Adaptive Cruise Control for Electric Bus based on Model Predictive Control with Road Grade Prediction

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Keywords: Adaptive Cruise Control, Model Predictive Control, Road Grade Prediction, Electric Bus.

Abstract: Adaptive Cruise Control (ACC) makes the driving experience safer and more pleasurable. To comprehensively deal with tracking capability and energy consumption issue of ACC-activated vehicle on rugged roads, this paper presents a MPC based vehicular following control algorithm with road grade prediction. A simulation model of ACC for electric bus based on MPC is built for analysing the performance of the algorithm. The simulation results show that road grade prediction can improve improves both energy consumption and tracking capability.

1 INTRODUCTION

Cruise Control (CC) executes the task of maintaining the vehicle speed at a desired value. However, it cannot reasonably alter the speed of the vehicle according to different situations. When the preceding vehicle equipped with CC is traveling slower than the latter, the driver has to step on the brake pedal in order to deactivate the Cruise Control and step on the accelerator when the preceding vehicle speeds up, (Howard, 2013). This drawback is overcome by the more advanced Adaptive Cruise Control (ACC), which is able to adjust the vehicle speed by analysing various influential factors, without manual intervention from the driver, (Howard, 2013; Shakouri et al., 2012, 2014).

Adaptive Cruise Control system (ACC) has been widely investigated due to its merits of reducing driver workload and ensuring safety, (Mba et al., 2016). Due to concerns about global warming and energy conservation, vehicle energy consumption has become a consideration of great importance for the automotive industry. Close attention has been given to another important issue in ACC, specifically energy consumption problem, (Li et al., 2017). Tsugawa and Ioannou suggested the use of ITS technologies, including adaptive cruise control, to reduce fuel consumption of vehicles, (Tsugawa, 2001; Ioannou et al., 2005; Bose et al., 2003). ACC system is designed to follow the vehicle in front automatically, simultaneously to reduce energy consumption to the full extent under the premise of ensuring safety. The design of an ACC system with multiple objectives can be naturally cast into a model predictive control (MPC) framework. MPC has already proved its merit in ACC design in literature, (Li et al., 2011). Nonetheless, ACC system based on MPC designed for conventional fuel vehicles is not suitable for electric buses which are equipped with regenerative braking system.

When taken into account, the road grade effect can play an important role in advanced navigation and navigation algorithms, where the system can help drivers avoid steep roads to achieve better fuel economy and reduce carbon dioxide emissions, (Boriboonsomsin et al., 2009). A research has found that fuel saving capability of ACC system can be strenthened by the prediction of road grade, (Lattemann et al., 2009). Knowledge about the upcoming road grade can be used in ACC to avoid unnecessary braking and shifting. Due to the relatively large mass of a city bus, such system can save a great deal of energy. In addition, road grade level has an effect on crash risk, (Wu et al., 2017). Therefore, if in the future road grade can be accurately predicted, the valuable data can reduce not only the energy consumption of buses, but also the risk of traffic accidents, (Zeng et al., 2015; Luo et al., 2015).

There are many methods to measure or estimate the current road slope during driving, (Kim et al., 2013). These methods generally rely on different types of sensors, mainly Global Position System

Bian, J., Qiu, B., Liu, Y. and Su, H.
Adaptive Cruise Control for Electric Bus based on Model Predictive Control with Road Grade Prediction.
DOI: 10.5220/0006641702170224
In *Proceedings of the 4th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2018)*, pages 217-224
ISBN: 978-989-758-293-6
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(GPS), inertial sensors, pressure sensors, (Boroujeni et al., 2013), wheel speed sensors, (Wragge-Morley et al., 2013), acceleration sensors, LIDAR, (Tsai et al., 2013), etc. GPS can provide the altitude and velocity information of the vehicle, but the signal accuracy is greatly influenced by the environment. GPS cannot provide reliable data in conglomerations of high-rise buildings and inside tunnels and so on, (Bae et al., 2001). IMU (Inertial Measurement Unit) can provide acceleration and angular velocity information and is not affected by environment factors. However, its measurement accuracy can be easily influenced by suspension movements, and its signal oscillation can be very serious, (Lee et al., 2012). Based on prior analysis, researchers have proposed some methods and algorithms to improve the accuracy of road slope estimation, such as Kalman filter, extended Kalman filter, (Srinivasaiah et al., 2014), etc.

