tracking error with regenerative braking

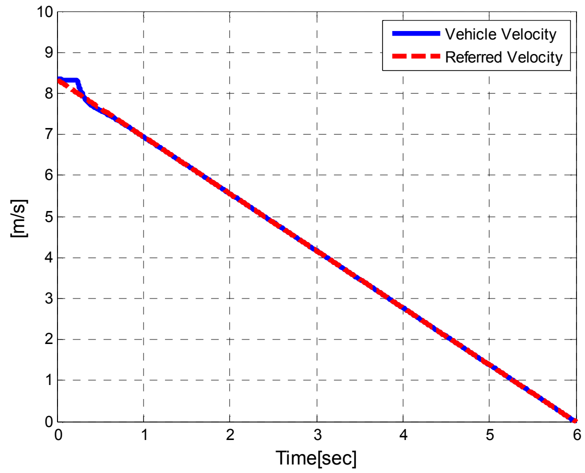

Fig.8 Control result of velocity with regenerative braking

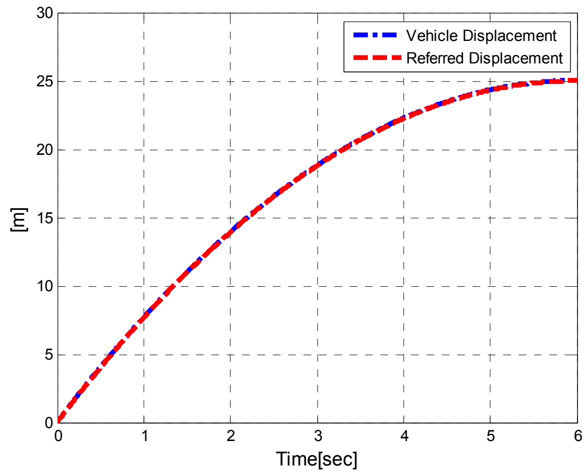

Fig.9 Control result of displacement with regenerative braking

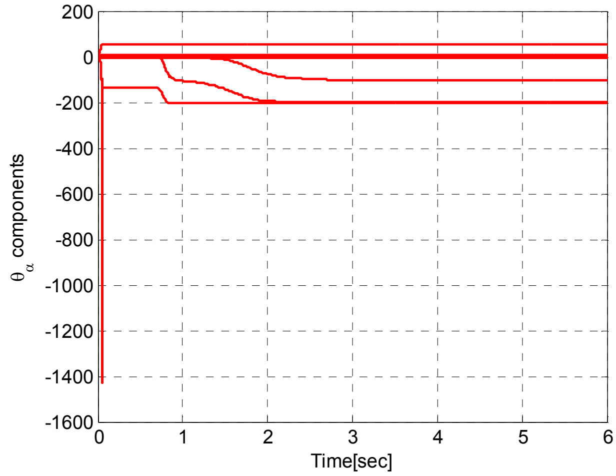

Fig.10 Components of θ_α with different initial state

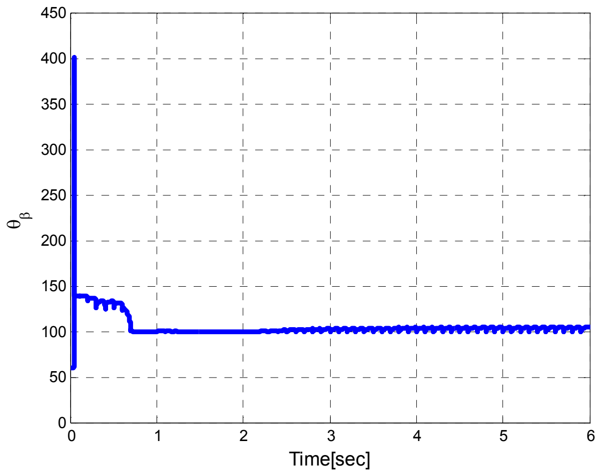

Fig.11 θ_β with different initial state

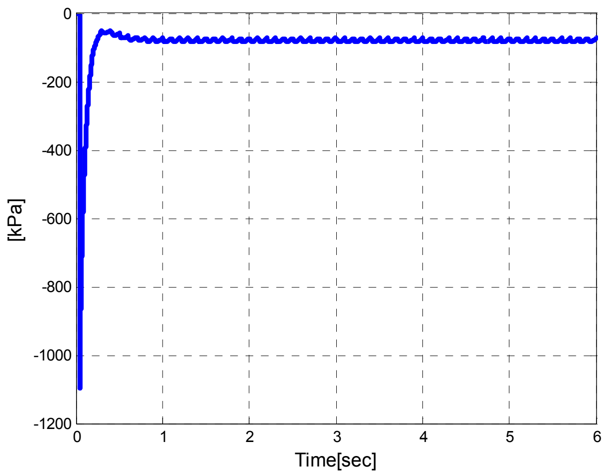

Fig.12 Actuator output with different initial state

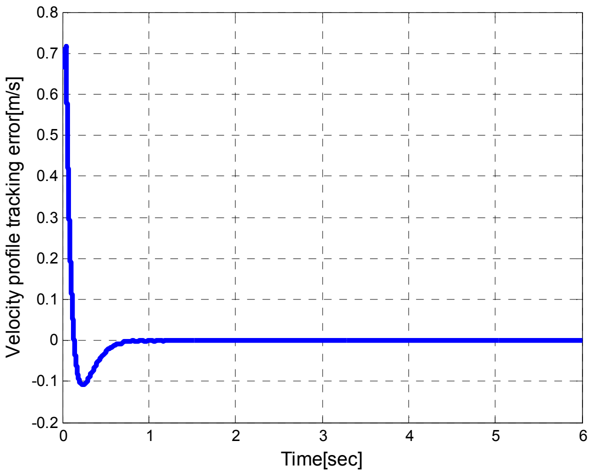

Fig.13 Velocity tracking error with different initial state

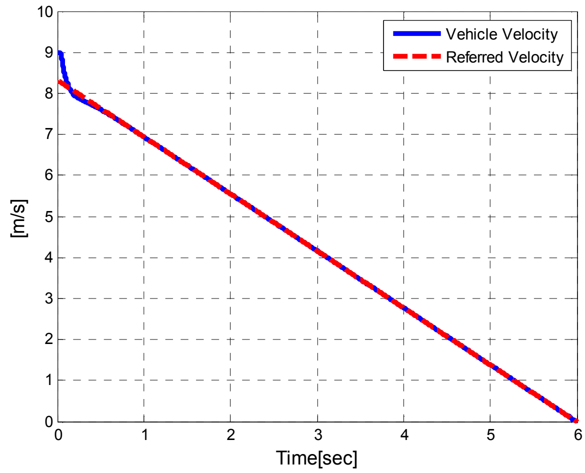

Fig.14 Control result of velocity with different initial state

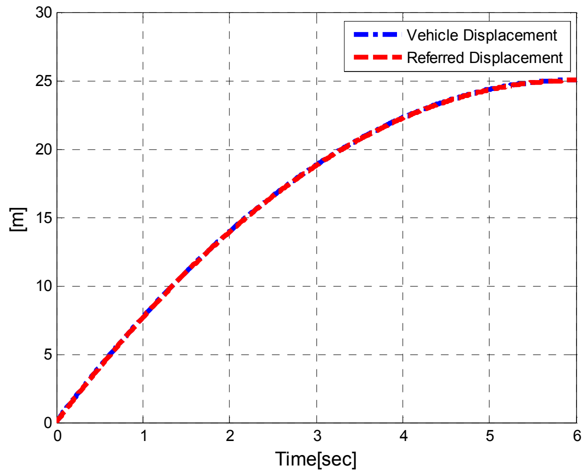

Fig.15 Control result of displacement with different initial state

5 Conclusion

In this paper, an adaptive fuzzy sliding model control scheme is proposed to achieve brake trajectory tracking of stopping a hybrid electric bus at a bus station. To enhance the tracking performance, the longitudinal system is converted an affine system and its nonlinearities are estimated by adaptive fuzzy method and projection method. The controller is derived from the approximates. The stability and convergence properties of the closed-loop systems are analytically proved by using Lyapunov stability theory and Barbalat's lemma. The simulation results demonstrate that the proposed controller has a good performance of tracking the pre-designed profile even the brake system has the regenerative braking or has different initial state from the velocity profile.

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