

Article

An Energy-Efficient Constant-Speed Downhill Control Approach for Heavy-Duty Electric Trucks with Hydraulic Retarders

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Abstract

Constant-speed control of hydraulic retarders is essential for improving driving safety and reducing driver workload on long downhill roads. For heavy-duty battery electric trucks (BETs), regenerative braking provides a fast-response braking source and enables energy recovery, offering the potential to improve both speed regulation and energy efficiency. This study proposes a two-mode constant-speed downhill control framework for BETs. In the retarder braking mode, a variable-argument proportional–integral–derivative (VAPID) controller is employed to regulate the hydraulic retarder, with its parameters optimized by an improved seeker optimization algorithm (ISOA). In the cooperative braking mode, a parallel dual-controller structure is adopted, where the retarder is governed by ISOA–VAPID and regenerative braking is regulated by a fuzzy-tuned PD controller according to real-time battery states. To further improve energy recovery, an optimization-based AMT gear-shifting schedule and coordinated strategy are incorporated. The proposed framework is validated through offline simulations, sensitivity analysis, and driver-in-the-loop experiments under constant-slope, variable-slope, and real-world downhill road conditions. Results show that the retarder braking mode outperforms benchmark methods in steady-state accuracy and dynamic response. In the cooperative braking mode, braking energy is effectively recovered while the battery charging load under unfavorable battery states is reduced. Moreover, AMT gear shifting improves energy recovery efficiency with negligible influence on constant-speed performance.

Keywords: heavy-duty battery electric trucks; hydraulic retarder; constant-speed control; regenerative braking; AMT gear shifting



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1. Introduction

Road freight transport has accounted for more than 72% of China's total freight volume in recent years, with the average vehicle tonnage continuing to increase [1]. Consequently, ensuring the driving safety of heavy-duty trucks (HDTs) has become increasingly critical, particularly on long downhill sections in mountainous regions [2]. Under such conditions, maintaining a stable vehicle speed requires continuous braking to dissipate accumulated kinetic and gravitational potential energy. Relying solely on service brakes may cause thermal fade or even brake failure, posing serious safety risks to HDTs [3]. Therefore,

auxiliary braking devices are essential for alleviating thermal loads on brake components and reducing wear of friction linings.

Conventional engine braking and exhaust braking have been widely adopted due to their low cost and minimal system modification requirements. However, their speed-dependent torque output and limited controllability make them unsuitable for accurate and adaptive longitudinal braking control. Accordingly, recent studies have focused on improving HDT braking performance through auxiliary braking system design and advanced control strategies. Lee et al. [4] proposed an improved electric exhaust brake system that replaces the pneumatic actuator with a DC motor and high-ratio reducer, effectively eliminating redundant components and reducing both system weight and cost. To overcome the low-speed torque deficiency and high-speed instability of conventional eddy current retarders, Xu et al. [5] introduced a novel design integrating eddy current and magnetorheological effects, along with an indirect adaptive fuzzy H_∞ control method. Similarly, Ergün et al. [6] replaced the conventional electromechanical switches and relays in electromagnetic retarders with a proportional–integral–derivative (PID) controller. The coil current was regulated via PWM duty cycles based on engine speed feedback, achieving speed control with a steady-state error of 4%. For hybrid HDTs, Bravo et al. [7] developed a parallel hydraulic-pneumatic regenerative braking system using a hydraulic pump/motor to store recovered energy in both a hydraulic accumulator and an air reservoir, enabling a 14% energy recovery rate during downhill braking in simulations. Additionally, novel retarders combining the advantages of eddy-current and hydraulic retarders have been proposed to improve braking performance under both low- and high-speed conditions [8,9]. Beyond auxiliary-braking actuation and control, structural optimization also provides useful references for HDT component design under complex operating constraints [10,11].

With the development of charging and battery-swapping infrastructure, long-haul battery electric trucks (BETs) have become an important pathway for improving energy efficiency and reducing carbon emissions in road freight transport [12,13]. For BETs, hydraulic retarders offer an attractive auxiliary braking solution because they can provide continuous braking capability with a compact structure and good compatibility with automated mechanical transmissions (AMTs). Xue et al. [14] developed a computational fluid dynamics (CFD) model of the oil filling and discharging process to analyze the effects of oil volume and rotor speed on transient braking response. Wang et al. [15] proposed a temperature prediction model for hydraulic retarders based on a back-propagation neural network (BPNN), offering valuable support for cooling system design, thermal management, and braking control. Huang et al. [16] established a mathematical model of hydraulic retarders based on Rankine vortex dynamics to characterize the relationship between braking torque and intrinsic retarder parameters, including rotor speed, control pressure, cavity diameter, and oil density. To address the response delay of hydraulic retarders, Chen et al. [17] introduced a learning-based torque tracking control method, incorporating end-to-end braking performance prediction and a deep Q-network controller. Chen et al. [18] further considered thermal safety and temperature-dependent torque characteristics of hydraulic retarders by integrating temperature-rise prediction with deep reinforcement learning. Wu et al. [19] developed a hydraulic retarder torque controller based on H-infinity and off-policy reinforcement learning to ensure speed tracking while suppressing disturbances caused by retarder oil temperature and road roughness. Collectively, these studies provide useful foundations for the design, modeling, and control of hydraulic retarders.

Constant-speed control is an important function of hydraulic retarders and maintains vehicle speed during downhill driving by regulating braking torque. This function enhances downhill driving safety and reduces driver workload. In practical applications, the target speed is typically set by the driver and maintained automatically until accelerator or brake pedal intervention returns the system to manual control. Considerable efforts have been devoted to the development of constant-speed control methods for hydraulic retarders. Lei et al. [20] designed a fuzzy logic-based controller that accounts for the influence of cooling system capacity on braking performance. In their subsequent study [21], PID, fuzzy, and fuzzy-PID controllers were comparatively evaluated, showing that fuzzy-based controllers achieved smaller overshoot and steady-state error than conventional PID control, while exhibiting better disturbance rejection under variable-slope conditions. Jing [22] proposed a derivative PID controller with immune feedback to adaptively adjust the proportional gain, and used fuzzy logic to tune the integral and derivative gains. Lei et al. [23] designed a neural network-based PID controller for water-medium hydraulic retarders, using online learning and training algorithms to dynamically optimize the PID parameters for enhanced constant-speed control performance. Mu et al. [24] proposed a parallel dual-controller scheme that combines fuzzy and PID outputs to balance control accuracy and adaptability. Overall, existing constant-speed control methods mainly rely on modified PID controllers, fuzzy controllers, or their hybrid combinations, and have achieved satisfactory speed regulation under typical operating conditions. Nevertheless, their parameter tuning and rule design often depend on empirical knowledge, which may limit adaptability and energy-efficiency optimization for BETs operating on variable-slope downhill roads. Optimization-based methods provide a more systematic approach for controller design and parameter tuning, and have been widely applied to vehicle system design and control under severe loading and complex operating conditions [25,26].

To further clarify the research gap, existing studies related to downhill braking control can be broadly divided into two categories. One category focuses on conventional HDTs, where service brakes or auxiliary retarders are regulated to ensure downhill braking safety and speed stability. The other category focuses on BETs, where braking torque is distributed between regenerative braking and friction braking to balance braking stability and energy recovery. Representative studies are summarized in Table 1.

Table 1. Summary of related heavy-vehicle braking control studies.

Ref.	Braking Actuators	Control Objective	Main Contribution
[23]	Hydraulic retarder	Constant-speed downhill control	Developed a neural-network PID controller to improve hydraulic-retarder speed regulation
[27]	Service brake	Long downhill braking safety	Optimized brake pedal force, speed range, and average speed using a genetic algorithm
[28]	Hydraulic retarder	Constant-speed downhill control	Developed a robust filling-rate controller to improve speed tracking under mass and slope variations
[29]	Regenerative braking + friction braking	Long downhill speed control and braking energy recovery	Designed a fuzzy braking-force distribution strategy according to road slope
[30]	Regenerative braking + friction braking	Braking stability and energy recovery	Developed a multi-mode composite braking control strategy for electric multi-axle heavy-duty vehicles
[31]	Regenerative braking + friction braking	Regenerative braking energy recovery	Proposed an MPC-based regenerative braking optimization strategy for pure electric mining dump trucks

As shown in Table 1, existing studies have advanced downhill braking control from the perspectives of braking safety, speed regulation, and energy recovery. However, the coordination between regenerative braking and the hydraulic retarder for constant-speed downhill control in BETs has received relatively limited attention. Regenerative braking has a fast dynamic response and can improve speed regulation while recovering braking energy during downhill driving. Nevertheless, relying solely on regenerative braking may lead to excessive charging power, thereby increasing battery charging current and thermal loads. In addition, AMT gear shifting during regenerative downhill braking can improve braking energy recovery by shifting the motor operating point toward a higher-efficiency region [32,33], while the torque transition during shifting must be coordinated to maintain speed stability. Therefore, constant-speed downhill control in BETs requires the coordinated use of regenerative braking and the hydraulic retarder to satisfy braking demand under battery charging constraints. Meanwhile, AMT gear shifting should be coordinated to improve energy recovery and suppress speed fluctuations during torque transition.

A cooperative constant-speed downhill control strategy is proposed for BETs equipped with a hydraulic retarder. The main contributions of this study are summarized as follows: (1) A variable-argument PID (VAPID) constant-speed controller is developed for the hydraulic retarder, with control parameters optimized using an improved seeker optimization algorithm (ISOA). (2) A cooperative constant-speed control method integrating regenerative braking and hydraulic retarder braking is proposed based on a parallel dual-controller architecture. In this method, a fuzzy-tuned PD controller regulates regenerative braking torque according to SOC and battery temperature. (3) An AMT gear-shifting schedule and coordination strategy for constant-speed downhill operation are developed to improve braking energy recovery while maintaining stable speed regulation during gear shifting.

The remainder of this paper is organized as follows. Section 2 presents the mathematical models of the BET and its braking system. Section 3 describes the proposed constant-speed control method. Section 4 validates the effectiveness of the proposed method through offline simulations and driver-in-the-loop (DiL) experiments. Section 5 summarizes the conclusions.

2. Mathematical Model

2.1. Vehicle Dynamic Model

The target vehicle in this study is a four-axle BET. Since the two rear axles have similar vertical loads and torque distributions due to the equal-load balancing suspension, they are simplified as a single equivalent drive axle. The forces acting on the vehicle during braking are shown in Figure 1, where rolling resistance is neglected. Accordingly, the longitudinal dynamics of the BET can be expressed as:

$$\begin{cases} m \frac{dv}{dt} + mg \sin \alpha = - \sum_{i=1,2,3} F_{xi} - F_w \\ F_w = C_D A \rho v^2 / 2 \\ F_{xi} = T_{bi} / r_w \end{cases} \quad (1)$$

where m is the vehicle mass; v is the vehicle speed; g is the gravitational acceleration; α is the road grade angle; F_{xi} is the ground braking force at the i -th axle; F_w is the aerodynamic drag force; C_D is the drag coefficient; A is the frontal area; and ρ is the air density. The main parameters of the BET are listed in Table 2.