This paper is organized as follows. The second part introduces the longitudinal vehicle dynamics. The third part introduces the MPC algorithm in this paper, including the state space description of the problem and the construction of cost function. The fourth part introduces the road grade prediction. A simulation model and results are shown in the fifth part, indicating the improvement of ACC based on MPC with road grade consideration.

2 LONGITUDINAL VEHICLE DYNAMICS

Figure 1 shows the schematic diagram of an electric bus's longitudinal model, where a_{accl} represents the acceleration pedal position, a_{brk} is brake pedal position, F_a is aerodynamic drag, F_f is rolling resistance and F_i is climbing resistance. The motor torque is mainly affected by the accelerator pedal signal and the motor speed. Compared with traditional vehicles, most electric vehicles are equipped with a regenerative braking system, which can recover energy while braking.

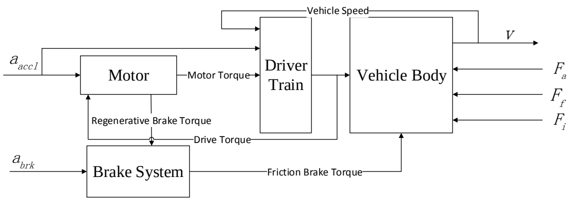

Figure 1: Longitudinal dynamics of electric bus.

3 ACC ALGORITHIM BASED ON MPC

3.1 Discrete State Space Model

With respect to inter-vehicular dynamics, we define two variables reflecting the tracking errors: clearance error Δd and speed error Δv. The discrete state space model can be described as:

$$
\begin{aligned}
& x(k+1) = Ax(k) + Bu(k) + Gv(k) \\
& y(k) = Cx(k) \\
& \Delta d = d - d_{des}, \Delta v = v_p - v_f \\
& x = [\Delta d \quad \Delta v], u = a_{fdes}, v = a_p \\
& A = \begin{bmatrix} 1 & T_c \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} -0.5T_c^2 \\ -T_c \end{bmatrix}, G = \begin{bmatrix} 0.5T_c^2 \\ T_c \end{bmatrix} \\
& y = [\Delta d_m \quad \Delta v_m]
\end{aligned} \tag{1}
$$

where C is identity matrix, T_c is the sample time, d is distance between two vehicles, d_{des} is desired distance, v_p is the preceding vehicle speed, v_f is the following vehicle speed, a_p is the preceding vehicle acceleration, a_{fdes} is the needed acceleration of following vehicle. For a typical ACC system, radar and accelerometer are equipped, which means the states are measurable.

3.2 Construction of Optimization Problem

Tracking capability, fuel economy, driver behaviour, driving safety, ride comfort and environmental issues, as well as limitations on the model and traffic flow, all of the above factors constrain the behaviour of the ACC system. In this paper, emphasis is given to energy consumption and tracking capability while allowing driver permissible tracking error.

According to MPC framework, the cost function to be optimized can perform a trade-off between the former two issues since they are reversely interactive with each other. Driver permissible tracking error issue mainly results from driver behaviour in actual traffic flow. If inter vehicular distance is larger, the cut-in of front vehicle from adjacent lane occurs frequently, thus leading to frequent decelerating of ego car and the deterioration of fuel economy. On the other hand, if the distance is smaller, driver is prone to intervene ACC control to avoid potential rear-end collision. Both strategies are sure to disturb ACC's regular working order. So, the upper and lower bounds of tracking errors usually exist, called the driver permissible tracking error.

Fine tracking capability does not mean that the energy consumption is optimal. ACC system designed for the electric bus is different from the one of traditional fuel vehicles. Because of the existence of regenerative braking system, the energy consumption cannot be simply regarded as the linear function of the squared value of the acceleration. An energy consumption model of electric bus is established as follow:

$$P_{wh}(v_f, a_{fdes}) = \left(\frac{Gf\cos\alpha}{3600} + \frac{G\sin\alpha}{3600}\right)v_f + \frac{C_D A}{76140}v_f^{3} + \frac{\delta m}{3600}v_f a_{fdes} \tag{2}$$

$$P_{req+} = \begin{cases} \dfrac{P_{wh}}{\eta_{Td}\eta_{Md}}, P_{wh} \geq 0 \\ 0, P_{wh} < 0 \end{cases}, P_{req-} = \begin{cases} 0, P_{wh} \geq 0 \\ P_{wh}\eta_{Tb}\eta_{Mb}(1-\beta)\beta_{elc}, P_{wh} < 0 \end{cases} \tag{3}$$

