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ISSN 2959-6157

Modeling and MPC-Based Control of an Electromechanical Brake Booster System

Ziyi Sun

Chang'an Dublin International College of Transportation, Chang'an University, Xi'an, China, 710016
2022903088@chd.edu.cn

Abstract:

With the rise of intelligent and electric vehicles, the demand for high-performance and responsive braking systems has significantly increased. This paper presents a braking control strategy based on model predictive control (MPC) for intelligent electric vehicles. The vehicles use an electromechanical brake booster called iBooster. A dynamic model is established to characterize the actuator dynamics and the vehicle's longitudinal motion. The control system employs a two-layer architecture: the upper layer utilizes Model Predictive Control (MPC) for deceleration planning, while the lower layer employs a PID controller to track the planned signal and achieve real-time actuator control. To test the control system, simulations are done under three road conditions. These are dry roads, slippery roads, and downhill slopes. Simulation results demonstrate that the control system accurately tracks the target deceleration with rapid response, minimal overshoot, and robust performance against disturbances. The system also works well when road friction is low or when gravity affects braking. In all cases, the system reaches the target within about three seconds. This method is useful for building safe and adaptive braking systems for electric vehicles.

Keywords: iBooster; Braking control; MPC; PID; Braking systems

1. Introduction

In recent years, intelligent connected vehicles and new energy vehicles have advanced rapidly, imposing higher requirements on vehicle control systems in terms of safety, response speed, and accuracy. The braking system is one of the key parts of the vehicle's control system which helps keep the vehicle safe and makes the trip more comfortable.

Traditional braking systems primarily rely on vacuum assistance, but they fail to deliver sufficiently fast response or precise control in intelligent driving scenarios. This limitation becomes even more significant in electric vehicles, where conventional vacuum sources are unavailable, prompting the development of electric brake boosters such as the iBooster [1]. These problems become more serious during frequent stops, slippery roads, or steep slopes. In these cases, the old systems often do not perform well.

The iBooster system is a new-type braking booster that uses an electric motor instead of vacuum to push the master cylinder, enabling faster operation and more precise control. This system has been adopted by many electric vehicles and intelligent vehicles. However, the iBooster system still faces challenges: its performance varies over time and under different conditions, making it difficult to achieve optimal control in various driving scenarios. Therefore, a better control method is still needed.

Additionally, Model Predictive Control (MPC) is a method that uses system models to predict future states and determine optimal control actions sequentially. MPC is particularly suitable for systems with multiple variables and constraints, as it enhances control performance while ensuring system stability. Using MPC in the iBooster system can help make braking faster and more stable, even on different roads. Recent studies have demonstrated that MPC-based controllers, when applied to regenerative and electro-hydraulic braking systems, can significantly reduce response delay and improve control accuracy [2].

This paper first establishes a dynamic model of the iBooster system, followed by the development of a control method integrating MPC with a PID controller for fine-tuning. Simulations are performed across various road conditions, including dry, wet, and uphill surfaces, to validate the control method's effectiveness and provide insights for future smart braking system design.

2. Controller Design

2.1 Control Objectives

As an electromechanical brake booster, the iBooster replaces traditional vacuum-based systems by using a motor to actuate the master cylinder. A detailed mechatronic architecture including the DC motor, ball-screw, and reaction disk, as well as its control mechanism, has been developed and validated in previous studies [3]. To design an effective control method, a model is required to characterize the relationship between input signals (e.g., motor torque or displacement) and brake pressure output.

The simplified model can be expressed as a second-order system:

$$P_b(s) = \frac{K}{\tau^2 s^2 + 2\zeta\tau s + 1} \cdot U(s) \tag{1}$$

In this formula: $P_b(s)$ is the Laplace transform the brake pressure, $U(s)$ is the input voltage or torque signal, K is the system gain, τ^2 is the time constant, and ζ is the damping ratio. A more detailed electromechanical model of the iBooster, including nonlinear effects and hysteresis, was proposed in [4].

To evaluate braking performance, a simplified longitudinal dynamics model is introduced. The vehicle's acceleration $a(t)$ under braking can be described by:

$$a(t) = \frac{F_b(t)}{m} = \frac{P_b(t) \cdot A_c}{m} \tag{2}$$

In this formula: $F_b(t)$ is the braking force, $P_b(t)$ is the brake pressure from iBooster, A_c is the effective area of the brake cylinder, m is the vehicle mass. This relationship is used in the MPC controller to predict future vehicle deceleration based on current system states.

