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A Control Algorithm for the Novel Regenerative–Mechanical Coupled Brake System with by-Wire Based on Multidisciplinary Design Optimization for an Electric Vehicle

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Abstract: Current regenerative braking systems in electric vehicles have several problems, such as complex structures, too many control parameters, and inconsistent braking responses. To solve these problems, a control algorithm with multidisciplinary design optimization (MDO) is proposed based on the novel regenerative-mechanical coupled brake-by-wire system. A dynamic model of the novel regenerative braking system was established to analyze the mechanism of coupled braking and propose a braking torque distribution strategy. To realize a better balance between the optimum braking stability and the maximum regenerative energy recovery based on the braking torque distribution strategy and sample points, the MDO mathematical model was developed to optimize the control parameters with the collaborative optimization algorithm. The finite sample points comprising the vehicle speed, battery state-of-charge, and braking severity were obtained through an optimal Latin hypercube design and represent the overall design space. A network was established based on the sample points and the optimization results. Using this network, the in-depth characteristics of the sample points and the optimization results were obtained through supervised learning to develop the control algorithm for vehicle braking. A simulation was performed using the normal braking condition, and the simulation results demonstrated that the control algorithm has higher control precision than conventional methods and better real-time performance than online optimization.

Keywords: multidisciplinary design optimization; regenerative braking; optimum control; regenerative–mechanical coupling

1. Introduction

Electric vehicles (EVs) have received significant attention because of the global environmental crisis and pressure on energy sources. Compared to conventional vehicles, electric vehicles can recapture kinetic energy during deceleration using a regenerative braking system without requiring any additional components [1]. A regenerative braking system can recover kinetic energy into a battery through an electric motor, which is also used to produce a regenerative braking torque to the wheels to realize braking [2]. Research shows that more than half of the braking energy can potentially be used in typical urban driving cycles [3]. Hence, to improve the energy efficiency, regenerative braking system, two types of regenerative braking control strategies are used: series and parallel. In the parallel strategy, the regenerative braking torque is added into the friction braking torque at a fixed proportion. In the series strategy, the proportion of the regenerative braking torque and the friction braking torque can



be modulated to control the overall braking torque for meeting the requirements [5]. The regenerative braking torque depends on the motor characteristics [6], the charging power capability of the battery [7], and the available tire–road friction [8]; hence, existing research has focused on improving the braking energy recovery efficiency by distributing the torque between regenerative braking and friction braking based on drivers' demands.

In engineering practice, several rule-based regenerative braking strategies have been proposed and used in recent years. For a rear-driven electric truck, a modified control strategy that determines how to distribute the braking force between the front and rear axles was proposed by Zhang to improve the recovery efficiency [9]. Xiao presented an integrated control strategy to coordinate regenerative and friction braking forces to deal with the braking stability and recovery efficiency when a vehicle performed normal deceleration and emergency braking [3]. To regenerate more braking energy and move closer to the ideal braking force distribution curve, a combined braking control strategy was developed for the rear wheel-driven series hybrid electric EV to adjust the proportions of regenerative braking and friction braking [10]. A regenerative braking cooperative control strategy was proposed by Jiweon for hybrid EVs equipped with a hydraulic brake on the rear wheels and an electronic wedge brake on the front wheels [11].

Optimization and control technologies have also been proposed to control the cooperative braking system. A genetic algorithm-based control strategy that determines how to distribute the brake torque between regenerative braking and electrohydraulic braking was developed by Kim [12]. Furthermore, to control the wheel slip, a sliding-mode controller was designed by Zhang to distribute the braking force between regenerative braking and antilock braking in emergency braking situations [13]. Fuzzy logic was applied in brake energy recovery systems. Compared to the conventional control strategy, the fuzzy logic control strategy presents a higher recovery efficiency in regenerative braking [14]. A sliding-mode controller based on the exponential reaching law for the antilock braking system was developed. The tracking of the slip ratio became rapid and accurate in adjusting the motor braking moment with the proposed sliding-mode controller [15]. A nonlinear-model predictive controller for regenerative braking control in EVs equipped with in-wheel motors was presented [16]. A control algorithm based on a model predictive control framework was proposed to recover more braking energy and maintain the optimal slip value. The framework could reduce the torque tracking error [17].

The feasibility of several control strategies is worth studying, and the optimization of control parameters that affect the comprehensive braking performance, including braking stability and energy recuperation efficiency, also needs attention. Sun presented a predictive control strategy using an offline process optimization stream to realize the balance between the maximum regenerative energy recuperation efficiency and the optimum braking stability [18,19]. However, a problem of inconsistent braking response exists because regenerative braking and friction braking are two independent systems. In addition, some sampling points have a large predictive error when using conventional approximation models because of the highly nonlinear relationship between sampling points and predictive values.