where α is the road gradient and while the vehicle is downhill, the value of α is negative, f is the rolling resistance coefficient, m is the vehicle mass, C_D is the coefficient of air resistance that is characterized by the shape of the vehicle's body, v_f is the vehicle speed, δ is a coefficient that characterizes the rotational inertia of the vehicle, A is the windward area, η_{Td} and η_{Tb} are the powertrain efficiency, η_{Md} and η_{Mb} are the motor efficiency, β is the ratio of front-rear braking force allocation, β_{elc} is the regenerative braking force coefficient. The cost function of MPC is established as:

$$\min J = K\sum_{k=1}^{P}(P_{req+}(k) + P_{req-}(k)) + L\sum_{k=1}^{P}\Delta d^2(k) \tag{4}$$

$$\begin{cases} 0 \leq \beta_{elc}(k) \leq \dfrac{P_{elcb\max}(k)}{P_{wh}(k)\eta_{Tb}\eta_{M}(1-\beta)} \\ a_{fdes\min} \leq a_{fdes}(k) \leq a_{fdes\max} \\ \Delta d_{\min} \leq \Delta d(k) \leq \Delta d_{\max} \end{cases} \tag{5}$$

$$a_{fdes\min} = \frac{P_{elcb\max}(k) \big/ \eta_{Tb}\eta_{M}(1-\beta)\beta_{elc} + P_{hydb\max}(k) - \left(\frac{Gf\cos\alpha}{3600} + \frac{G\sin\alpha}{3600}\right)v_f - \frac{C_D A}{76140}v_f^{3}}{\frac{\delta m}{3600}v_f} \tag{6}$$

$$a_{fdes\max} = \frac{P_{elcd\max}(k)\eta_T\eta_M - \left(\frac{Gf\cos\alpha}{3600} + \frac{G\sin\alpha}{3600}\right)v_f - \frac{C_D A}{76140}v_f^{3}}{\frac{\delta m}{3600}v_f} \tag{7}$$

where P is the control horizon, K and L are the weight coefficients, $P_{elcb\max}$ is the maximum regenerative braking power and $P_{elcd\max}$ is the maximum driving power, which depends on the motor and the battery. $P_{hydb\max}$ is the maximum hydraulic braking power.

Pseudo-spectral (PS) is an effective numerical method for solving optimal control problem (OCP). It uses the zeroes of orthogonal polynomials as collocations, and uses global interpolation to approximate the original continuous variables, and transforms the OCP into a nonlinear programming problem (NLP). And there are a variety of mature and effective methods for solving NLP, (Elnagar et al., 1995). Compared with other traditional methods, PS features the high precision and fast convergence, (Xu et al., 2015), so this paper chooses PS as the tool for solving MPC optimization problems.

4 ROAD GRADE PREDICTION

According to the longitudinal dynamics of electric bus, without road grade taken into account in ACC,

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the difference between a_{fdes} and a_f may be beyond expectation, which may lead to safety problems. Therefore, considering the road grade is very meaningful for ACC, especially when the road grade is predictable in the control period.

4.1 Road Grade Estimation

4.1.1 Measuring Road Slope with IMU

IMU sensors have been widely used for road slope estimation because it can provide 3-D angular velocity (Figure 2). The road slope can be obtained by integrating the Y-axis angular velocity, (Wang et al., 2013), as shown in the following:

$$\theta_{IMU} = \int_{t_0}^{t} \omega_Y dt + \theta_{t0} \tag{8}$$

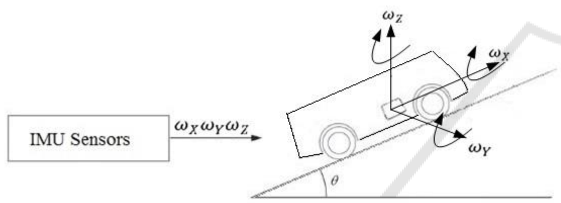

Figure 2: Measuring Road Slope with IMU.