To ensure effective braking performance under a wide range of operating conditions, the control system must meet several key objectives. First, the system must generate accurate and timely brake pressure in response to driver inputs or upper-level control commands, while ensuring smooth deceleration to maintain ride comfort and prevent abrupt jerks or wheel lock-up.

Second, the control algorithm must adapt to fluctuations in road conditions and vehicle dynamics. For instance, braking behavior on dry asphalt varies significantly from that on wet or downhill surfaces, requiring the controller to detect these changes and adjust its response to ensure safety and control stability.

Finally, the control system should achieve these goals while satisfying physical constraints of the system, such as actuator limits and brake pressure bounds. It should also avoid unnecessary control effort, ensuring efficiency and long-term component durability.

2.2 Controller Architecture

The control system employs a two-layer architecture: the upper layer uses MPC to generate predictive control commands based on current system states and future trajectories, while the lower layer applies a PID controller to track these commands and adjust actuator dynamics in real time.

This architecture ensures that the system can handle constraints and optimize performance at a high level, while maintaining fast and stable execution at the actuator level. It also improves disturbance rejection and control smoothness under changing conditions.

2.3 Model Predictive Control Design

The predictive controller estimates the system's future behavior over a short time window. At each moment, it chooses the control input that gives the best balance between tracking the desired deceleration and keeping the

ISSN 2959-6157

control signal smooth. Such predictive formulations have been widely adopted in automotive braking systems for their ability to handle constraints and multi-variable dynamics [5].

$$J=\sum_{k=1}^{N_P}(a_{ref}(k)-a(k)+\lambda\sum_{k=0}^{N_c}(\mathrm{u(k+1)\text{-}u(k)})^2 \tag{3}$$

In this formula, a_{ref} is the desired deceleration, $a(k)$ is the predicted deceleration at future time kk, $u(k)$ is the control input, N_P is how far ahead the controller looks (prediction horizon), N_c is how many steps it controls (control horizon), λ controls how smooth the input changes are.

The controller also respects limits on input and output, such as maximum brake pressure or actuator limits:

$$u_{min} \leqslant u(k) \leqslant u_{max}\},\mathrm{a}_{min} \leqslant \text{ \mathrm\{}a(k) \leqslant a_{max}$$

Only the first control input is applied, and the process repeats at the next time step.

2.4 PID Execution Layer

To achieve high-precision tracking of upper-level MPC commands, a PID controller is employed in the lower layer for real-time adjustment. This layer refines the control signals generated by the predictive layer, ensuring that the actuator accurately tracks the optimal deceleration or pressure commands with fast response.

The PID controller is applied to the actuator input, such as motor displacement or force, depending on the system configuration. Its role is to reduce steady-state error and improve system stability, especially when the system is affected by small disturbances or unmodeled dynamics.

The control law is expressed as:

$$u(t)=K_p e(t)+K_i\int_0^t e(\tau)d\tau+K_d\cdot\frac{de(t)}{dt} \tag{4}$$

Among them, $u(t)$ is the control input to the actuator , $e(t)$ is the error between the reference and the actual output. K_P, K_i, K_d: are the proportional, integral, and differential gain coefficients respectively.

PID parameters can be tuned via simulation or empirical approaches such as the Ziegler-Nichols method. In this study, gain values are optimized to balance fast response and minimal overshoot across different scenarios.

2.5 Scenario Adaptation Strategy

The braking control system must adapt to different road and driving conditions to maintain stable and safe performance. In this work, three typical scenarios are considered: dry road, low-adhesion surface, and downhill slope. For each case, the control parameters are adjusted to meet specific performance requirements.

On dry roads, the tire–road friction is high, allowing stronger braking forces and faster system responses. In this case, the controller uses a shorter prediction horizon and a smaller weight on input smoothness, allowing quicker reactions without exceeding physical limits.

On wet or slippery roads, the available friction is lower. To reduce the risk of skidding, the controller increases the weight on smoothness and may reduce the allowable deceleration range. This results in more conservative braking behavior, which improves vehicle stability.