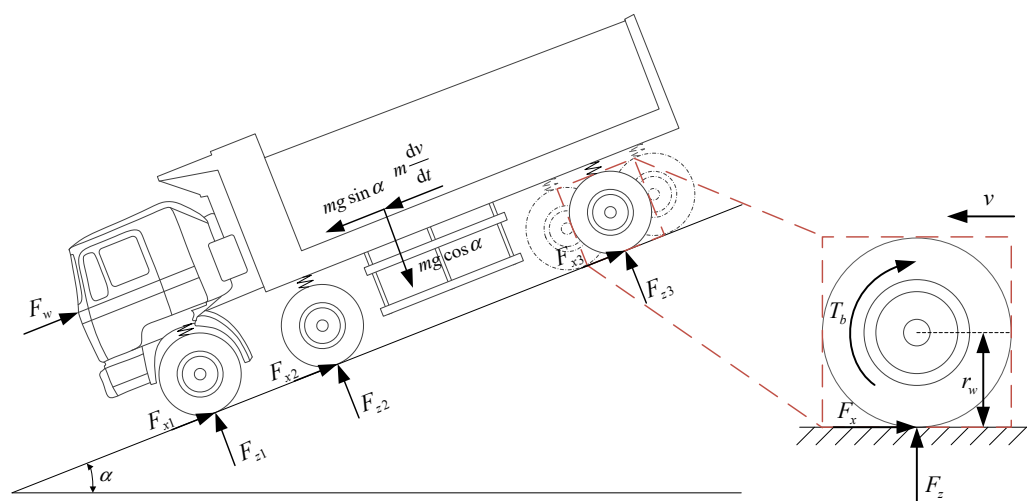


Figure 1. Longitudinal vehicle dynamics model.

Table 2. Main parameters of the BET.

Parameter	Value	Parameter	Value
Vehicle mass	45,000 kg	Frontal area	9.45 m ²
Axle spacing	1.8/3.2/1.4 m	Drag coefficient	0.65
Center of gravity height	1.8 m	AMT gear ratio	8.5/4.9/3.0/1.9/1.2/1
Distance from first axle to CG	4.1 m	Final drive ratio	5.7

Wheel slip is assumed to be negligible to simplify the braking force calculation. The ground braking force can be calculated from the wheel radius r_w and the braking torque T_{bi} , as follows:

$$T_{bi} = \begin{cases} T_{frc} & i = 1, 2 \\ T_{frc} + T_{reg} + T_{rtd} & i = 3 \end{cases} \quad (2)$$

where T_{frc} , T_{reg} and T_{rtd} represent the friction braking torque, regenerative braking torque, and retarder braking torque, respectively. Both the regenerative and retarder braking torques are applied exclusively to the drive axle, i.e., the equivalent rear axle. The composite braking system follows the configuration described in [34].

2.2. Regenerative Braking System Model

The regenerative braking system shares the same electromechanical structure as the electric drive system of the BET. During braking, the power flow is reversed, transferring energy from the wheels through the drivetrain and electric motor to the battery.

2.2.1. Motor Model

During regenerative braking, the motor operates in generator mode, converting mechanical energy into electrical energy for battery charging while generating braking torque at the drive axle. A motor model is established based on bench test data. Voltage and current measurements are collected under different torque and speed conditions to identify the motor external characteristics and efficiency maps, as shown in Figure 2. The continuous torque refers to the maximum torque that the motor can continuously provide without triggering thermal protection and is adopted as the regenerative braking torque limit in this study.

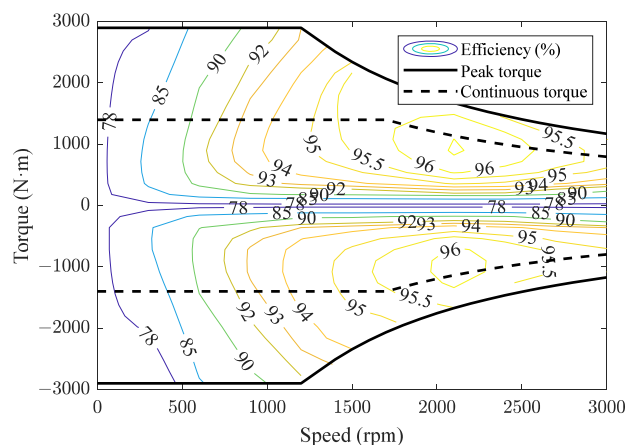


Figure 2. Motor characteristic diagram.

The maximum available motor torque T_{m_max} can be expressed as:

$$T_{m_max} = \begin{cases} T_{m_c} \eta_m(T_m, \omega_m), & \omega_m \leq \omega_b \\ \frac{9550 P_{m_c} \eta_m(T_m, \omega_m)}{\omega_m}, & \omega_m > \omega_b \end{cases} \quad (3)$$

where T_{m_c} is the continuous torque; $\eta_m(\cdot)$ is the motor efficiency at torque T_m and rotational speed ω_m ; P_{m_c} is the continuous power; and ω_b is the base speed.

To characterize the transient behavior of the drive motor during regenerative braking, a first-order lag model is adopted to describe the dynamic relationship between the required motor torque T_{m_req} and the actual output torque T_m :

$$T_m = \frac{1}{\tau_m s + 1} T_{m_req} \quad (4)$$

where τ_m is the motor response time constant.

The bus power P_{dc} of the motor controller during regenerative braking can be expressed as:

$$P_{dc} = T_m \cdot \omega_m \cdot \eta_m(T_m, \omega_m) \quad (5)$$

2.2.2. Battery Model

The power battery serves as the energy storage component in the regenerative braking system, storing the braking energy recovered by the motor. In this study, the Rint equivalent circuit model is employed to describe the battery electrical behavior. Owing to its simple structure and low computational cost, this model is suitable for control-oriented simulation and real-time verification [35], although the transient battery current and recovered energy may have certain deviations due to the simplified battery dynamics. The Rint model comprises an ideal voltage source U_{oc} and an internal resistance R_0 . According to Kirchhoff's law, the battery terminal voltage U_t and current I can be derived as:

$$\begin{cases} I = \frac{U_{oc} - \sqrt{U_{oc}^2 - 4R_0 P_{dc}}}{2R_0} \\ U_t = P_{dc} / I \end{cases} \quad (6)$$

The battery charging efficiency η_{bat} is defined as:

$$\eta_{bat} = \frac{P_{bat}}{P_{dc}} = \frac{U_{oc}}{U_{oc} - IR_0} = \frac{U_{oc}(U_{oc} - \sqrt{U_{oc}^2 - 4R_0 P_{dc}})}{2R_0 P_{dc}} \quad (7)$$

where P_{bat} is the battery power.

The battery SOC is estimated using the ampere-hour integral method, given by:

$$\text{SOC}(t) = \text{SOC}(t_0) - \int_{t_0}^t \frac{U_{oc} - \sqrt{U_{oc}^2 - 4R_0\eta_{bat}(t)P_{dc}(t)}}{2R_0Q_{bat}} dt \quad (8)$$

where $\text{SOC}(t)$ and $\text{SOC}(t_0)$ denote the state of charge at time t and the initial time, respectively, and Q_{bat} is the nominal battery capacity.

Considering the significant influence of temperature on battery characteristics, the battery temperature model is expressed as:

$$\theta_{bat}(t) = \theta_{bat}(t_0) + \frac{1}{m_{bat}c_{bat}} \int_{t_0}^t \left[I^2(t)R_0 - I(t)\theta_{abs} \frac{\partial U_{oc}}{\partial \theta} - h_c A_{bat}(\theta_{bat}(t-1) - \theta_a) \right] dt \quad (9)$$

where $\theta_{bat}(t)$ and $\theta_{bat}(t_0)$ denote the battery temperatures at time t and the initial time, respectively; m_{bat} is the battery mass; c_{bat} is the specific heat capacity; θ_{abs} is the absolute temperature; $\partial U_{oc}/\partial \theta$ is the reaction heat coefficient; h_c is the convective heat transfer coefficient; A_{bat} is the battery surface area; and θ_a is the ambient temperature.

2.2.3. Transmission System Model

The transmission system serves as the energy transfer component in the regenerative braking system, comprising an AMT, a driveshaft, and a final drive. For the torque transfer model in the regenerative braking system, the internal shift actuator dynamics as well as damping and elastic effects are not explicitly modeled, while the torque transition during gear shifting is considered in the subsequent control design. Accordingly, the regenerative braking torque at the wheels can be expressed as:

$$T_{reg} = T_m i_g i_0 / \eta_{AMT} \eta_{trans} \quad (10)$$

where i_g and i_0 are the gear ratios of the AMT and final drive, respectively; η_{AMT} is the AMT transmission efficiency, which varies with input torque and speed, as shown in Figure 3 for each gear; and η_{trans} is the combined transmission efficiency of the driveshaft and final drive.

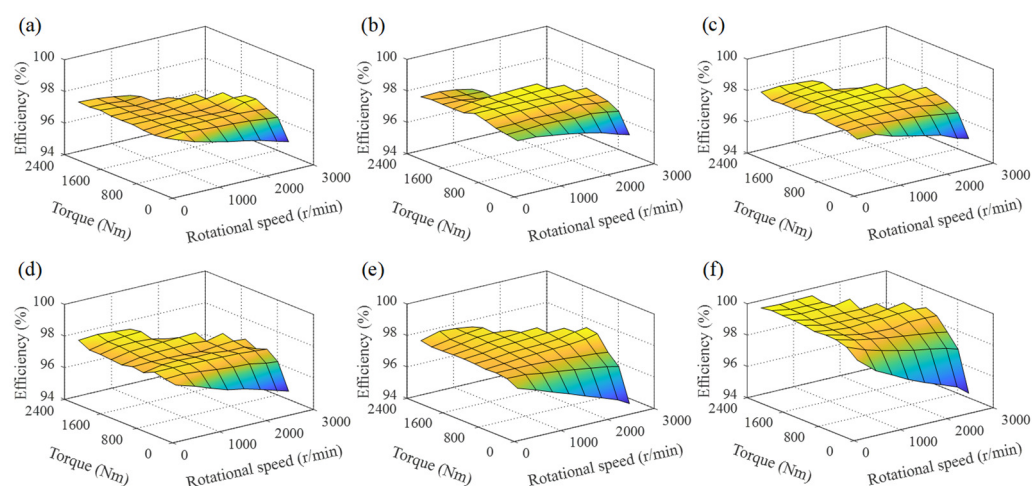


Figure 3. AMT efficiency maps for different gears. (a) 1st gear; (b) 2nd gear; (c) 3rd gear; (d) 4th gear; (e) 5th gear; (f) 6th gear.

