A hybrid damping control strategy for high-speed trains running on existing tracks

Yi Wu, Jing Zeng, Huailong Shi, Bin Zhu and Qunsheng Wang

Abstract
With the rapid development of railways in China, effective coordination of the operation of high-speed trains on existing tracks can bring significant economic benefits to railway transportation. However, high-speed trains running on existing tracks will have to cope with larger track irregularities and navigate smaller curve radii, potentially increasing their vibrations. In order to improve the quality of operation of high-speed trains on existing railways, a self-adjusting hybrid damping control (SAHDC) strategy utilizing a fuzzy controller is adopted in this study. A secondary lateral magneto-rheological damper (MRD) is controlled to balance the vibration between the car body, bogie, and wheelset. The MRD behavior is described using a viscoelastic-plastic (VEP) model and nonlinear autoregressive exogenous (NARX) inverse model. A dynamical vehicle model with 50 DOFs is constructed and simulated under different existing track conditions. The results show that the SAHDC can guarantee the required ride quality of the car body, while reducing the vibration of the bogie frame and wheelsets as much as possible during travel on straight and curved tracks and suppressing derailment on turnouts.

Keywords
High-speed train, existing track, self-adjusting hybrid damping control, magneto-rheological damper, fuzzy control

Introduction
Concern the interconnectivity, economics, and operational efficiency, the high-speed trains need to and have to be accommodated on the existing and newly built high-speed railway lines. This mixed-line operation leads to more complexity in vehicle operational environment, including diversified track irregularities, track geometries, turnouts, and rail profiles, etc. The track irregularities of existing railways are significantly more severer than those of the high-speed tracks,1 as a result, the wheel/rail interacting vibration and vehicle oscillations would be stronger under poor track conditions. The curve radii of the existing railways are also smaller than those of high-speed lines, which could lead to larger wheel-rail lateral forces and higher derailment risk. The divergences of operational environment on the existing railway and the high-speed railway obviously differ the vehicle dynamics characteristics. Thus, the two-stage suspension system of bogie are critical to isolate the excitations of the wheel/rail interaction from the car body, and the performance of the suspension system determines the running safety and ride comfort of the vehicle. Due to the ability limitation of passive suspension in vibration isolation, the high-speed train with a passive suspension shows insufficient adaptability to the track excitations as well as the operation modes. To solve this problem. Applying an active control on the suspension system is a feasible way to improve the operation adaptability of high-speed trains on various types of tracks. Both semi-active and full-active control suspension can be benefit to the vehicle dynamics performance, and they have been the topic in the railway industry for decades.

Significant progress has been made on researching the semi-active control strategy for railway vehicle due to their feasibility, reliability and practicability.2 Several strategies have been proposed to improve the vehicle dynamics performance. Sinha et al.3 applied the optimal control theory to the suspension system, and Williams4 compared several control
systems for active suspension. It is found that the optimal control theory propose a very efficient method of designing a regulator of an active suspension, however, this theory is difficult to be applied in a large system. Some researches showed that the lateral ride comfort of the vehicle could be improved by an adaptive prediction controller and an H∞ control algorithm. Due to their desirable response characteristics, magnetorheological dampers (MRDs) were proposed as actuators in control system. The skyhook (SH) damping control strategy is one of the most mature control algorithms and has been studied extensively. Improving the ride quality and reducing car body vibration are the main objectives of this control strategy, which reduces effectively the amplitude and root mean square (RMS) of the car body vibrations. Furthermore, its variant can also be applied to reduce the derailment risk. Gao et al. and Wang et al. studied the application of SH control method in special running condition, it is found that the SH control method had good performances under strong side wind and poor track irregularities conditions. Some other researches on the SH strategy have deeply improved the control algorithms. For example, in literature, car body velocity was replaced by the acceleration as the target parameter in the acceleration-driven-damper (ADD) strategy. A mixed strategy called SH-ADD was also developed by Savarese, the results showed that the SH-ADD algorithm had similar feature of the behavior of SH and ADD methods and reduced the vibration amplitude in a wider frequency bandwidth. Other researchers conducted quarter-car experimental models to study the groundhook (GH) control and hybrid damping control (HDC) method, which combining the SH and GH control. The results show that the traditional SH damping control strategy can only suppress the low-frequency vibrations of the car body, thus a modified SH-ADD control strategy is adopted to reduce the car body vibrations in a wide frequency range. However, this strategy inevitably amplifies additional force on the bogie, which enhance the vibration of the bogie, especially for high-speed vehicles running on poor-condition tracks. The vehicle vibrations under a fixed value of hybrid damping coefficient were analyzed, while literature rarely focuses on the relationship between the required hybrid damping coefficient and vehicle vibrations, even though a fixed coefficient is not optimal for variability of existing lines.