4.1.2 Measuring Road Slope with GPS

GPS receivers have been widely used for road slope estimation because GPS provides both vehicle altitude and velocity information in the navigation frame. Using 3-D velocities from a GPS receiver (Figure 3), the road slope can be estimated by calculating the ratio of vertical velocity to horizontal velocity, (Bae et al., 2001). By combining the change of road altitude, the road slope measurement is more accurate.

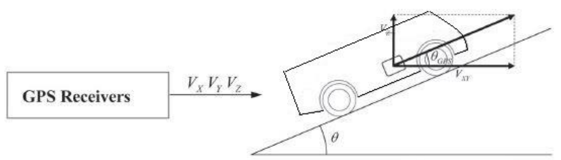

Figure 3: Measuring Road Slope with GPS.

The road slope can be determined by calculating the arctangent value of the vertical velocity divided by the horizontal velocity measurement:

$$\theta_{GPS} = \tan^{-1}(V_Z / V_{XY}) = \tan^{-1}(V_Z / \sqrt{V_X^2 + V_Y^2}) \tag{9}$$

However, road slope estimation methods based on GPS might be hampered by temporary losses of satellite connection and multipath errors. The GPS and IMU data are processed by Kalman filter to estimate the current road grade.

4.1.3 Road Invariant Model

As the road is changing slowly, in a short period the road model can be considered as:

$$\theta(k) = \theta(k-1) \tag{10}$$

Estimating the current road slope and using the road invariant model can predict the road grade within the control horizon.

4.2 Data Acquisition Experiment

Driving cycles are usually used to assess the performance of vehicles from several aspects, for example, fuel consumption and pollution emissions. However, conventional driving cycles like NEDC are only series of data points representing the speed of vehicles at different time. To take real-world road gradient information into account in ACC, information given by conventional driving cycles is insufficient and road gradient data need to be added to constitute a new driving cycle.

Two routes carefully chosen in Beijing were traced and raw data of road gradient and velocity were acquired simultaneously for further processing and analysis. One route is high way which contains some flyovers and the other route is city road which is chosen to avoid any flyovers. The data of vehicle speed and road grade were collected simultaneously, which can be seen in Figure 4.

5 SIMULATION AND ANALYSIS

In order to study whether road grade has influence on ACC, a simulation is carried out based on the nonlinear electric bus longitudinal model. The parameters used for simulation are given in Table 1.

Table 1: Parameters of electric bus.

Parameters	Symbol	Unit	Value
Curb weight	M	Kg	5600
Motor power (default/ peak)	P	kW	80/130
Motor torque (default/ peak)	T	Nm	350/900
Transmission ratio	i_G		5.39
Dynamic rolling radius	r	mm	336
Aerodynamic drag coefficient	C_D		0.6
Frontal area	A	m^2	4.95
Distance of gravity centre to front wheel centre	L_a	mm	2050
Distance of gravity centre to rear wheel centre	L_b	mm	1645

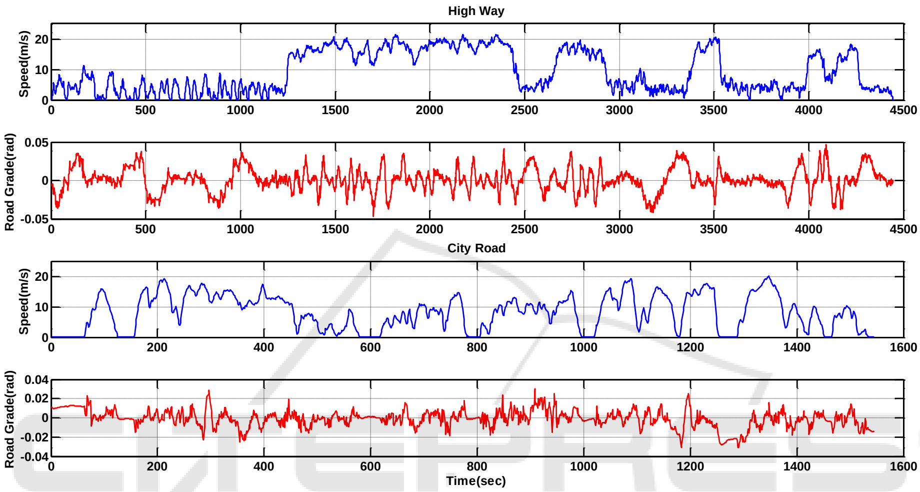

Figure 4: Data of speed and road grade.