2.3. Hydraulic Retarder System Model

In this study, a parallel hydraulic retarder is adopted, in which the rotor is connected to the AMT output shaft via a speed-increasing gear, while the stator is fixed to the retarder

housing. The hydraulic retarder is actuated by a pneumatic control system, and its working principle is illustrated in Figure 4. During braking, compressed air enters the oil tank through a proportional solenoid valve and forces oil into the working chamber, where hydrodynamic resistance is generated to provide braking torque. The generated heat is transferred by the circulating oil and dissipated through the heat exchanger and cooling system. Therefore, the continuous braking power of the hydraulic retarder is limited by the heat dissipation capacity of the cooling system.

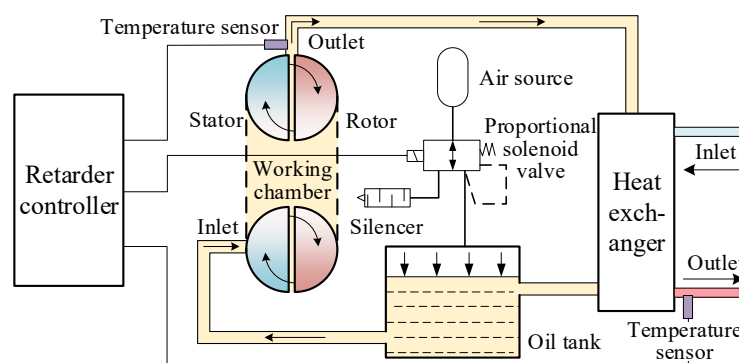


Figure 4. Working principle of the hydraulic retarder.

During braking torque regulation, the retarder controller modulates the current supplied to the proportional solenoid valve, thereby adjusting the compressed air pressure and the oil filling volume in the working chamber. The retarder response is governed by the pressure build-up and release process in the oil tank, while the resulting braking torque depends mainly on control pressure and rotational speed. Accordingly, a pneumatic control system model is established to describe the oil-tank pressure dynamics, and an output torque model based on bench test data is used to determine the resulting braking torque. The resulting hydraulic retarder model is used in the subsequent simulation analysis and DiL real-time verification.

2.3.1. Pneumatic Control System Model

The proportional solenoid valve is the main regulating element of the pneumatic control system. It adjusts the intake air pressure and thus controls the oil filling rate in the working chamber. Therefore, the oil tank pressure is regarded as an intermediate dynamic variable between the electrical control command and the retarder braking torque. Based on the operating characteristics of the proportional solenoid valve, the rate of pressure change p_{op} in the oil tank can be expressed as:

$$\frac{dp_{op}}{dt} = \begin{cases} \frac{K}{V_{op}} C_d p_{pv} A_{in} \sqrt{2RT} f\left(\frac{p_{op}}{p_{pv}}\right), & p_{pv} > p_{op} \\ 0, & p_{pv} = p_{op} \\ -\frac{K}{V_{op}} C_d p_{pv} A_{out} \sqrt{2RT} f\left(\frac{p_0}{p_{op}}\right), & p_{pv} < p_{op} \end{cases} \quad (11)$$

where K is the adiabatic index; V_{op} is the volume of the compressible air space inside the oil tank; C_d is the flow coefficient; R is the gas constant; T is the absolute temperature; p_{pv} is the output pressure of the proportional valve; A_{in} is the cross-sectional area of the OUT port; A_{out} is the cross-sectional area of the EXH port; and p_0 is the atmospheric pressure.

2.3.2. Output Torque Model

The working chamber of the hydraulic retarder involves complex gas–liquid two-phase flow, making analytical torque modeling difficult. To balance accuracy and computational efficiency, an output torque model derived from bench test data is adopted in this study.

Figure 5 illustrates the relationship among output braking torque, rotational speed, and control air pressure. The four solid lines represent the output torque at control air pressures of 120, 180, 240, and 300 kPa, respectively, while the red dashed lines indicate the peak 450 kW and continuous 300 kW braking power limits. During prolonged downhill braking, the continuous braking power limit is used as the thermal operating boundary of the hydraulic retarder. Thus, the available retarder torque is constrained by both the pressure–speed–torque map and the allowable braking power to avoid continuous operation beyond the heat dissipation capacity.

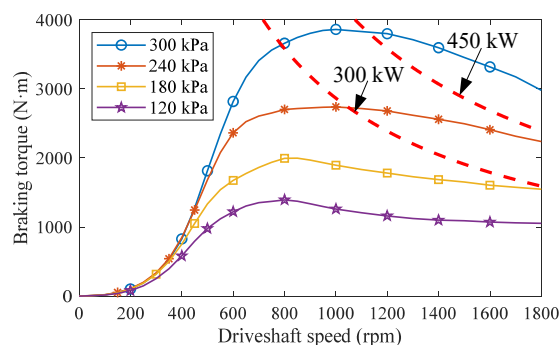


Figure 5. Hydraulic retarder torque characteristic curve.

To model the retarder output torque, a two-dimensional lookup table is constructed based on the measured pressure–speed–torque data. The output torque is calculated as:

$$T_{rtd} = f_T(p_{op}, n_r) \quad (12)$$

Owing to the strong nonlinearity of the retarder torque characteristics, Lagrange interpolation is employed in the lookup process. For a given rotational speed n_r and control pressure p_{op} , the neighboring pressure torque data points $(p_{op,j}, T_{rtd,j})$ are extracted from the measured characteristic map, and the output torque T_{rtd} is calculated by Lagrange interpolation as:

$$T_{rtd}(p_{op}) = \sum_{j=0}^k T_{rtd,j} \cdot l_j(p_{op}) \quad (13)$$

where $l_j(\cdot)$ denotes the Lagrange basis polynomial, given by:

$$l_j(p_{op}) = \prod_{i=0, i \neq j}^k \frac{p_{op} - p_{op,i}}{p_{op,j} - p_{op,i}} = \frac{p_{op} - p_{op,0}}{p_{op,j} - p_{op,0}} \cdots \frac{p_{op} - p_{op,j-1}}{p_{op,j} - p_{op,j-1}} \cdot \frac{p_{op} - p_{op,j+1}}{p_{op,j} - p_{op,j+1}} \cdots \frac{p_{op} - p_{op,k}}{p_{op,j} - p_{op,k}} \quad (14)$$

3. Constant-Speed Downhill Control Method

During downhill driving, drivers often need to modulate the brake pedal continuously to maintain a safe and stable vehicle speed, which can cause fatigue over extended periods. To reduce this burden, modern hydraulic retarders are commonly equipped with constant-speed control functions. During downhill operation, the equivalent braking intensity required to balance the grade resistance is approximately equal to the sine of the road grade angle [36]. Since the maximum highway longitudinal grade is generally below 10%, the required braking intensity for constant-speed downhill driving can be satisfied by rear-axle braking torque alone, without front-axle braking, while meeting the braking force distribution requirement.

For BETs, integrating regenerative braking with a hydraulic retarder for constant-speed downhill control not only improves control performance but also enables effective energy recovery. According to the available regenerative braking capability, the proposed

method operates in two modes: retarder braking mode (RBM) and cooperative braking mode (CBM). In RBM, constant-speed control is realized solely by the hydraulic retarder. In CBM, regenerative braking and hydraulic retarder braking are coordinated to maintain vehicle speed.

3.1. Retarder Braking Mode Control

Traditional constant-speed control methods for hydraulic retarders often rely on expert knowledge to formulate logic- or fuzzy-based rules. However, their adaptability may be limited under varying operating conditions. To address this issue, a VAPID controller is employed for hydraulic retarder constant-speed control, and its parameters are optimized using ISOA.

PID control has been extensively adopted in industrial applications owing to its simple structure, ease of implementation, and high reliability. A standard PID controller generates control actions based on the deviation between the system output and the setpoint through proportional, integral, and derivative terms:

$$u(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \frac{de(t)}{dt} \quad (15)$$

where $e(t)$ is the system error, and K_p , K_i , and K_d are the proportional, integral, and derivative gains, respectively. The proportional term determines the response speed, the integral term eliminates steady-state error but may increase overshoot, and the derivative term suppresses overshoot and improves transient response. Appropriate tuning of these parameters is critical for achieving satisfactory control performance.

Hydraulic retarders exhibit nonlinear torque characteristics and response delay, which may degrade the performance of conventional fixed-gain PID controllers and cause overshoot or oscillations. To improve adaptability, the VAPID controller defines the PID gains as error-dependent functions, enabling online gain adjustment according to the speed error. The gain adjustment principles are designed as follows.

(1) Proportional gain K_p : When the absolute error $|e|$ is large, a larger K_p is used to accelerate the system response speed. As $|e|$ decreases, K_p is reduced to improve system stability and suppress oscillations.

(2) Integral gain K_i : When $|e|$ is large, a smaller K_i is used to mitigate integral windup and limit overshoot. As $|e|$ decreases, K_i is increased to accelerate convergence and reduce steady-state error.

(3) Derivative gain K_d : When $|e|$ is large, a smaller K_d is used to avoid excessive sensitivity to rapid error variations. As $|e|$ decreases, K_d is increased to enhance damping and improve disturbance rejection.

In this study, Gaussian-type functions are used to define the VAPID gains, as illustrated in Figure 6. The width parameters α_p , α_i , and α_d determine the sensitivity of each gain to the speed error. By tuning these width parameters, the transition between fast response and stable regulation can be adjusted. The parameter expressions are given as:

$$K_p = K_{p0} [1 + K'_p (1 - \exp(-e^2 / \alpha_p^2))] \quad (16)$$

$$K_i = K_{i0} [1 + K'_i \exp(-e^2 / \alpha_i^2)] \quad (17)$$

$$K_d = K_{d0} [1 + K'_d \exp(-e^2 / \alpha_d^2)] \quad (18)$$

where K_{p0} , K_{i0} , and K_{d0} denote the base gains, and K'_p , K'_i , and K'_d denote the gain adjustment coefficients.

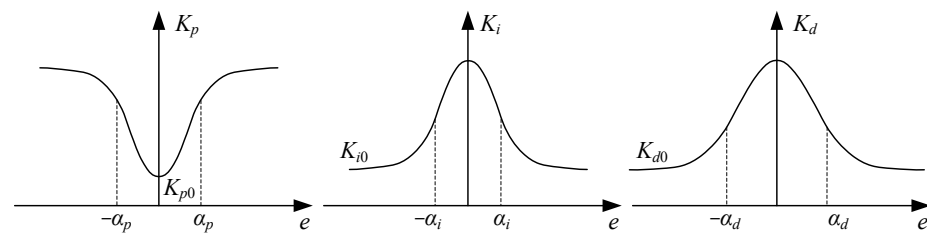


Figure 6. Relationship between VAPID control parameters and error.