On downhill slopes, the vehicle is influenced by gravitational force, prompting the controller to extend the prediction horizon and apply consistent braking force over time, thereby preventing excessive speed accumulation.

These conditions are common in daily driving and help evaluate how the system responds to different levels of grip and load. Similar considerations are discussed in recent work on adaptive regenerative braking strategies that dynamically adjust control behavior based on weather conditions and driving styles [6].

3. Simulation and Results

3.1 Simulation Setup

To evaluate the performance of the proposed control system, numerical simulations were conducted via MATLAB. The MPC component employs a fixed prediction horizon of 15 steps and a control horizon of 5 steps, consistent with industrial MPC simulation practices [7].

To emulate realistic driving environments, the actuator behavior is modeled through scenario-specific response functions. These functions introduce parameters such as damping, delay, and external disturbances to reflect varying physical conditions. This flexible modeling strategy supports the evaluation of control robustness and adaptability under different operational contexts.

3.2 Scenario 1: Dry Road

This simulation case corresponds to a high friction driving environment, commonly encountered on dry asphalt roads. Under such conditions, the road surface offers ample tire–road adhesion, which permits the braking system to deliver rapid dynamic responses. Furthermore, the likelihood of wheel slip or loss of traction is considerably reduced. The objective of this scenario is to assess the controller's ability to accurately follow the reference deceleration profile when operating under ideal and controlled conditions.

Similar studies have evaluated brake control systems under high-friction conditions to assess tracking precision [8].

Due to predictable system behavior and limited disturbances, the MPC operates with relaxed constraints, while the PID requires minimal compensation.

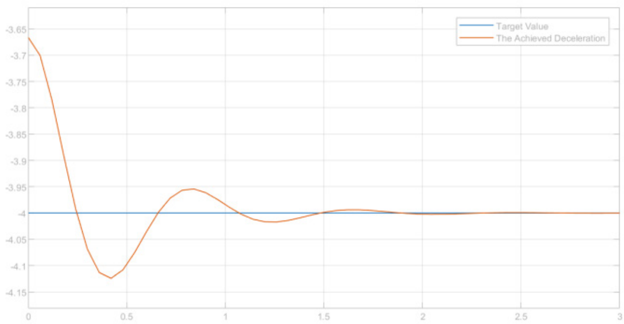

Figure 1. Deceleration tracking on dry road

The Figure 1 illustrates the tracking performance of the braking system in achieving the target deceleration under dry road conditions, when using the MPC and PID control architectures. Among them, the blue curve represents the target deceleration value set by the upper-level MPC controller (Target Value), while the orange curve shows the actual deceleration achieved after the lower-level PID controller drives the iBooster (The Achieved Deceleration).

According to the Figure 1, the actual response initially exhibited a slight overshoot and undershoot, demonstrating the dynamic regulation characteristics of the system. The response curve exhibits the typical characteristics of an underdamped second-order system, gradually converging and stabilizing around the target value of -4 m/s² within approximately 2 seconds, with overall stable fluctuations and good control accuracy. The total response time of the system is less than 3 seconds, meeting the requirements of the intelligent braking system for response speed and steady-state performance.

3.3 Scenario 2: Slippery Surface

Slippery surfaces offer limited grip, making excessive braking prone to wheel lockup. Thus, the braking system employs conservative control: the MPC increases the input smoothness weight in the cost function to reduce abrupt force changes, while narrowing the deceleration range to avoid exceeding road friction limits.

The PID controller in this case plays a critical role in maintaining stability. Small disturbances in actuator behaviors or the interaction between tire and road can significantly affect system performance. Thereby, the feedback control must be responsive and restrained.

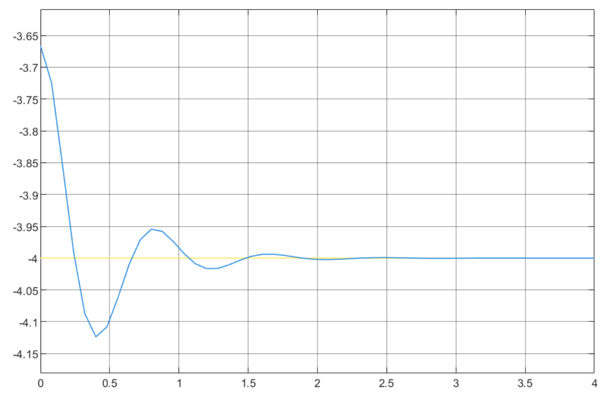

Figure 2. Deceleration tracking on slippery road

Figure 2 shows the dynamic tracking performance of the dual-layer control system for vehicle deceleration under wet road conditions. In the figure, the yellow line represents the target deceleration, which is set at -4 m/s², and the blue line represents the actual deceleration response generated by the iBooster actuator under the coordinated action of the PID controller.