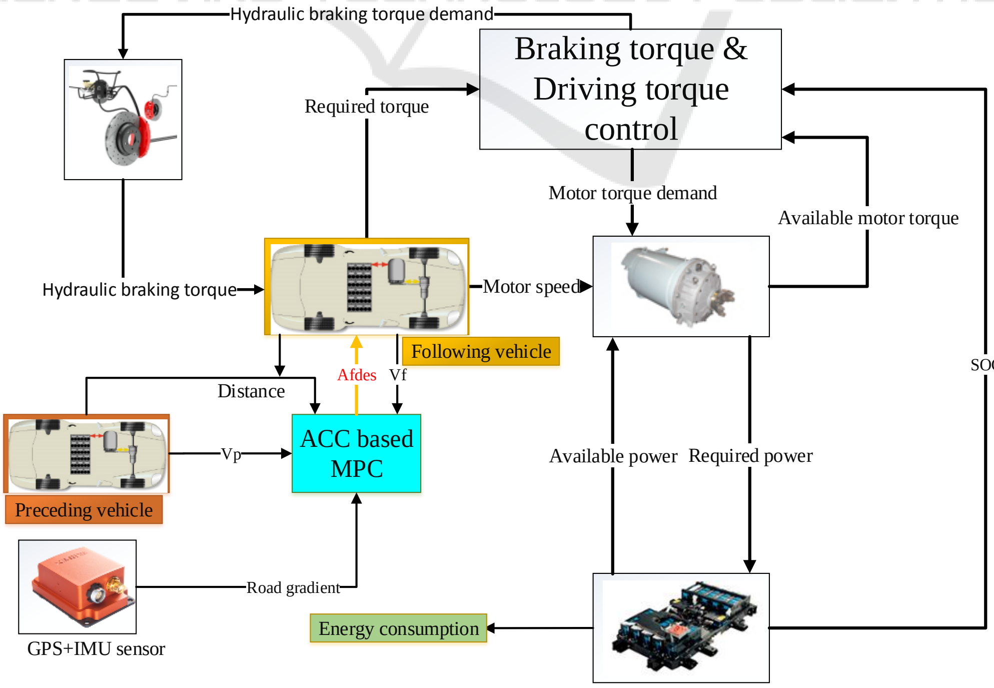

Figure 5: Simulation model.

5.1 Hydraulic Brake System

A schematic diagram of a hydraulic braking system is shown in Figure 6. The inlet valve (normally open) and the outlet valve (normally closed) are set upstream and downstream respectively of the wheel cylinder. p_m is the master cylinder pressure, which is the input pressure of the inlet valve and p_w is the wheel cylinder pressure, which is the load pressure in the hydraulic control system. The structure of the wheel cylinder is simplified to a combination of piston and spring. For an electrified vehicle in the regenerative deceleration process, when the driver depresses the brake pedal, the brake pressure p_m will be generated in the master cylinder, which can indicate the total brake demand of the vehicle. The regenerative braking torque provided by the motor will be exerted on the drive axle. Meanwhile, to assist the overall braking operation, the expected brake pressure p_w can be obtained and applied to the wheel cylinder by modulating the inlet valve, (Lv et al., 2017).

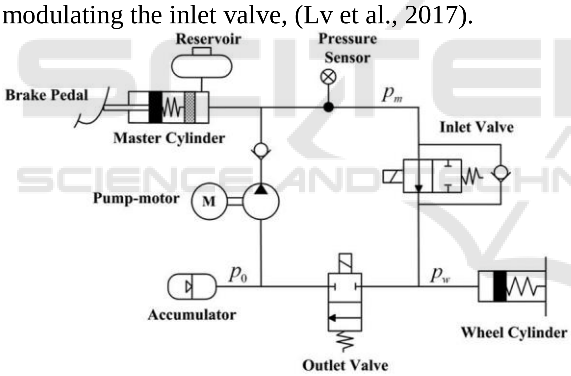

Figure 6: Schematic diagram of the hydraulic braking system.

For an electric vehicle, the total braking torque T_b is cooperatively provided by the regenerative braking torque and friction braking torque according to:

$$T_b = i_G T_{regen} + T_{hb} = \frac{4\mu_b r_{fb} A_w}{\beta} p_m \tag{11}$$

where β is set at 0.4 in this paper, μ_b is the friction coefficient of the brake disc, p_m is the pressure of the master cylinder, r_{fb} is the effective friction radius of the brake disc, A_w is the contact area, and T_{regen} is the regenerative braking torque.