To enable effective constant-speed control under varying vehicle speeds and road grade conditions, the undetermined parameters of the VAPID controller are optimized using an improved seeker optimization algorithm (ISOA). In the offline optimization stage, a multi-condition training set is constructed by combining different target speeds and road grades, so that the optimized VAPID parameters can adapt to different downhill braking demands. The overall optimization framework is illustrated in Figure 7.

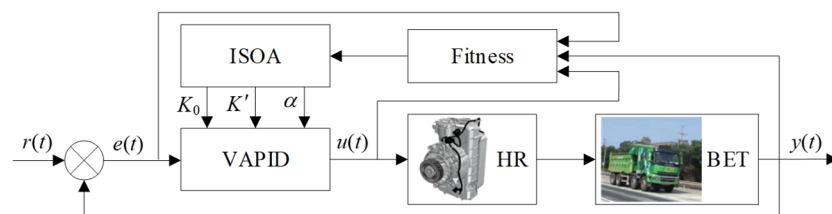


Figure 7. Framework of VAPID parameter optimization.

The seeker optimization algorithm (SOA) is a population-based heuristic optimization method inspired by human search behavior. In SOA, a population of seekers is employed, where the position of each seeker represents a candidate solution in the search space. The search direction is determined by the seeker's egotistic, altruistic and pro-activeness behavior, while the step length is governed by uncertainty reasoning behavior [37]. Through iterative position updates, the population gradually searches for the optimum solution.

In the proposed optimization framework, the ISOA is employed to tune the VAPID parameters, where each seeker encodes a candidate parameter set. Assuming that the population consists of s seekers, the position vector of the i -th seeker is defined as

$$\mathbf{P}_i = [K_{p0,i}, K_{i0,i}, K_{d0,i}, K'_{p,i}, K'_{i,i}, K'_{d,i}, \alpha_{p,i}, \alpha_{i,i}, \alpha_{d,i}] \quad (19)$$

This gives a nine-dimensional search space. The population can be expressed as:

$$\mathbf{P} = [\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_s]^\top \quad (20)$$

The fitness function is used to evaluate candidate parameter sets and guide the iterative update of the population. Considering typical downhill constant-speed braking scenarios and the maximum road grade associated with different speed levels, the target speeds are set to 30, 40, 50, and 60 km/h. The corresponding road grade ranges are selected as 4–8% for 30 km/h, 3–7% for 40 km/h, and 3–6% for both 50 km/h and 60 km/h. Therefore, a total of $N_c = 18$ operating conditions are included in the optimization process. The total fitness value of each candidate parameter set is defined as the average fitness over all training conditions:

$$J = \frac{1}{N_c} \sum_{j=1}^{N_c} J_j \quad (21)$$

where J_j is the fitness value under the j -th operating condition.

For each operating condition, the vehicle speed error is used as the main performance index to evaluate constant-speed tracking accuracy. The squared controller output is introduced to limit excessive retarder control action and avoid unnecessarily large braking torque demand. In addition, an overspeed penalty is included to prevent excessive vehicle speed during downhill braking. For the j -th operating condition, J_j is calculated as:

$$J_j = \begin{cases} \int_0^T (\omega_1 |e_j(t)| + \omega_2 u_j^2(t)) dt, & e(t) \geq 0 \\ \int_0^T (\omega_1 |e_j(t)| + \omega_2 u_j^2(t) + \omega_3 |e_j(t)|) dt, & e(t) < 0 \end{cases} \quad (22)$$

where T is the simulation duration for one operating condition, $e_j(t) = v_{\text{ref},j} - v_j(t)$ is the vehicle speed error under the j -th condition, $v_{\text{ref},j}$ is the target speed, $v_j(t)$ is the actual vehicle speed, and $u_j(t)$ is the controller output. When $e_j(t) < 0$, the actual vehicle speed exceeds the target speed, and the overspeed penalty term is activated. ω_1 , ω_2 , and ω_3 are weighting coefficients, with $\omega_3 \gg \omega_1$.

To reduce the computational cost caused by repeated fitness evaluations, the pneumatic control system of the hydraulic retarder is simplified as a first-order lag element during the offline VAPID parameter optimization. The time constant of the simplified link is set to 0.25 s, and the retarder braking torque is calculated from the pressure-speed-torque map according to the actual pressure and retarder speed. This simplification is adopted only in the parameter optimization stage.

Compared with the baseline SOA, the ISOA introduces two additional strategies to improve population diversity and reduce premature convergence. First, Sin chaotic opposition-based learning is used to generate a more uniformly distributed initial population by combining Sin chaotic mapping with opposition-based learning. Second, generalized opposition-based learning is applied as a generation-jumping strategy during iteration to guide the population away from local optima. The mathematical formulations of these two strategies are provided in Appendix A. The implementation steps for ISOA-based VAPID parameter optimization are summarized as follows:

- (1) Initialize the seeker position using Sin chaotic opposition-based learning.
- (2) Evaluate the fitness value of each seeker at its current position.
- (3) Update the individual historical best position of each seeker.
- (4) Update the global best position of the population.
- (5) Determine the search direction and step length, and update each seeker's position.
- (6) Check whether the population jumping condition is satisfied. If so, apply generalized opposition-based learning to update the population.
- (7) Evaluate the termination criterion. If it is not satisfied, return to step (2).

The ISOA parameters used for VAPID parameter optimization are listed in Table 3.

Table 3. ISOA parameters for VAPID parameter optimization.

Parameter	Value
Population size	30
Maximum iteration number	100
Generation-jumping probability	0.2
Stall iteration threshold	25

The optimization is terminated when the maximum iteration number is reached or when the best fitness value shows no improvement for 25 consecutive iterations. With a population size of 30 and a maximum iteration number of 100, each ISOA run involves at most 3000 main candidate evaluations. Since each fitness evaluation contains 18 operating conditions, each run corresponds to at most 54,000 single-condition simulations. In the

offline optimization, the simulation duration for each operating condition is set to 5 s, and the sampling time is set to 0.02 s. This computational cost is introduced only during offline parameter tuning and does not increase the computational burden of the real-time VAPID controller. To examine the influence of random initialization, five independent optimization runs are performed using different random seeds. The best fitness value is recorded at each iteration to analyze the convergence behavior. The final VAPID parameter set is selected from the run with the minimum fitness value.

3.2. Cooperative Braking Mode Control

In the cooperative braking mode, regenerative braking is introduced during downhill driving to recover braking energy and improve the energy efficiency of BETs. In addition, its fast dynamic response contributes to improved constant-speed control performance. Considering the different dynamic characteristics of regenerative braking and hydraulic retarder braking, a parallel dual-controller structure is adopted, as illustrated in Figure 8. In this structure, the two braking sources are regulated by separate control loops, which helps reduce direct controller interference and improve braking torque coordination. The hydraulic retarder is regulated by the ISOA-VAPID controller, while regenerative braking torque is regulated by a PD controller. Compared with PID control, PD control has a simpler structure and avoids integral accumulation. Any residual steady-state error during constant-speed operation can be compensated by the hydraulic retarder.

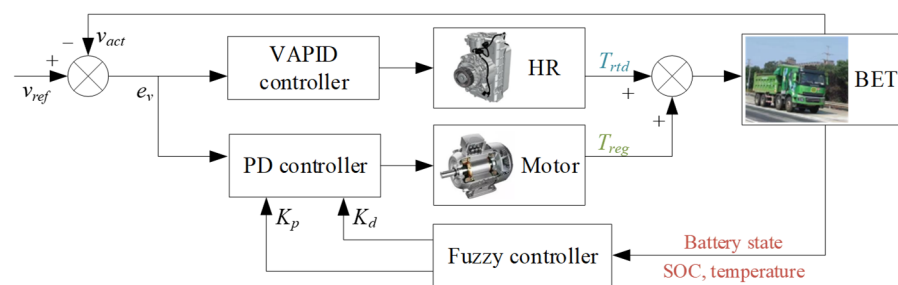


Figure 8. Block diagram of the cooperative braking mode controller.

In this structure, regenerative braking serves as the fast-response braking source to improve transient speed regulation, while the hydraulic retarder provides continuous auxiliary braking torque for long-duration constant-speed downhill control. The regenerative braking contribution is adjusted in real time according to battery state to reduce battery charging load. In the parallel controller structure, changing the proportional gain of the regenerative braking controller directly affects its torque contribution, while the derivative gain influences the transient response and damping characteristics. Therefore, a fuzzy logic controller is employed to adaptively tune the PD gains, enabling battery-state-dependent regenerative braking regulation. In this controller, battery SOC and temperature are used as inputs, while the proportional gain K_p and derivative gain K_d of the PD controller are used as outputs. When the battery approaches unfavorable charging conditions, such as excessively high SOC, excessively low SOC, high temperature, or low temperature, the regenerative braking contribution is reduced. The remaining braking demand is then compensated mainly by the hydraulic retarder to maintain constant-speed downhill control.

The allowable battery charging current is mainly constrained by SOC and temperature. When SOC is excessively high, the battery charging acceptance decreases, and large regenerative charging current may increase the charging load. When SOC is excessively low, the battery internal resistance and thermal sensitivity may increase, making high-current charging unfavorable. At high temperatures, high-current charging may further increase the thermal load and accelerate battery aging. At low temperatures, the electrochemical

reaction rate decreases, and high charging current may increase the risk of lithium plating on the anode [38]. Therefore, regenerative braking is restricted under these unfavorable battery states. Fuzzy rules are established based on the battery charging characteristics, as summarized in Table 4, where VL, L, M, H, and VH denote very low, low, medium, high, and very high levels, respectively. In addition, MF1-MF7 represent ordered fuzzy output levels corresponding to different scaling factors of the PD gains, ranging from the minimum to the maximum adjustment magnitude. The corresponding membership functions are illustrated in Figure 9.

Table 4. Fuzzy rule base for PD gain adjustment.

Temperature	SOC				
	VL	L	M	H	VH
VL	MF1	MF2	MF5	MF1	MF1
L	MF2	MF4	MF6	MF1	MF1
M	MF3	MF6	MF7	MF2	MF1
H	MF1	MF2	MF3	MF1	MF1

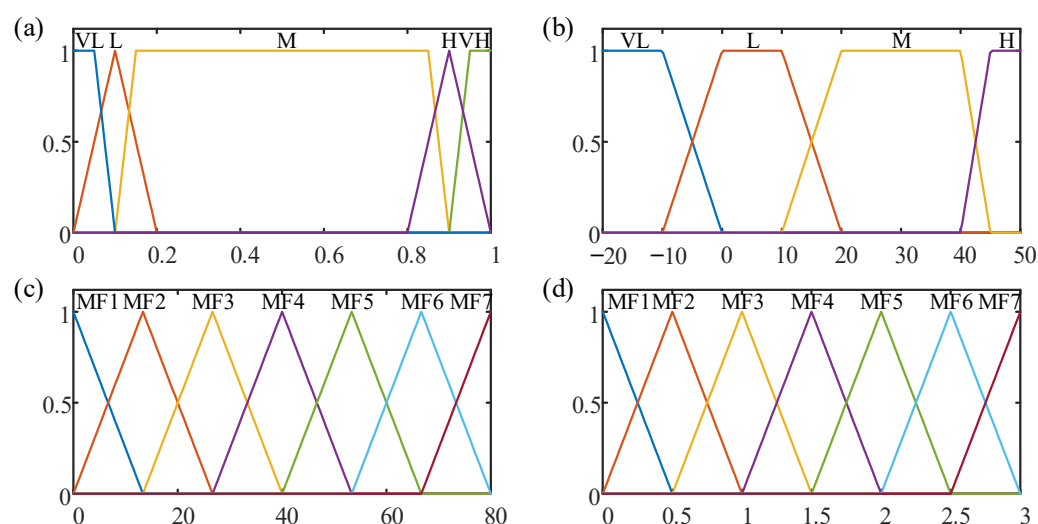


Figure 9. Membership functions of the fuzzy controller. (a) Battery SOC; (b) battery temperature; (c) Kp; (d) Kd.