As evidenced in the literature survey, several problems exist, such as complex structures, too many control parameters, and inconsistent braking response, because current braking systems comprise two independent systems, the regenerative and friction braking systems. It is difficult to maintain good regenerative braking efficiency and regenerative braking effectiveness stability because it is necessary to switch between the regenerative braking system and the friction braking system during braking. Moreover, a strong coupling relationship exists between the regenerative system and the friction braking system. Obtaining a good comprehensive braking performance using conventional optimization methods is difficult. To solve these problems, first, the mathematical model of the novel regenerative–mechanical coupled brake-by-wire system is presented herein to reveal the coupled braking mechanism. Next, two disciplines, namely the optimum braking stability and the maximum regenerative energy recovery efficiency, are defined to optimize the comprehensive

braking performance of the vehicle. The optimization results are obtained using a collaborative optimization algorithm. Thereafter, a network is built based on the optimization results and the sample points comprising the vehicle speed *v*, battery state-of-charge (*SoC*), and braking severity *z*. Afterwards, through supervised learning, the in-depth characteristics of the sample points and the optimization results are obtained based on the deep learning network to establish the deep learning control algorithm. Finally, the deep learning control algorithm is verified to have higher control precision than conventional methods and a better real-time performance than online optimization in a dynamic simulation.

This paper is organized as follows: Section 2 describes the mechanism of the novel regenerative–mechanical coupled brake-by-wire system; Section 3 presents a mathematical optimization model and describes the multidisciplinary design optimization (MDO) method for optimizing the control parameters of the novel regenerative–mechanical coupled brake-by-wire system; Section 4 presents a deep learning control algorithm based on the optimization results and sample points obtained using a deep learning network, and Section 5 presents the simulations, followed by the concluding remarks in the final section.

2. Novel Regenerative–Mechanical Coupled Brake-by-Wire System

2.1. Structure of the Novel Regenerative–Mechanical Coupled Brake-by-Wire System

The novel regenerative–mechanical coupled brake-by-wire system, which takes advantage of brake-by-wire and regenerative braking [20,21], is built based on the mechanism of mechanical-electrical-magnetic energy conversion (Figure 1).



Figure 1. Novel regenerative-mechanical coupled brake-by-wire system.

As shown in Figure 1, during braking, the in-wheel motors equipped on the front and rear wheels perform regenerative braking and recover kinetic energy into the battery. The transmission path of the regenerative braking torque is as follows: motor stator→motor rotor→wheel.

The screw is fixed on the motor stator; hence, when the electromagnetic torque generated by the motor stator is transmitted to the screw, the motive force of friction braking will be converted to generative friction braking torque. The transmission path of the regenerative braking torque is as follows: motor stator \rightarrow screw and nut \rightarrow elastic element \rightarrow brake caliper and brake disc \rightarrow motor rotor \rightarrow wheel.

The electromagnetic torque generated by the feedback current performs braking in the novel regenerative–mechanical coupled brake-by-wire system. At the same time, the friction braking torque can be generated by the electromagnetic braking torque, which is the driving force for friction braking, without additional energy consumption. The coupled braking process involving regenerative braking

and friction braking is then realized. Hence, the electromagnetic torque can be controlled to modulate the braking severity and maintain the optimum comprehensive performance in terms of energy recovery and braking stability through mechanical/electrical/magnetic MDO.

This study focuses on the normal deceleration process that has a braking severity ranging from 0 to 0.4 with enough adhesive force from the dry pavement. Considering the characteristics of both motor and battery, the vehicle speed is limited within 10 km/h to 100 km/h, and the battery *SoC* is a value in the range of 0.2–0.8.

2.2. Mathematical Model of the Novel Regenerative–Mechanical Coupled Brake-by-Wire System

During braking, the electromagnetic torque T_e between the motor rotor and the motor stator is generated by the feedback current I_L in the motor rotor coil under the effect of electromagnetic induction. The regenerative braking torque T_{be} is then generated by T_e in the brake wheels through the connection device. Neglecting the tube pressure drop of the feedback brake circuit and the motor self-friction torque in the steady state, T_e and T_{be} can be expressed as follows [22]:

$$\begin{cases} T_e = K_e I_L \\ T_{be} = T_e \end{cases}$$
(1)

where K_e is the torque coefficient (Nm/A).

As shown in Figure 1, the screw cannot slide, but can only rotate along with the motor stator. The nut cannot rotate, but can only slide along with the guide block. The screw and the nut are joined by a non-locking spiral. The screw is fixed to the motor stator; hence, the thrust force F_N can be generated by the electromagnetic torque through the transmission mechanism. F_N can be expressed as follows [23]:

$$F_N = \frac{\eta_1 T_e}{R_c \tan(\alpha_s + \rho_s)} \tag{2}$$

where η_1 is the mechanical efficiency of the transmission mechanism; R_c is the friction radius of the screw end plane (m); α_s is the lead angle of the screw (rad); and ρ_s is the equivalent friction angle of the screw and the nut (rad).

When F_N overcomes the elastic force F_s of the elastic element, the friction braking torque will be generated by the brake caliper in the clamping brake disc and transmitted to the brake wheels through the motor rotor and connection device. The friction braking torque T_{bc} is then described as follows:

$$T_{bc} = 2i_c \mu_c R_p \cdot F_c \tag{3}$$

where $F_c = \max(F_N - F_s, 0)$, i_c is the transmission ratio of the transmission mechanism; μ_c is the friction coefficient of the brake disc, and R_p is the radius of the brake pressure (m).