5.2 Electric Powertrain System

The electric powertrain is shown in Figure 7, which can be described as:

$$\begin{aligned} T_m &= \frac{F_{whdes} r}{\eta_{Td} i_G}, \left(T_m > 0\right) \\ T_m &= \frac{F_{whdes} r - T_{wh}}{i_G} \eta_{Tb}, \left(T_m < 0\right) \end{aligned} \tag{12}$$

where T_m is the torque of electric motor. When the motor is on drive mode, T_m >0; and T_m <0 when the motor works as a generator. F_{whdes} is the desired force on wheel, r is the rolling radius of wheel, i_G is the transmission ratio.

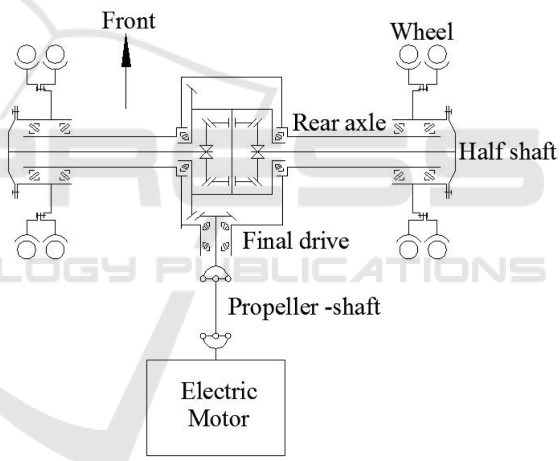

Figure 7: Electric Powertrain.

5.3 Motor and Battery

According to the motor map, it is useful to find the motor's external characteristics of torque, drive efficiency and generation efficiency. The motor torque is simplified as a first-order inertia system:

$$T_{Mdes} = \tau_M \dot{T}_M + T_M \tag{13}$$

where T_{Mdes} is the desired motor torque, T_M is the actual motor torque, τ_M is time coefficient.

The battery model with the internal dissipation is used to analyse the performance characteristics of an electric battery. The input of the model is the demand power of the motor, the output is the battery's SOC, voltage, current and output power.

5.4 Simulation Results

In order to verify the performance of ACC, simulation patterns for actual road conditions is adopted here. The speed and road grade profiles are illustrated in Figure 4. Tracking Error Index (TEI) is composed of both speed error and distance error, (Li et al., 2008):

$$TEI = \frac{1}{N}\sum_{k=1}^{N}\left(\left|\frac{\Delta d(k)}{K_{DV}}\right| + \left|\Delta v(k)\right|\right) \tag{14}$$

where N is length of simulation pattern, K_{DV} is weighting coefficient, reflecting different emphasis on Δd and Δv. Here, according to actual driver experiment data, we select K_{DV} =10. The *TEI* values with its corresponding energy consumption under city road and high way simulation patterns are shown in Table 2. With road grade taken into consideration, in high way pattern, the *TEI* value is reduced by 2.6 % while energy consumption per 100km decreases 4.9%. With respect to city road pattern, they are 1.0% and 3.1%. A conclusion can be drawn from Figure 4 and Table 2 that there is greater promotion of energy consumption in high way pattern than in city road with road grade prediction because the high way is more varied in altitude than the city road.

Table 2: Performance of ACC based MPC.

Simulation Pattern		TEI	Energy Consumption (kWh/100km)
High Way	ACC without road grade prediction	0.069	38.68
	ACC with road grade prediction	0.067	36.80
City Road	ACC without road grade prediction	0.097	41.77
	ACC with road grade prediction	0.096	40.45

6 CONCLUSIONS

In this paper, MPC is used as ACC algorithm. This paper proposes to use Kalman filter to estimate the current road grade with data gathered via GPS and IMU sensor; and to use the road invariant model to predict the road grade within the control horizon of MPC, making possible the optimization of the track performance and the reduction of energy consumption. Based on the establishment of an electric bus simulation model, and the use of collected speed and road grade data, simulation results verify the improvement of performance of ACC with road grade prediction.

ACKNOWLEDGEMENTS

This research was made possible in part by the generous support of Collaborative Innovation Centre of Electric Vehicles in Beijing.

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