3.3. AMT Gear-Shifting Control Strategy

During prolonged downhill braking, gear selection has a cumulative influence on braking energy recovery because it changes the motor operating point and the transmission efficiency. Existing studies on shift control during regenerative braking have mainly focused on motor efficiency, while the variation in AMT transmission efficiency across different gear positions is often not explicitly considered. Therefore, the overall efficiency of the regenerative braking system is adopted as the control objective to derive the shift schedule under constant-speed downhill cooperative braking conditions. In addition, to address the power interruption during AMT shifting, a coordination strategy is proposed to maintain speed stability during the torque transition.

3.3.1. AMT Shift Schedule

The AMT bench test results show that transmission efficiency varies significantly with gear position, input torque, and rotational speed. During regenerative braking, higher transmission efficiency reduces the energy loss caused by bearing friction and gear meshing, thereby increasing the electrical energy recovered by the battery. Therefore, both motor

efficiency and AMT transmission efficiency should be considered in the shift schedule design. Accordingly, vehicle speed and wheel-end regenerative braking torque demand are selected as the input variables. Since AMT gear position is a discrete variable, an exhaustive search method is employed to determine the optimal gear under each operating condition by maximizing the battery charging power:

$$\max P_b = T_m \omega_m \eta_m \eta_{bat} = \frac{T_{reg} \eta_{trans}}{i_g i_0} \omega_m \eta_m \eta_{bat} \quad (23)$$

The AMT gear optimization results are illustrated in Figure 10, with the right sub-figure providing a magnified view of the red rectangular region. The numerical values represent the additional recovered power obtained by selecting the optimal gear instead of a suboptimal gear. The results indicate that the 6th gear accounts for the largest proportion of optimal gear selections, mainly because it has relatively high transmission efficiency over a wide operating range. When the required regenerative braking torque is large, lower gears allow the motor to operate at lower torque and higher speed, which corresponds to higher motor efficiency. In such cases, the overall efficiency of the regenerative braking system is improved, thereby enhancing energy recovery performance.

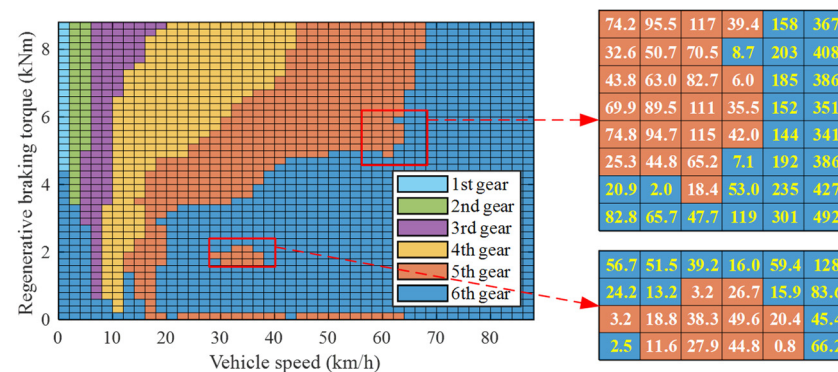


Figure 10. AMT gear optimization results.

Due to the inherent power interruption during AMT gear shifting, regenerative braking torque is temporarily unavailable during shift transitions. As a result, excessively frequent gear changes during constant-speed downhill braking can cause energy loss and may degrade speed regulation performance [39]. To mitigate this issue, the optimized AMT shift schedule is further refined according to the following operational principles, with the modified results shown in Figure 11.

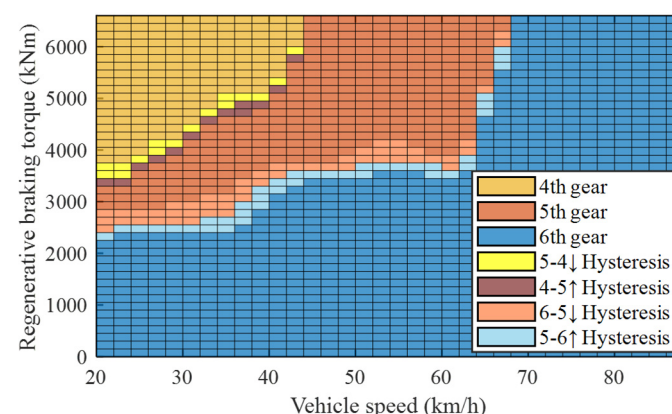


Figure 11. Optimized AMT shift schedule for constant-speed downhill driving.

(1) Since actual downhill speeds rarely fall below 20 km/h and gear shifting at such low speeds provides limited energy recovery benefit, gear shifting is inhibited below 20 km/h.

(2) During constant-speed downhill control, speed fluctuations are generally within 2 km/h. Therefore, the vehicle speed range is discretized at 2 km/h intervals, and gear changes within each speed interval are minimized to avoid unnecessary shifting.

(3) Near the boundaries of the optimized gear regions in Figure 11, the recovered power difference between adjacent gears is small. In these regions, frequent gear changes may bring limited energy benefit but degrade speed stability. Therefore, a gearshift hysteresis module is introduced, as expressed in:

$$\begin{cases} \text{Upshift, } T_{reg} < T_{opt_us} - \Delta T_{hy} \\ \text{Downshift, } T_{reg} > T_{opt_ds} + \Delta T_{hy} \end{cases} \quad (24)$$

where T_{opt_us} and T_{opt_ds} represent the regenerative braking torque thresholds for upshifting and downshifting, respectively, and ΔT_{hy} denotes the gearshift hysteresis threshold.

3.3.2. AMT Shift Coordination Strategy

The AMT shifting process in electric vehicles generally consists of five stages [40], namely motor torque release, gear disengagement, speed synchronization, gear engagement, and motor torque restoration, as illustrated in Figure 12. After a shift command is received, the motor torque is first reduced to zero to enable gear disengagement. The transmission is then shifted to neutral, and the motor speed is adjusted to synchronize the target gear. Once the speed deviation satisfies the engagement condition, the target gear is engaged, and the motor torque is restored to the desired level.

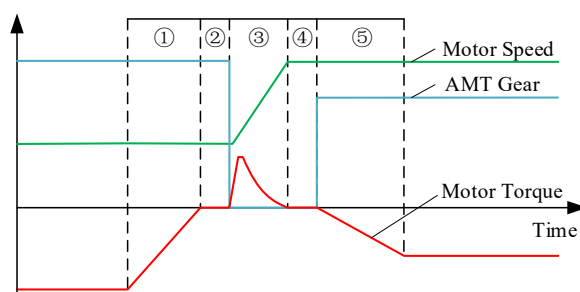


Figure 12. AMT shifting process.

Since this study focuses on the influence of gear shifting on energy recovery and constant-speed control performance, the detailed actuator control and motor speed synchronization processes are not explicitly modeled. Instead, gear disengagement, speed synchronization, and gear engagement are simplified as a unified power interruption phase, during which regenerative braking torque is unavailable. This simplification captures the main transient influence of AMT shifting on cooperative braking control. Since regenerative braking provides only part of the total braking torque in CBM, the hydraulic retarder can compensate for the remaining braking demand during this interval.

In conventional AMT shift control, the motor torque release and restoration rates are constrained by the maximum allowable jerk j_{max} to ensure smooth shifting [41], as expressed in Equation (25). To minimize shift duration, the motor torque is typically ramped down and restored at the maximum permissible rate, approximately 7 kN·m/s.

$$\frac{dT_m}{dt} \leq \frac{\delta m r}{i_g i_0 \eta_{trans}} j_{max} \quad (25)$$

However, in constant-speed cooperative braking mode, rapid changes in regenerative braking torque during gear shifting may prevent the hydraulic retarder from compensating for the torque deficit in time, resulting in noticeable speed fluctuations. Therefore, the motor torque release and restoration rates are reduced to allow sufficient retarder response during gear transitions. Considering the dynamic filling and discharging characteristics of the hydraulic retarder, the torque change rates during motor torque release and restoration are set to $-3.5 \text{ kN}\cdot\text{m/s}$ and $4.5 \text{ kN}\cdot\text{m/s}$, respectively.

4. Simulation Results and Analysis

4.1. Offline Simulation

To evaluate the effectiveness of the proposed constant-speed control method, offline simulations were conducted for both the retarder braking mode (RBM) and the cooperative braking mode (CBM) under constant-slope, variable-slope, and real-world downhill road conditions.

4.1.1. Retarder Braking Mode

(1) Constant-slope road condition

The RBM was first evaluated under a 5% constant road grade with a target vehicle speed of 40 km/h and compared with three classical constant-speed control methods, including logic rule-based control, fuzzy control, and PID control [20].

As shown in Figure 13, the vehicle speed initially overshoots due to the response delay of the retarder braking torque, and then gradually converges to the target value as the controller intervenes. The rule-based controller exhibits pronounced fluctuations, stabilizing after 27 s with a steady-state error exceeding 1 km/h. The fuzzy controller achieves high steady-state accuracy but shows a relatively slow transient response, whereas the PID controller responds faster but exhibits mild oscillations. In contrast, the proposed VAPID controller adjusts the PID gains online according to the vehicle speed error, thereby improving both transient response and steady-state tracking accuracy. The quantitative comparison in Table 5 further confirms this improvement.

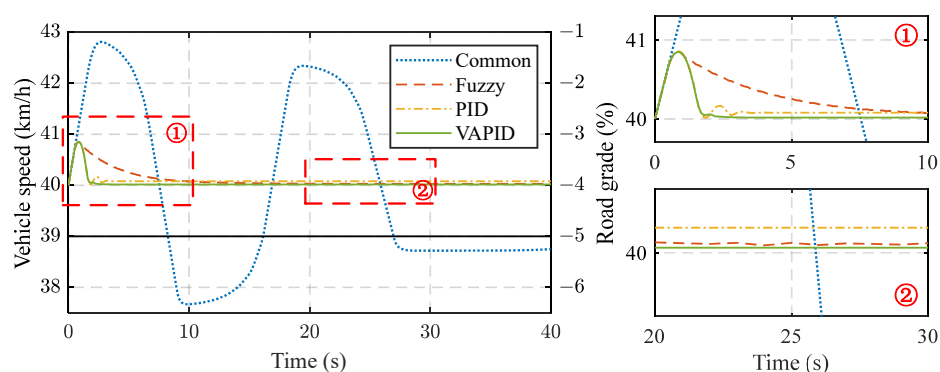


Figure 13. Simulation results of RBM under constant-slope road condition.