Therefore, T_{bc} can be generated by T_e in the novel regenerative–mechanical coupled brake-by-wire system, and T_{bc} can be coupled with T_{be} to the brake wheels. The total braking torque T_b can then be described as follows:

$$T_b = T_{be} + T_{bc} \tag{4}$$

As Equations (1)–(4) show, compared to the current braking systems that comprise two independent systems, namely the regenerative and friction braking systems, the novel regenerative–mechanical coupled brake-by-wire system can realize optimal dynamic matching between the regenerative torque and the friction torque and a brake-by-wire coupling of regenerative braking and friction braking. The integration of the entire braking system is considerably improved, and its structure is simplified.

2.3. Braking Torque Distribution Strategy

The research object is a distributed four-wheel-drive EV. Based on longitudinal braking dynamics in straight-line travel, the braking force provided by the ground, regenerative braking torque, and friction braking torque on the left and right wheels of the front axle are equal, and so are the torques on the left and right wheels of the rear axle.

The torques of each wheel can be expressed as follows:

$$T_{be1} + T_{be2} = \frac{T_{Hbe}}{2}$$

$$T_{bc1} + T_{bc2} = \frac{T_{Hbe}}{2}$$

$$F_{xb1} = \frac{T_{be1} + T_{be1}}{R_e}$$

$$F_{xb2} = \frac{T_{be2} + T_{be2}}{R_e}$$

$$T_{Hbe} + T_{Hbc} = T_{Hb}$$

$$T_{Hb} = mgzR_e$$
(5)

where T_{be1} and T_{be2} are the regenerative braking torques on the left wheel of the front and rear axles, respectively (Nm); T_{Hbe} is the total regenerative braking torque (Nm); T_{bc1} and T_{bc2} are the friction braking torques on the left wheel of the front and rear axles, respectively (Nm); T_{Hbc} is the total friction braking torque (Nm); F_{xb1} and F_{xb2} are the tire-ground braking forces on the left wheel of the front and rear axles, respectively (N); R_e is the effective tire radius (m); T_{Hb} is the total braking torque (Nm); *m* is the kerb mass (kg); *g* is the acceleration caused by gravity (m/s²), and *z* is the braking severity.

The braking torque distribution strategy aiming at an optimal overall performance in terms of the braking stability and the regenerative braking energy recovery rate is proposed for a novel regenerative–mechanical coupled brake-by-wire system. The strategy can be described as follows:

First, the proportion of the total regenerative braking torque in the overall braking torque is determined as follows:

$$\frac{2(T_{be1} + T_{be2})}{T_{Hb}} = \alpha \tag{6}$$

where α is the distribution coefficient of the regenerative braking torque.

Second, the proportion of the regenerative braking torque between the front and rear axles is determined as follows:

$$\frac{2T_{be1}}{T_{Hbe}} = \gamma \tag{7}$$

where γ is the distribution coefficient of the regenerative braking torque on the front axle.

Third, the proportion of the friction braking torque between the front and rear axles is determined as follows:

$$\frac{2T_{bc1}}{T_{Hbc}} = \lambda \tag{8}$$

where λ is the distribution coefficient of the friction braking torque on the front axle.

Combining Equations (5)–(8) gives the following:

$$\begin{cases} T_{be1} = \frac{\alpha \gamma mgzR_e}{2} \\ T_{be2} = \frac{\alpha(1-\gamma)mgzR_e}{2} \\ T_{bc1} = \frac{(1-\alpha)\lambda mgzR_e}{2} \\ T_{bc2} = \frac{(1-\alpha)(1-\lambda)mgzR_e}{2} \end{cases}$$
(9)

The braking force distribution coefficient β is defined as follows:

$$\beta = \frac{2(T_{be1} + T_{bc1})}{T_{Hb}} = \alpha(\gamma - \lambda) + \lambda$$
(10)

3. Mathematical Optimization Models of the Novel Regenerative–Mechanical Coupled Brake-by-Wire System

3.1. Optimization Objectives

From the perspective of driving safety and energy economy, the optimum braking stability and the maximum regenerative energy recovery efficiency are treated as optimization objectives based on the novel regenerative–mechanical coupled brake-by-wire system discussed in this paper.

3.1.1. Ideal Braking Stability Objective

During braking, if the braking force is distributed in the form of an I curve, any wheel locking in advance will be prevented, and the optimum braking stability will be obtained [10,24]. The ideal braking force distribution, which is the goal of optimum braking stability, can be expressed as follows:

$$\begin{cases} \mu_{f} = \mu_{r} \\ \mu_{f} = \frac{2F_{xb1}}{F_{z1}} \\ \mu_{r} = \frac{2F_{xb2}}{F_{z2}} \\ \beta = \frac{F_{xb1}}{F_{xb1} + F_{xb2}} \end{cases}$$
(11)

where μ_f and μ_r are the utilization of adhesion coefficients on the front and rear axles, respectively, and F_{z1} and F_{z2} are the front and rear axle loads, respectively (N).