Based on Figure 2, when road surface adhesion decreases, the system shows clear overshoot and undershoot at the initial stage. In particular, noticeable oscillations occur within the first 1.5 seconds. This reflects the negative effect of low adhesion on braking performance. However, the control system reduces the error effectively within about 3 seconds. The response gradually converges to the target value. Similar studies have confirmed that MPC-based controllers can maintain stability under low-adhesion conditions, such as wet asphalt surfaces [10]. These results demonstrate that the control structure has a certain robustness and dynamic adaptability.

3.4 Scenario 3: Downhill Slope

Maintaining safe speed during downhill driving is particularly challenging due to the continuous gravitational pull which increases forward motion. Under such circumstances, gravitational force adds to the vehicle's forward motion. Increasing braking demand and potentially leading to overspeed if control is insufficient.

To address this condition, the predictive controller extends the prediction horizon to better anticipate the long-term effects of the downhill force. This allows the system to plan braking actions over a longer time span and apply control more gradually and consistently.

During test, the system is not only expected to achieve target deceleration but also to maintain speed within safe limits over time. Special attention is given to the controller's ability to avoid brake saturation and to provide a continuous braking effect under increased load.

ISSN 2959-6157

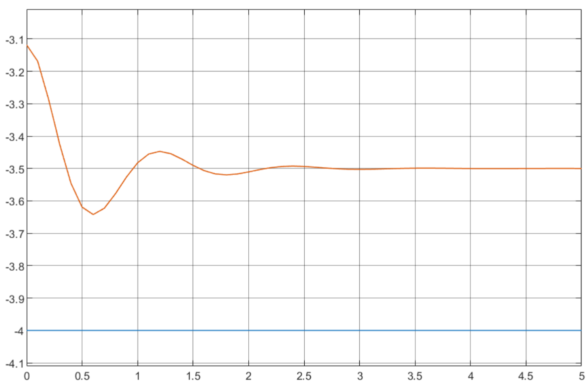

Figure 3. Deceleration tracking on downhill slope

In Figure 3, the blue curve indicates the target deceleration set by the controller (−4 m/s²). The orange curve illustrates the system response under the gravitational disturbance caused by the downhill slope. In the beginning, the system is affected by a continuous external force from the slope. This leads to a clear deviation from the target value. A minimum response appears around 0.6 seconds. After that, the system enters a fluctuation phase. This oscillation continues until approximately 2 seconds. Ultimately, the system stabilized at −3.5 m/s², leaving a steady-state error of 0.5 m/s² due to the lack of disturbance compensation in the current control structure. This aligns with prior findings that MPC-based controllers outperform PI designs on downhill slopes, thanks to their ability to handle slope-induced disturbances [10].

4. Conclusion

This study has proposed a hierarchical braking control framework integrating Model Predictive Control (MPC) and PID control to enhance deceleration performance for intelligent electric vehicles with iBooster systems. The strategy, rooted in an electromechanical braking architecture, involves modeling actuator dynamics and vehicle longitudinal motion, coupled with a two-layer control design: upper-level MPC and lower-level PID. A mathematical model that describes both actuator dynamics and longitudinal vehicle motion was built. Additionally, a hierarchical control framework was designed, combining a model predictive controller at the upper level with a PID controller at the lower level. To test the performance of the proposed method, numerical simulations were carried out under typical road conditions, including dry pavement, slippery surfaces, and downhill sections.

However, the study has limitations: it relies solely on simulations (lacking real-time control validation) and does not account for brake actuator constraints. The control results may change when the road condition is very nonlinear. They may also change when there are outside forces not included in the model. Future research should incorporate disturbance observers and learning-based controllers to enhance adaptability under unknown or varying road conditions. Hardware-in-the-loop testing is also essential to validate the system in real-world scenarios.

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