Table 5. Performance comparison of RBM under constant-slope condition.

Metric	Rule-Based	Fuzzy	PID	VAPID
Overshoot (km/h)	2.81	0.85	0.86	0.85
Settling time (s)	27.72	15.53	3.24	2.57
Steady-state error (km/h)	1.25	0.03	0.08	0.02

(2) Variable-slope road condition

The RBM was further evaluated under variable-slope road conditions, where the road grade varied sinusoidally between 4% and 6%, as shown in Figure 14. Under the continuously varying road grade, the conventional control methods exhibit different degrees of speed fluctuation. Among all compared methods, the proposed VAPID controller maintains the smallest speed deviation and keeps the vehicle speed closest to the target value. The RMSE results in Table 6 further confirm its better adaptability to road grade variations.

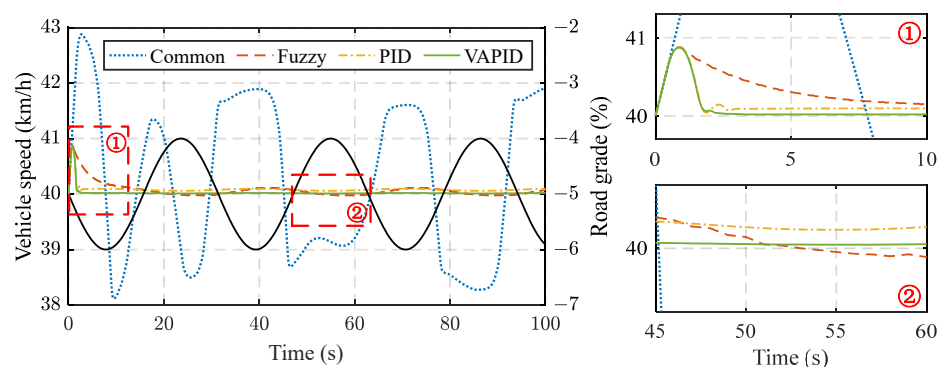


Figure 14. Simulation results of RBM under variable-slope road conditions.

Table 6. RMSE comparison under the variable-slope road condition.

Metric	Rule-Based	Fuzzy	PID	VAPID
RMSE (km/h)	1.41	0.15	0.11	0.08

4.1.2. Cooperative Braking Mode

(1) Constant-slope road condition

The CBM was evaluated under a constant-slope road condition with three battery operating states corresponding to different SOC and temperature levels, and the target vehicle speed was set to 40 km/h. The simulation results are shown in Figure 15.

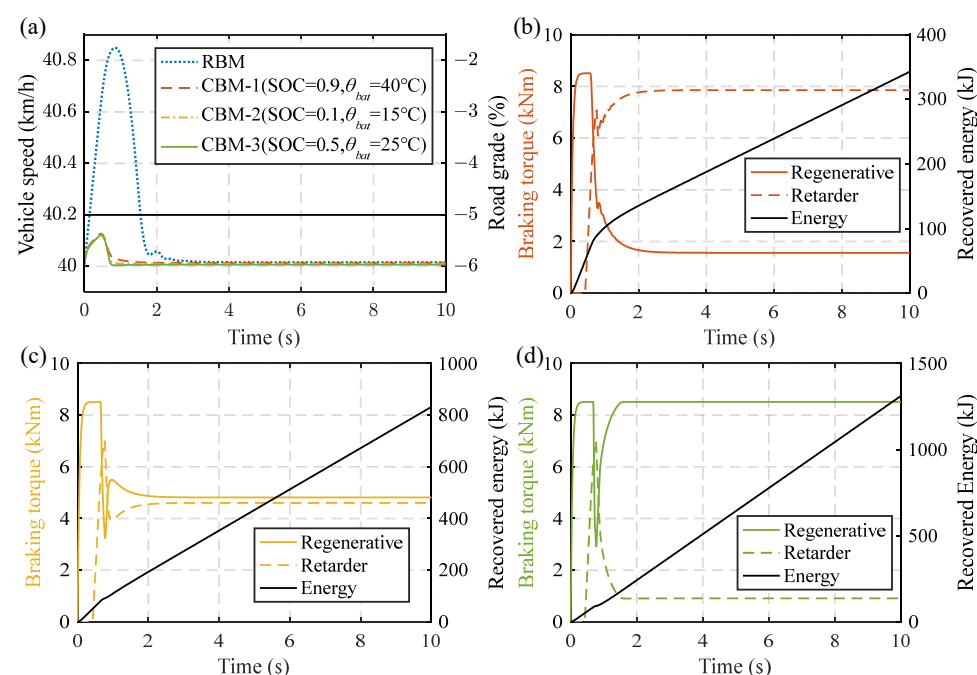


Figure 15. Simulation results of CBM under the constant-slope road condition. (a) vehicle speed comparison; (b) CBM-1; (c) CBM-2; (d) CBM-3.

As shown in Figure 15a, compared with RBM, CBM substantially reduces the initial speed overshoot and allows the vehicle to reach steady operation more rapidly, mainly due to the fast torque response of regenerative braking. The torque distribution and braking energy recovery under different battery conditions are illustrated in Figure 15b–d, with detailed performance metrics summarized in Table 7.

Table 7. Performance comparison under constant-slope condition.

Metric	RBM	CBM-1	CBM-2	CBM-3
Overshoot (km/h)	0.85	0.13	0.12	0.12
Settling time (s)	2.57	1.21	0.78	0.74
Steady-state error (km/h)	0.02	0.01	0.01	0.01

These results show that CBM maintains good constant-speed control performance while dynamically regulating the regenerative braking proportion according to battery state, thereby reducing excessive charging demand under unfavorable battery states.

To further evaluate the effect of fuzzy tuning on battery charging load, an additional 1 km downhill simulation was conducted under CBM-1 and CBM-2. Here, PD denotes the fixed-parameter PD controller, while Fuzzy-PD denotes the proposed fuzzy-tuned PD controller. The peak charging current magnitude during the steady-state interval and the maximum battery temperature rise were selected as battery charging load indicators.

As shown in Table 8, compared with PD, Fuzzy-PD significantly reduces the battery charging load under unfavorable battery states. Specifically, the peak charging current magnitude is reduced by 78.84% under CBM-1 and by 38.58% under CBM-2. Meanwhile, the maximum battery temperature rise is also considerably suppressed in both cases. These results indicate that the fuzzy tuning strategy effectively reduces the current and thermal loads imposed on the battery during regenerative braking.

Table 8. Battery charging load metrics under different PD controllers.

Metric	CBM-1		CBM-2	
	PD	Fuzzy-PD	PD	Fuzzy-PD
Peak charging current magnitude (A)	186.94	39.55	187.00	114.85
Maximum battery temperature rise (°C)	0.85	0.05	0.99	0.39

(2) Variable-slope road condition

The CBM with AMT gear shifting was further evaluated under a variable-slope road condition. After the vehicle speed stabilized, a downshift from 6th to the optimal 4th gear was triggered at approximately 2 s, as illustrated in Figure 16. This gear shift is intended to improve motor efficiency and braking energy recovery. However, the power interruption during AMT shifting temporarily eliminates regenerative braking torque, which may cause torque mismatch and speed fluctuation. Therefore, the proposed coordination shift strategy reduces the motor torque release and restoration rates to better match the retarder response.

Figure 16a,b show the motor efficiency and braking energy recovery with and without gear shifting. After shifting, the motor operates in a higher-efficiency region, resulting in improved motor efficiency. Although regenerative braking is temporarily interrupted during shifting, the energy recovery advantage gradually becomes more evident as the braking duration increases. Figure 16c,d compare the braking torque and vehicle speed under conventional shift control and the proposed coordination shift strategy. Under conventional control, the motor torque is released and restored rapidly during the power-interruption interval, whereas the retarder torque cannot vary at the same rate. As shown in

the enlarged view of Figure 16c, the delayed retarder response causes a temporary reduction and fluctuation in the total braking torque, leading to noticeable speed fluctuations between 2 s and 3.2 s in Figure 16d. In contrast, the proposed coordination strategy smooths the motor torque transition and allows the retarder torque to build up more gradually. This reduces the transient braking torque gap and suppresses the corresponding speed fluctuation. Although the coordinated strategy slightly prolongs the gear-shifting duration, it maintains stable speed regulation during the power-interruption phase.

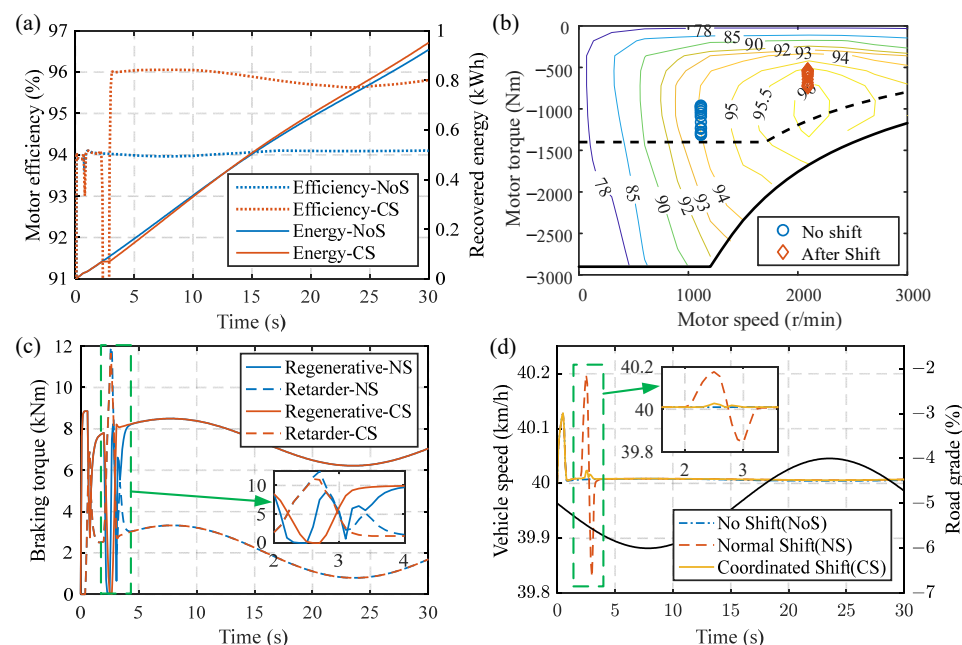


Figure 16. Simulation results of CBM under the variable-slope road condition. (a) motor efficiency and recovered energy; (b) motor operating points; (c) braking torque comparison; (d) vehicle speed comparison.