According to the braking theory, F_{z1} and F_{z2} can be expressed as follows:

$$\begin{cases} F_{z1} = \frac{mg}{L} \left(L_r + zh_g \right) \\ F_{z2} = \frac{mg}{L} \left(L_f - zh_g \right) \end{cases}$$
(12)

where *L* is the axle base (m); L_r is the rear axle to mass center distance (m); h_g is the height of the mass center (m), and L_f is the front axle to mass center distance (m).

Combining Equations (11) and (12), the optimum braking stability, which is the ideal braking force distribution, can be obtained as follows:

$$\beta_{opt} = \frac{\left(L_r + zh_g\right)}{L} \tag{13}$$

3.1.2. Ideal Regenerative Energy Recovery Efficiency Objective

The braking energy recovery efficiency η_e can generally be defined as the proportion of battery-stored energy, which is produced by motors, and total vehicle braking loss energy during the regenerative braking process [25].

$$\eta_e = \frac{\int_0^t (T_e \omega_m \eta_m - P_{inv} - P_{bat}) dt}{E_V + E_I}$$
(14)

where η_e is a value in the range of 0–1; ω_m is the motor speed (rad/s); η_m is the charging efficiency of the motor; P_{inv} is the loss power of the inverters (KW); P_{bat} is the loss power during battery recharge (KW); t is the braking time (s), and E_V and E_J are the total kinetic energy losses in the translational and rotational motions of the vehicle, respectively (J).

On the premise of meeting the requirements of braking severity, the maximum braking energy recovery efficiency η_{opt} is reached when the total energy lost during vehicle braking is completely recovered and stored in the battery.

$$\eta_{opt} = 1 \tag{15}$$

3.2. Boundary Conditions

3.2.1. Braking Stability Constraints

Based on braking theory [24], the braking stability can be obtained when the utilization of adhesion coefficient on the rear axle is lesser than or equal to that on the front axle.

$$\mu_r \le \mu_f \tag{16}$$

Therefore, the braking force distribution coefficient is limited, and can be expressed as follows:

$$\beta \ge \beta_{opt} = \frac{\left(L_r + zh_g\right)}{L}; 0 \le z \le 0.8$$
(17)

The braking force distribution coefficient should also be limited based on braking regulations. The limits of the braking force distribution based on the braking regulation ZBT 24007-1989 can be expressed as follows [19]:

$$\begin{aligned} \beta &\geq \frac{L_r + zh_g}{L} & (0 \leq z \leq 0.3) \\ \frac{(z - 0.08)(L_r + zh_g)}{zL} &< \beta \leq \frac{(z + 0.08)(L_r + zh_g)}{zL} & (0.15 \leq z \leq 0.3) \\ \beta &\geq 1 - \frac{(z + 0.25)L}{0.74(L_f - zh_g)z} & (0.3 \leq z \leq 0.8) \\ 1 - \frac{(L_f - zh_g)(\frac{z - 0.1}{0.85} + 0.2)}{zL} \leq \beta \leq \frac{(zh_g + L_r)(\frac{z - 0.1}{0.85} + 0.2)}{zL} & (0.2 \leq z \leq 0.8) \end{aligned}$$
(18)

3.2.2. Electromagnetic Torque Constraints

During regenerative braking, as shown in Equations (1) and (14), the electromagnetic torque, which affects the regenerative braking torque and the regenerative braking energy recovery efficiency, is simultaneously limited by the motor speed, battery *SoC*, and braking severity. Therefore, the electromagnetic torque can be defined as follows:

$$0 \le T_{ei} \le \min\left(T_{max}, T_{battery}\right) \tag{19}$$

where i = 1, 2; T_{max} is the maximum charge torque of the motor (Nm); $T_{battery}$ is the maximum rechargeable torque of the battery (Nm); and T_{max} and $T_{battery}$ can be obtained from Equations (20) and (21), respectively.

$$T_{max} = f_{T_e}(n)\eta_m \tag{20}$$

where *n* is the motor speed (r/min); $f_{T_e}(n)$ is the charging torque of the motors; $f_{T_e}(n)$ can be obtained from the relationship curve of *n* vs. $f_{T_e}(n)$ through interpolation method, and η_m can be obtained from the relationship curve of *n*, $f_{T_e}(n)$ vs. η_m , through interpolation method.

$$T_{battery} = T_{charging} \eta_{charging} \tag{21}$$

where $T_{charging}$ is the rechargeable torque of the battery (Nm); $\eta_{charging}$ is the rechargeable torque efficiency of the battery; $T_{charging}$ can be obtained using Equation (22) given below [26], and $\eta_{charging}$ can be obtained from the relationship curve of I_c vs. charging efficiency and the relationship curve of SoC vs. charging efficiency under a constant battery temperature using the interpolation method.

$$T_{charging} = \begin{cases} \frac{9550(E_{SoC} - I_c R_b)I_c}{n} & (0 \le SoC \le 0.3) \\ \frac{9550(\frac{0.85}{0.55} - S_{OC}(E_{SoC} - I_c R_b)I_c)}{n} & (0.3 < SoC \le 0.85) \\ 0 & (0.85 < SoC \le 1) \end{cases}$$
(22)

where E_{SoC} is the battery voltage (V); I_c is the charging current (A), and R_b is the internal resistance of the battery (Ω). E_{SoC} can be obtained from the relationship curve of SoC vs. E_{SoC} through the interpolation method. R_b can be obtained from the relationship curve of SoC vs. R_b through interpolation.