(3) Real-world downhill road condition

Finally, the proposed AMT gear-shifting control strategy was validated on a real-world downhill road, with the target vehicle speed set to the average speed of this road segment, i.e., 52 km/h. After the vehicle speed stabilized, AMT gear shifting was triggered at approximately 2 s, shifting from 6th gear to the optimal 5th gear. The simulation results are shown in Figure 17.

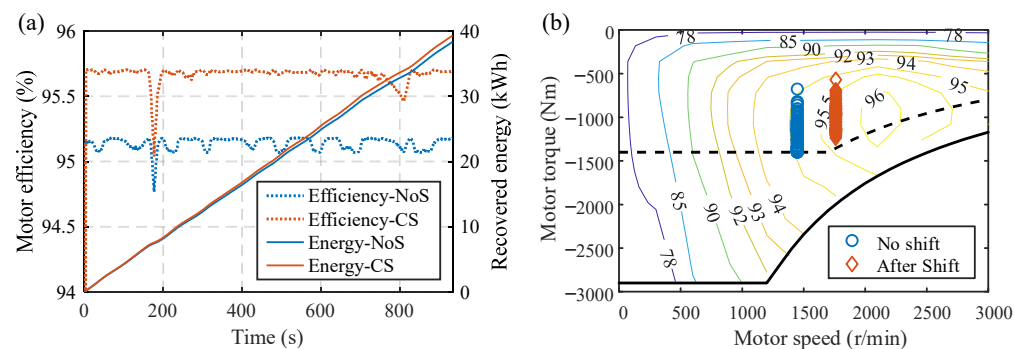


Figure 17. AMT gear-shifting performance under the real-world downhill condition. (a) motor efficiency and recovered energy; (b) motor operating points.

After gear shifting, the average motor efficiency increased from 95.14% to 95.67%, and the recovered braking energy increased by 3478 kJ, corresponding to a 2.52% improve-

ment compared with the no-shift scenario. These results confirm that the proposed AMT gear-shifting control strategy can further improve energy recovery during constant-speed downhill driving.

4.1.3. Sensitivity Analysis Under Parameter Variations and Disturbances

To further evaluate the robustness of the proposed constant-speed control method, sensitivity analysis was conducted under different road grades and vehicle masses. The nominal condition was set as 45,000 kg vehicle mass and 5% road grade. The road grade was varied from 4% to 6% while keeping the vehicle mass at 45,000 kg, and the vehicle mass was varied from 40,000 kg to 50,000 kg while keeping the road grade at 5%. The maximum speed overshoot, settling time, and steady-state speed error were selected as evaluation metrics, as shown in Figure 18.

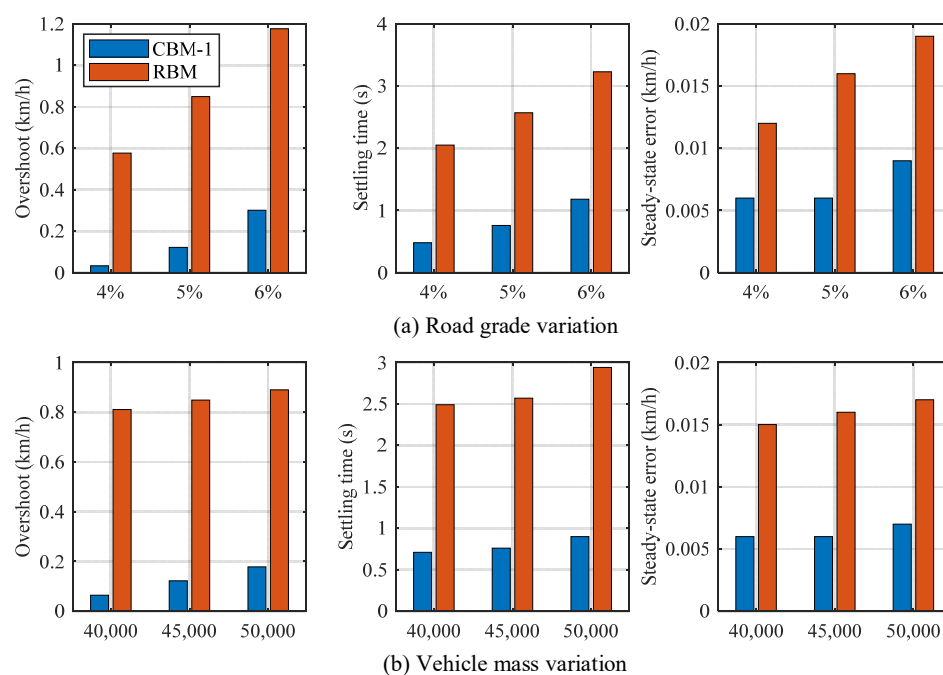


Figure 18. Sensitivity analysis under road grade and vehicle mass variations.

As shown in Figure 18a, the increase in road grade leads to higher braking demand and thus larger speed overshoot and longer settling time. However, CBM-1 maintains a maximum speed overshoot of 0.03–0.30 km/h, a settling time below 1.18 s, and a steady-state speed error lower than 0.01 km/h under all tested road grades. In contrast, RBM exhibits larger overshoot and longer settling time, especially under the 6% grade condition. Figure 18b shows that vehicle mass variation has a relatively moderate influence on CBM-1. When the vehicle mass increases from 40,000 kg to 50,000 kg, the maximum speed overshoot of CBM-1 increases from 0.06 km/h to 0.18 km/h, and the settling time remains within 0.71–0.90 s. Overall, CBM-1 shows smaller speed overshoot, shorter settling time, and lower steady-state speed error than RBM under both road grade and vehicle mass variations, indicating better robustness to changes in downhill braking demand.

In addition to vehicle mass and road grade variations, the effects of vehicle-speed measurement noise and retarder command delay were evaluated under the nominal constant-slope condition of 45,000 kg vehicle mass and 5% road grade. Gaussian white noise with a standard deviation of 0.1 km/h was added to the measured vehicle speed signal used by the controller. In addition, an extra 0.1 s pure time delay was inserted into the hydraulic retarder command channel before the retarder actuation model. Since slight speed fluctuations may remain after stabilization under noise and delay disturbances, the steady-state

error in this subsection is defined as the mean absolute speed error over the stable control interval. The results are summarized in Table 9.

Table 9. Sensitivity analysis under sensor noise and retarder command delay.

Control Mode	Test Condition	Overshoot (km/h)	Settling Time (s)	Steady-State Error (km/h)
CBM-1	Nominal	0.12	0.76	0.01
	Speed noise: $\sigma = 0.1$ km/h	0.23	1.67	0.13
	Retarder delay: 0.1 s	0.14	0.86	0.01
RBM	Nominal	0.85	2.57	0.02
	Speed noise: $\sigma = 0.1$ km/h	1.02	3.22	0.25
	Retarder delay: 0.1 s	1.00	3.35	0.10

As shown in Table 9, vehicle-speed measurement noise and retarder command delay affect the control performance in different ways. Speed measurement noise mainly increases the mean steady-state speed error because it directly enters the speed feedback loop and causes small fluctuations in the control command after stabilization. This effect is more evident in CBM-1 because the fast-response regenerative braking controller is more sensitive to speed feedback variations. Nevertheless, CBM-1 still maintains lower overshoot, shorter settling time, and smaller mean steady-state speed error than RBM under the same noise condition. Retarder command delay mainly affects the transient response by slowing down retarder torque build-up. Compared with RBM, CBM-1 is less affected by the additional retarder delay because the faster regenerative braking response helps compensate for the delayed retarder action. Overall, the proposed controller maintains stable speed regulation under both tested disturbances, while CBM-1 achieves better dynamic performance but requires more reliable vehicle-speed feedback.

The influence of vehicle mass on braking energy recovery was further evaluated under a 5% constant road grade. The recovered energy and energy recovery rate under different vehicle masses are listed in Table 10.

Table 10. Energy recovery performance under different vehicle masses.

Vehicle Mass (kg)	Recovered Energy (kJ)	Energy Recovery Rate (%)
40,000	1292.40	16.47
45,000	1309.32	14.83
50,000	1315.44	13.41

As shown in Table 10, the recovered energy slightly increases with vehicle mass because the downhill braking demand becomes larger. However, the energy recovery rate decreases under heavier load conditions. This is because the increased braking demand cannot be fully absorbed by regenerative braking, and a larger proportion of the braking torque needs to be provided by the hydraulic retarder. These results show that the proposed cooperative braking strategy can maintain effective energy recovery under vehicle mass variation, while the regenerative braking contribution is limited by the available motor braking capability and battery charging acceptance.

4.2. DiL Real-Time Simulation

To further validate the effectiveness and real-time feasibility of the proposed method, DiL real-time simulation experiments were conducted. In the DiL tests, the driver activated the constant-speed downhill control function through a button on the driving simulator after a brief orientation, while the subsequent speed regulation and braking coordination were executed by the proposed controller. Therefore, the driver input mainly affected the

activation speed of the control function. The DiL simulation platform consists of a Logitech G29 driving simulator, a Speedgoat real-time target machine, and a host PC, as illustrated in Figure 19.

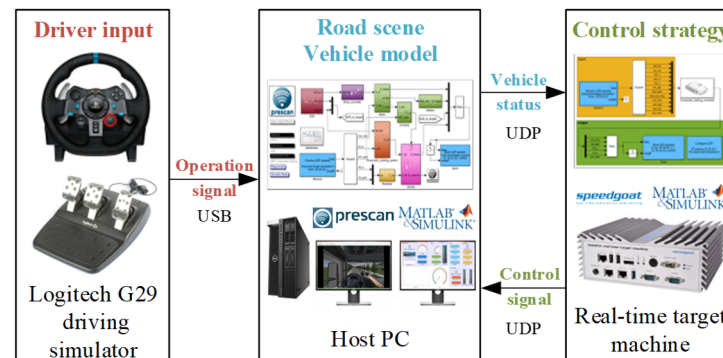


Figure 19. DiL real-time simulation platform architecture.

The driving simulator captures driver inputs, including steering wheel button signals and pedal operations. The host PC executes the road environment, vehicle dynamics, and brake actuation system models, while providing a virtual driving scene and a Dashboard-based human–machine interface. The target machine implements the proposed control method, processes driver inputs and vehicle state information, and outputs control commands to the host PC to achieve real-time closed-loop control. In terms of software, the vehicle dynamics model, brake actuation system model, and control method are built in MATLAB/Simulink (R2024a), while the road environment and DiL interface are developed in PreScan. The PreScan model is compiled and integrated with Simulink for co-simulation.