3.2.3. Other Constraints

The braking force of each wheel should be lower than the maximum road adhesive force.

$$\begin{cases} \frac{(T_{be1}+T_{bc1})}{R_e} \le F_{z1}\mu_{\max} \\ \frac{(T_{be2}+T_{bc2})}{R_e} \le F_{z2}\mu_{\max} \end{cases}$$
(23)

where μ_{max} is the maximum road adhesion coefficient.

3.3. Optimization Variables

The number of constraints and optimization variables must be decreased to reduce the difficulty of optimization. α , γ , and λ can be considered as the optimization variables based on the braking torque distribution strategy, and they are controlled within the range of 0 to 1.

3.4. Sample Points

The design space of the novel regenerative–mechanical coupled brake-by-wire system is a continuous space consisting of the vehicle speed *v*, battery *SoC*, and braking severity *z*. The continuous design space should be discretized into different sample points and be represented by finite sample points through the design of experiments to optimize the control parameters of the system at any braking condition. An optimal Latin hypercube design, which has a better space-filling performance and uniformity than other designs of experiments methods [27], was applied to select the sample points. Table 1 lists the selected sample points.

Sampling Points	SoC	<i>v</i> (km/h)	z
1	0.3251	72.986	0.0910
2	0.3263	83.968	0.1270
3	0.6377	91.824	0.2799
4	0.4357	99.279	0.1419
5	0.2962	72.665	0.1867
497	0.3347	60.160	0.1805
498	0.2733	97.916	0.0898
499	0.7747	87.094	0.2693
500	0.3034	99.679	0.2861

Table 1. Selected sample points.

According to Equations (17)–(22), some constraint parameters (i.e., T_{max} , $T_{battery}$, β_{opt} , β_{lower} , and β_{upper}) can be calculated based on the selected sample points in Table 1. The calculation results are used in the control parameter optimization process.

3.5. Collaborative Optimization

Two disciplines are established as follows to optimize the comprehensive braking performance:

min
$$f_1 = \left(\frac{\beta - \beta_{opt}}{\beta_{opt}}\right)^2$$
 and (24)

$$\min f_2 = \left(\frac{\eta_e - \eta_{opt}}{\eta_{opt}}\right)^2 \tag{25}$$

where min stands for the minimum of the objective function; Equation (24) is the optimum braking stability discipline, and Equation (25) is the maximum regenerative energy recovery efficiency discipline.

In the optimization process, the optimum braking stability and the maximum regenerative energy recovery efficiency are regarded as equal weights. Therefore, the system level can be defined as follows:

$$\min F = \left(\frac{\beta - \beta_{opt}}{\beta_{opt}}\right)^2 + \left(\frac{\eta_e - \eta_{opt}}{\eta_{opt}}\right)^2 \tag{26}$$

As Equations (1), (6)–(8), (10), (14), (24), and (25) show, the two disciplines and system level have the same variables (i.e., α , γ and λ). Accordingly, α , γ and λ are recorded as z_1 , z_2 and z_3 in the system level and x_1 , x_2 and x_3 in the discipline level, respectively, to distinguish the variables in the system level and disciplines. In addition, constraints (Section 3.2) are introduced in the optimization.

The mathematical model of the system-level optimization can then be described as follows:

$$\begin{cases} \min F(z_1, z_2, z_3) = \left(\frac{\beta - \beta_{opt}}{\beta_{opt}}\right)^2 + \left(\frac{\eta_e - \eta_{opt}}{\eta_{opt}}\right)^2 \\ S.t. \ G_i^*(z) \le \varepsilon, i = 1, 2 \end{cases}$$
(27)

where *S.t.* denotes the constraints that need to be satisfied; ε is controlled within the range of 0 to 10^{-6} , and $G_i^*(z)$ represents the consistency constraints.

The mathematical model for the optimization of the two disciplines can be established as follows:

$$\begin{array}{ll} \min & G_{1}(x_{1}, x_{2}, x_{3}) = (z_{1} - x_{1})^{2} + (z_{2} - x_{2})^{2} + (z_{3} - x_{3})^{2} \\ S.t. & 0 \leq x_{1}, x_{2}, x_{3} \leq 1 \\ & \beta \geq \frac{L_{r} + zh_{g}}{L} & (0 \leq z \leq 0.8) \\ & \frac{(z - 0.08)(L_{r} + zh_{g})}{zL} < \beta \leq \frac{(z + 0.08)(L_{r} + zh_{g})}{zL} & (0.15 \leq z \leq 0.3) \\ & \beta \geq 1 - \frac{(z + 0.25)L}{0.74(L_{f} - zh_{g})z} & 0.3 \leq z \leq 0.8 \\ & 1 - \frac{(L_{f} - zh_{g})(\frac{z - 0.1}{zL} + 0.2)}{zL} \leq \beta \leq \frac{(zh_{g} + L_{r})(\frac{z - 0.1}{0.85} + 0.2)}{zL} & 0.2 \leq z \leq 0.8 \end{array}$$

and

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\end{array} & G_2(x_1, x_2, x_3) = (z_1 - x_1)^2 + (z_2 - x_2)^2 + (z_3 - x_3)^2 \\
\end{array} \\
\begin{array}{ll}
\begin{array}{ll}
\end{array} & S.t. & 0 \leq x_1, x_2, x_3 \leq 1 \\
\end{array} & 0 \leq T_{bei} \leq \min\left(T_{max}, T_{battery}\right) \\
\begin{array}{ll}
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\begin{array}{ll}
\end{array} & \left(\frac{T_{be1} + T_{bc1}}{R_e}\right) \leq F_{z1}\mu_{max} \\
\end{array} \\
\begin{array}{ll}
\begin{array}{ll}
\end{array} & \left(\frac{T_{be2} + T_{bc2}}{R_e}\right) \leq F_{z2}\mu_{max}
\end{array}
\end{array}$$
(29)

where Equation (28) is the mathematical model for the optimization of the optimum braking stability discipline, and Equation (29) is the mathematical model for the optimization of the maximum regenerative energy recovery discipline.

The two disciplines have the same variables (i.e., α , γ and λ); hence, if any variable changes, the two disciplines will change at the same time. Whether they will simultaneously reach an optimum state under complicated constraints is a key point in this study. A collaborative optimization algorithm was selected to solve the optimization problem. Figure 2 shows the collaborative optimization algorithm for the novel regenerative–mechanical coupled brake-by-wire system.



Figure 2. Collaborative optimization algorithm.

As shown in Figure 2, the collaborative optimization algorithm consists of a system level and two disciplines. Adaptive simulated annealing, which has the advantages of better identification of local optimal solutions, a high convergence speed, and low requirements for initial conditions [28], was applied in this study because of the strongly nonlinear characteristic of the mathematical model.

In the optimization process, the system variables (z_1, z_2, z_3) that exist as fixed values in each discipline level are sent from the system level to the discipline level. Based on the system variables, the shared variables (x_1, x_2, x_3) , which are satisfied by the constraints and objects of each discipline, are determined via optimization in each discipline. The object of each discipline, which is calculated using shared variables, is then sent to the system level and exists as fixed values in the system level. If the object of each discipline satisfies the consistency constraints and the object of the current system level satisfies the convergence condition, the optimization will be terminated, and the optimal values will be exported; otherwise, the system level will resend the system variables to the discipline level.

4. Deep Learning Control Algorithm

In the design space consisting of the vehicle speed *v*, battery *SoC*, and braking severity *z*, each parameter in the sample points has a large changing range, and a strong nonlinearity exists between the optimization results and the corresponding sample points. Therefore, compared to conventional methods, such as the response surface, neural network, and Kriging, the deep learning method is more suitable for the development of a vehicle braking control algorithm [29] based on the novel regenerative–mechanical coupled brake-by-wire system. By building a network model with multiple hidden layers, the in-depth characteristics of the optimization results and the corresponding sample points are analyzed through deep learning. Hence, the deep learning control algorithm can be obtained based on the in-depth characteristics.

Aiming at the novel regenerative–mechanical coupled brake-by-wire system, a deep learning network with an input layer, an output layer, and three hidden layers was built with the design of experiment sample points treated as input parameters and the optimization variables treated as output parameters. Each hidden layer had 10 nodes. The input and output layers had three nodes. Through bottom-to-top supervised learning, the multiple-layer characteristics of the input data will be represented in the form of weight values. The input parameters (v, z, and SoC) were then

forward-propagated to build the deep learning control algorithm. The optimization parameters $\hat{\alpha}$, $\hat{\gamma}$, and $\hat{\lambda}$ were calculated based on the deep learning control algorithm, and can be expressed as follows:

$$\begin{bmatrix} \hat{a} \\ \hat{\gamma} \\ \hat{\lambda} \end{bmatrix}^{T} = \begin{pmatrix} \begin{pmatrix} \begin{pmatrix} \begin{bmatrix} SoC \\ z \\ v \end{bmatrix}^{T} \\ +b_{1} \\ +b_{2} \\ +b_{3} \\ +b_{4} \end{pmatrix} w_{2} \\ \end{pmatrix} w_{3} \\ w_{4} \\ w_{5} + b_{5} \end{cases} w_{5}$$
(30)

where w_1 is the 3 × 10 weight matrix; w_2-w_4 are the 10 × 10 weight matrices; w_5 is the 10 × 3 weight matrix; b_1-b_4 are the 1 × 10 bias matrices, and b_5 is the 1 × 3 bias matrix.