A downhill road section from Dalingyakou to Fengyukou in Shaanxi Province, covering the 48–45 km range with average grades of 5%, 8%, and 5%, respectively, was selected as the test road. The corresponding PreScan road scene was constructed using altitude data derived from mileage stakes. The initial battery SOC and temperature were set to 50% and 25 °C, respectively. The G29 steering wheel buttons served as input signals. When the driver pressed the button, the constant-speed downhill control was activated, and the current vehicle speed was recorded as the target speed.

Figure 20 shows the real-time simulation results under the retarder braking mode. At the start, as the vehicle speed increased, the driver depressed the brake pedal. When the speed dropped to the desired value, as indicated by the intersection of the pink dotted lines in the enlarged view, the driver activated constant-speed control using the steering wheel button. The hydraulic retarder then generated braking torque to regulate the vehicle speed. The vehicle speed fluctuated slightly before stabilizing near the target value within 5 s, with a speed deviation of less than 1 km/h.

As the road slope increased, the retarder’s maximum output torque became insufficient to maintain the target speed, causing the vehicle speed to rise around 110 s. The driver then depressed the brake pedal and deactivated the constant-speed control function. After the speed returned to the target value, the driver reactivated constant-speed control using the steering wheel button. A slight speed drop occurred after reactivation due to the delayed release of the pneumatic braking system, and the speed stabilized again within 3 s. Minor speed fluctuations appeared around 95 s and 173 s because the road grade was nearly zero at the transitions between adjacent road segments, where the vehicle speed slightly decreased under the effect of aerodynamic drag.

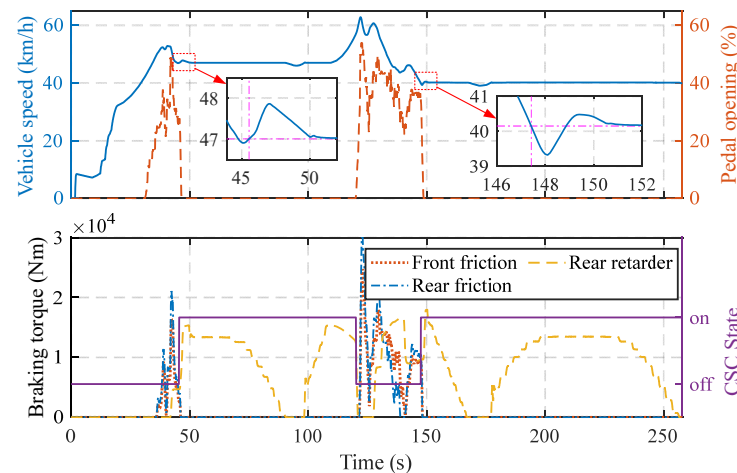


Figure 20. DiL simulation results of retarder braking mode.

Figure 21 shows the real-time simulation results under the cooperative braking mode. After the constant-speed control was activated, the vehicle speed stabilized near the target value within 1.5 s under the combined action of regenerative braking and retarder braking. Owing to the rapid dynamic response of regenerative braking torque, CBM achieved quicker stabilization and smaller speed fluctuations than RBM. Moreover, CBM extended the road-grade range over which constant-speed control could be maintained, with only a slight speed increase observed during the steepest section around 150 s. Overall, the DiL real-time simulation results are consistent with the offline simulation results, further verifying the effectiveness and real-time feasibility of the proposed constant-speed control method.

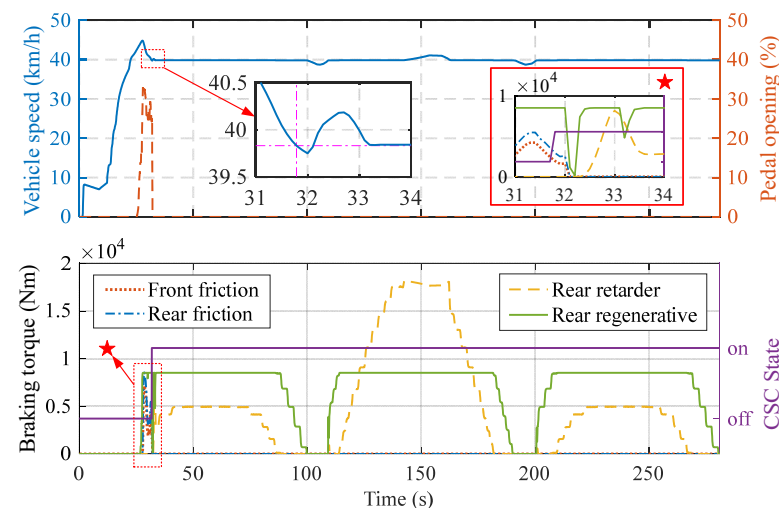


Figure 21. DiL simulation results of cooperative braking mode.

4.3. Assumptions and Limitations

Although the proposed constant-speed control method shows good speed regulation and energy recovery performance under the investigated downhill conditions, several assumptions and limitations should be clarified to define its application scope.

First, the proposed controller is mainly designed for downhill constant-speed braking under normal road adhesion conditions. Vehicle slip caused by low-adhesion roads or emergency braking is not considered in the present control framework. In practical applications, vehicle speed is usually estimated from wheel-speed signals. When severe wheel slip occurs, the deviation between the wheel-speed-based estimated speed and the

actual vehicle speed may become large, and ABS may intervene. Under such conditions, the constant-speed downhill control function should be suspended, and the basic braking stability control system should take over.

Second, the available braking capability of the motor and hydraulic retarder is constrained by their thermal operating limits. During prolonged high-power braking, both actuators may experience excessive temperature rise and trigger thermal protection or power derating. In this study, these thermal constraints are represented by prescribed power thresholds. Under extreme conditions, such as very steep road grades and heavy vehicle loads, if regenerative braking is restricted due to high SOC or other unfavorable battery states, the hydraulic retarder alone may be insufficient to meet the total braking demand. In this case, additional friction braking torque is required to ensure braking safety.

Third, several component models used in this study are control-oriented simplified models. For example, the Rint battery model is used to describe the electrical behavior required for regenerative braking analysis, but it does not fully capture detailed transient battery dynamics. Similarly, the hydraulic retarder model does not explicitly consider the influence of oil temperature on fluid viscosity and the resulting torque variation. These simplifications are suitable for control strategy development and real-time simulation, but they may affect the prediction accuracy of battery current, recovered energy, and retarder braking torque under extreme operating conditions.

5. Conclusions

This study developed a constant-speed downhill control approach for BETs by integrating hydraulic retarder braking, regenerative braking, and AMT gear-shifting control. In RBM, an ISOA-optimized VAPID controller was designed to improve the adaptability of hydraulic retarder constant-speed control under varying downhill conditions. In CBM, a parallel dual-controller structure was proposed, in which regenerative braking was regulated by a fuzzy-PD controller according to battery SOC and temperature, while the hydraulic retarder compensated for the remaining braking demand. In addition, an AMT gear-shifting strategy based on the overall efficiency of the regenerative braking system was developed to improve braking energy recovery.

Offline simulations show that, in RBM, the proposed VAPID controller outperforms logic rule-based, fuzzy, and PID controllers, achieving a settling time of 2.57 s and a steady-state error of 0.02 km/h under a 5% constant road grade, and an RMSE of 0.08 km/h under variable-slope road conditions. In CBM, the fast response of regenerative braking reduced the initial speed overshoot and shortened the settling time, while battery-state-based regulation reduced the charging load under unfavorable battery conditions. The AMT gear-shifting control strategy further improved motor efficiency and increased braking energy recovery by 2.52% under real-world downhill road conditions, with limited influence on speed stability. Sensitivity analysis further showed that both RBM and CBM maintained stable speed regulation under road grade and vehicle mass variations. Under speed measurement noise and retarder command delay, CBM still achieved better dynamic performance than RBM, although it showed higher sensitivity to vehicle-speed feedback noise. DiL real-time simulations further verified the effectiveness and real-time feasibility of the proposed method, with vehicle speed converging to the target value within approximately 5 s in RBM and 1.5 s in CBM.

This research provides valuable theoretical support and practical reference for developing hydraulic retarder constant-speed control functions and improving the downhill safety of long-haul BETs. Nevertheless, the present study still has limitations in battery and hydraulic retarder modeling, as the battery constraint is mainly based on SOC and temperature and the retarder thermal effect is represented by the allowable braking power

constraint. Future work will improve the fidelity of these models to provide more accurate constraint boundaries for constant-speed downhill control.

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Appendix A

Appendix A.1. Sin Chaotic Opposition-Based Learning

The baseline SOA initializes seeker positions randomly, which may lead to uneven population distribution and insufficient population diversity. To improve the initial search quality, Sin chaotic mapping is combined with opposition-based learning in the ISOA. The Sin chaotic sequence is generated as follows:

$$c_{i,j} = \sin(\pi c_{i-1,j}) \quad i = 1, 2, \dots, N \quad (A1)$$

where $c_{i,j} \in (0, 1)$ denotes the chaotic sequence value of the i -th seeker in the j -th dimension. The chaotic sequence is mapped to the search space to obtain the initial seeker position:

$$x_{i,j}^0 = x_j^{\min} + c_{i,j} \cdot (x_j^{\max} - x_j^{\min}) \quad (A2)$$

where $x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the j -th decision variable, respectively. The corresponding opposite position is then calculated as:

$$\bar{x}_{i,j}^0 = x_j^{\min} + x_j^{\max} - x_{i,j}^0 \quad (A3)$$

The fitness values of $x_{i,j}^0$ and $\bar{x}_{i,j}^0$ are compared, and the best N candidate solutions are selected to form the initial population. This strategy improves the uniformity of the initial population and enhances the global exploration capability at the beginning of the optimization.

Appendix A.2. Generalized Opposition-Based Learning

During the iterative process of SOA, population diversity may gradually decrease, which increases the risk of premature convergence. To alleviate this issue, generalized opposition-based learning is introduced as a generation-jumping strategy in the ISOA. For a seeker position $x_{i,j}$, the generalized opposite position is defined as:

$$\tilde{x}_{i,j} = k(x_j^{\min} + x_j^{\max}) - x_{i,j} \quad (A4)$$

where k is a random number uniformly distributed in (0,1). If the generated position exceeds the search boundary, it is regenerated within the feasible interval:

$$\tilde{x}_{i,j} = \begin{cases} k(x_j^{\min} + x_j^{\max}) - x_{i,j}, & x_j^{\min} \leq \tilde{x}_{i,j} \leq x_j^{\max} \\ \text{rand}(x_j^{\min}, x_j^{\max}), & \tilde{x}_{i,j} < x_j^{\min} \parallel \tilde{x}_{i,j} > x_j^{\max} \end{cases} \quad (\text{A5})$$

Generation jumping is performed when the jumping condition $\text{rand}(0,1) < J_r$ is satisfied, where J_r is the jumping rate. The candidate solutions generated by the current population and the generalized opposite population are evaluated together, and the best N solutions are retained for the next iteration. Compared with the baseline SOA, this strategy helps maintain population diversity during the search process and reduces the probability of being trapped in local optima.

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