Combining Equations (1)–(8) based on the optimization variables $\hat{\alpha}$, $\hat{\gamma}$, and $\hat{\lambda}$, \hat{I}_{L1} , \hat{I}_{L2} , \hat{F}_{s1} , and \hat{F}_{s2} can be expressed as follows:

$$\begin{cases}
\hat{I}_{L1} = \frac{\hat{\alpha}\hat{\gamma}mgzR_e}{2K_e} \\
\hat{I}_{L2} = \frac{\hat{\alpha}(1-\hat{\gamma})mgzR_e}{2K_e} \\
\hat{F}_{s1} = \left(\frac{\eta_1\hat{\alpha}\hat{\gamma}}{2R_c \tan(\alpha_s + \rho_s)} - \frac{(1-\hat{\alpha})\hat{\lambda}}{4i_c\mu_c R_p}\right)mgzR_e \quad (F_{N1} > F_{s1}) \\
\hat{F}_{s1} = \frac{\eta_1\hat{\alpha}\hat{\gamma}mgzR_e}{2R_c \tan(\alpha_s + \rho_s)} \quad (F_{N1} \le F_{s1}) \\
\hat{F}_{s2} = \left(\frac{\eta_1\hat{\alpha}(1-\hat{\gamma})}{2R_c \tan(\alpha_s + \rho_s)} - \frac{(1-\hat{\alpha})(1-\hat{\lambda})}{4i_c\mu_c R_p}\right)mgzR_e \quad (F_{N2} > F_{s2}) \\
\hat{F}_{s2} = \frac{\eta_1\hat{\alpha}(1-\hat{\gamma})mgzR_e}{2R_c \tan(\alpha_s + \rho_s)} \quad (F_{N2} \le F_{s2})
\end{cases}$$
(31)

where \hat{l}_{L1} and \hat{l}_{L2} are the braking currents on the left novel regenerative–mechanical coupled brake-by-wire system of the front and rear axles, respectively (A); and \hat{F}_{s1} and \hat{F}_{s2} are the elastic forces of the elastic element on the left novel regenerative–mechanical coupled brake-by-wire system of the front and rear axles, respectively (N).

5. Simulation Results and Discussion

A braking simulation of the vehicle, which had a novel regenerative–mechanical coupled brake-by-wire system, was realized under different braking conditions using the MATLAB[®]/Simulink[®] (the Mathworks Co., VersionR2013b, Natick, MA, USA) software program to verify the deep learning control algorithm.

The simulation conditions were set to ($v_{initial} = 60 \text{ km/h}$, $SoC_{initial} = 0.5$), ($v_{initial} = 60 \text{ km/h}$, $SoC_{initial} = 0.7$), ($v_{initial} = 40 \text{ km/h}$, $SoC_{initial} = 0.5$), and ($v_{initial} = 40 \text{ km/h}$, $SoC_{initial} = 0.7$) based on the common driving conditions of the target vehicle to compare the control parameters under different working conditions. The simulation process consisted of six braking processes. Each braking process had different braking severities of 0.05, 0.1, 0.15, 0.2, 0.3, and 0.4 (Figures 3–7). Table 2 lists the simulation parameters.

Tal	ole	2.	Simu	lation	paran	neters.
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Value	Parameter	Value
885	Coefficient of road adhesion	0.85
2.347	Initial speed of braking/(km/h)	40,60
0.54	Motor peak power/(KW)	11
1.103	Motor nominal speed/(r/min)	1500
1.244	Number of motor	4
0.304	Initial battery SoC	0.5, 0.7
	Value 885 2.347 0.54 1.103 1.244 0.304	ValueParameter885Coefficient of road adhesion2.347Initial speed of braking/(km/h)0.54Motor peak power/(KW)1.103Motor nominal speed/(r/min)1.244Number of motor0.304Initial battery SoC



Figure 3. Simulation results of *v* and *SoC*.

With the change of the braking severity, the trend of the vehicle velocity and the battery *SoC* are presented in Figure 3. As Figure 3 shows, during braking, the vehicle speed continuously decreases, and the battery *SoC* continuously increases. Compared with high initial *SoC* ($SoC_{initial} = 0.7$), at low initial *SoC* ($SoC_{initial} = 0.5$), the ability of recover electric energy is better, and the vehicle can recover more electric energy with higher initial braking speed. Furthermore, at high initial *SoC*, the initial braking speed has little effect on the regenerative braking energy recovery.



Figure 4. Simulation results of α , γ , and λ .



Figure 5. Simulation results of η and β .



Figure 6. Simulation results of *I*.



Figure 7. Simulation results of *F*.

Figure 4 shows the trend of the optimization variables α , γ , and λ during braking. At high initial *SoC* and high initial braking speed ($v_{initial} = 60 \text{ km/h}$), based on the characteristics of the in-wheel motor and the battery in the target vehicle, the proportion of the total regenerative braking torque in the overall braking torque is lower, and the proportion of the regenerative braking torque between the front axle and rear axles is higher. Moreover, under other conditions, these two proportions change only to a small extent. The vehicle speed and the *SoC* have little effect on the proportion of the friction braking torque between the front and rear axles.

Figure 5 presents the braking energy recovery efficiency and the braking torque distribution. Figures 6 and 7 illustrate the control parameters *I* and *F*, respectively. As Figure 5 shows, the change in the vehicle speed has an impact on the regenerative braking energy recovery efficiency. Based on the characteristics of the in-wheel motor and the battery in the target vehicle, it has a regenerative braking energy recovery efficiency higher than 60 km/h, when the vehicle initial braking speed reached 40 km/h. At the low initial *SoC*, the vehicle has a higher regenerative braking energy recovery efficiency than the high initial *SoC*. In the entire braking process, the braking force distribution coefficient is close to the optimum value in the specified range, and the vehicle has good braking stability. Figures 6 and 7 show that based on the novel regenerative–mechanical coupled brake-by-wire system, the regenerative braking current of the motor and the elastic force of the elastic element can be realized through optimization variables α , γ , and λ .

As Figures 3–7 show, during braking, the vehicle speed continuously decreased, and the battery *SoC* continuously increased. Compared to the current braking systems, in the novel regenerative–mechanical coupled brake-by-wire system, a dynamic matching between the regenerative braking torque and friction braking torque is realized by controlling the electromagnetic torque of the motor and the elastic force of the elastic element to maintain a high braking energy recovery

efficiency and a good braking stability. The entire braking system has a higher integration and a simpler structure.

The required braking torque can be entirely provided by the regenerative braking torque when the braking severity is low (z = 0.05). At the same time, friction braking is not part of the braking process, and the vehicle had a high braking energy recovery efficiency. With an increasing braking severity, the regenerative braking torque cannot provide the required braking torque, and friction braking starts to occur. At this time, determining the control parameters that can maintain a good comprehensive braking performance using conventional optimization methods is difficult. However, based on the collaborative optimization algorithm, the target vehicle has a high energy recovery efficiency and a braking force distribution coefficient close to the optimum value in the specified range. Ultimately, during the entire braking process, the deep learning algorithm was developed based on the collaborative optimization algorithm. The deep learning algorithm was obviously superior to the conventional methods.

The multiple correlation coefficient (R²) was used to evaluate the accuracy of the control parameters obtained using the deep learning control algorithm. The R² values of $\hat{\alpha}$, $\hat{\gamma}$, and $\hat{\lambda}$ were 0.9889, 0.9817, and 0.9912, respectively.

A relative error between the control parameters of the deep learning control algorithm and the online optimization values (α_0 , γ_0 , λ_0) is defined to better evaluate the effectiveness of the deep learning control algorithm:

$$\begin{cases} S_{\alpha} = \left| \frac{\alpha_0 - \hat{\alpha}}{\alpha_0} \right| 100\% \\ S_{\gamma} = \left| \frac{\gamma_0 - \hat{\gamma}}{\gamma_0} \right| 100\% \\ S_{\lambda} = \left| \frac{\lambda_0 - \hat{\lambda}}{\lambda_0} \right| 100\% \end{cases}$$
(32)

where S_{α} , S_{γ} , and S_{λ} are the relative errors of α_0 , γ_0 , and λ_0 , respectively.

Figure 8 shows that compared to conventional methods [18,19], a smaller relative error can be found between the control parameters of the deep learning control algorithm and the online optimization values. The maximum value of the relative error was only 3.89%, which was within the expected error by 5%. The online optimization simulation required 43.7 h. However, the simulation based on the deep learning control algorithm required 6.9 s. The deep learning control algorithm can solve the poor real-time performance problem of the online optimization.



Figure 8. Relative errors between the deep learning control algorithm and the online optimization simulations.

Hence, the deep learning control algorithm has a higher control precision than the conventional methods and a better real-time performance than the online optimization.

6. Conclusions

A deep learning control algorithm based on the novel regenerative–mechanical coupled brake-by-wire system was proposed herein. The main concluding remarks are as follows:

- (1) (A coupled braking mathematical model was built based on the novel regenerative-mechanical coupled brake-by-wire system. A braking torque distribution strategy involving regenerative braking and friction braking was also presented under a certain braking severity. Compared to the current braking systems, the novel regenerative-mechanical coupled brake-by-wire system had a higher integration and a simpler structure.
- (2) To achieve an optimal braking performance, an optimization model was established based on collaborative optimization theory. In this model, the comprehensive braking performance of the vehicle was treated as the object of the system level, and the braking stability and the regenerative energy recovery efficiency were treated as two disciplines. Optimal control parameters were then obtained based on the novel regenerative–mechanical coupled brake-by-wire system by coordinating the two objectives of the optimal braking stability and the optimal regenerative braking energy recovery efficiency.
- (3) By building a deep learning network, the deep learning control algorithm was developed using the in-depth characteristics of the sample points and the offline optimization results to obtain a higher control precision than the conventional methods.
- (4) The deep learning control algorithm can solve the problem of the poor real-time performance observed in online optimization. Hence, the deep learning control algorithm has a considerable application potential.

The results of this study demonstrated the characteristics of the novel regenerative-mechanical coupled brake-by-wire system and confirmed the feasibility of this system. This system offers an improved system integration and a simpler structure for use in EVs compared to the current braking systems. The deep learning control algorithm developed herein can serve as an important reference for manufacturers and researchers aiming to achieve optimal comprehensive braking performance in EVs with high control precision and good real-time performance.

The normal deceleration process was discussed herein. Considering emergency braking conditions, a deep learning control algorithm with a wider applicability will be studied in the future. Methods for reducing the error between the control parameters of the deep learning control algorithm and online optimization values will also be studied.

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