In this investigation, a HDC control strategy for both enhancing the ride quality and the hunting stability of a high-speed train is proposed when it is operated on various railways. The proposed self-adjusting HDC (SAHDC) strategy combines the SH-ADD and GH control to restrain the vibration on the car body but also on the bogie, and the adjusting damping coefficients are adjusted through using a fuzzy controller. The MRD model and its inverse model is described by a viscoelastic-plastic (VEP) model and nonlinear autoregressive exogenous (NARX) inverse model, respectively. The paper is organized as follows. First, the models for an existing track, high-speed train dynamics, and MRD are introduced. Then, the control system model is established using the SAHDC control strategy and numerical experiments on its performance are conducted, which apply the novel strategy to a vehicle system operating in typical existing railway conditions.

| Item                               | Value  | Unit   |
|------------------------------------|--------|--------|
| Car body mass, $m_c$               | 39     | t      |
| Car body roll moment of inertia, $I_{cx}$ | 87.75  | t·m²   |
| Car body pitch moment of inertia, $I_{cy}$ | 1451.19 | t·m²  |
| Car body yaw moment of inertia, $I_{cz}$ | 1404   | t·m²   |
| Bogie frame mass, $m_b$            | 2.789  | t      |
| Bogie frame roll moment of inertia, $I_{tx}$ | 1.846  | t·m²   |
| Bogie frame pitch moment of inertia, $I_{ty}$ | 1.205  | t·m²   |
| Bogie frame yaw moment of inertia, $I_{tz}$ | 2.792  | t·m²   |
| Wheelset mass, $m_w$               | 1.728  | t      |
| Primary longitudinal stiffness, $k_{xp}$ | 13.700 | kN·m⁻¹ |
| Primary lateral stiffness, $k_{yp}$ | 5490   | kN·m⁻¹ |
| Primary vertical stiffness, $k_{zp}$ | 1280   | kN·m⁻¹ |
| Primary vertical damping, $c_{zp}$ | 9.8    | kN·s·m⁻¹ |
| Secondary longitudinal stiffness, $k_{xs}$ | 164    | kN·m⁻¹ |
| Secondary lateral stiffness, $k_{xs}$ | 167    | kN·m⁻¹ |
| Secondary vertical stiffness, $k_{zs}$ | 241    | kN·m⁻¹ |
| Secondary longitudinal damping, $c_{xs}$ | 2500   | kN·s·m⁻¹ |
Vehicle and suspension modelling

Multibody model of high-speed vehicle system

The vehicle is modeled using multibody dynamics software SIMPACK based on the parameters of a high-speed train listed in Table 1. The model is assumed to comprise 15 rigid bodies (including a car body, two bogie frames, eight axle boxes, and four wheelsets) and 50 degrees of freedom (DOFs). The car body, bogie frames, and wheelsets have six DOFs each that allow for free movements and rotations in the longitudinal, lateral, and vertical directions, while the axle box can only rotate around the wheelset axis. The wheelsets are connected to the bogie frame through the primary suspension, represented by spring and damper elements, and the bogie frame is constrained to the car body by the secondary suspensions, in which air springs, traction rods, and lateral, vertical and yaw dampers are used. The original passive secondary lateral dampers are replaced by semi-active MRDs modeled in MATLAB/Simulink. A co-simulation model is established using the SIMPACK and MATLAB/Simulink interaction module, as shown in Figure 1.

To validate the vehicle model, the natural frequency of rigid motions of car body are calculated and compared to the experimental results tested in laboratory, as shown in Table 2. Considering the five rigid modes, the maximum error of the natural frequency between the tested and simulated results is less than 8%, which proves that the numerical model is accurate and reliable.

Magnetorheological damper model

In this paper, the viscoelastic-plastics (VEP) model is adopted to describe the MRD, which has fewer parameters and higher accuracy compared to the conventional Spencer and Pang viscoelastic-plastic models. The model is shown in Figure 2 and can mathematically be described as follows

\[
F = k(I)(x - y) + c(I)y + f_c(I)\tanh(\alpha(I)y)
\]

where \(F\) is the MRD output force, \(k\) represents the stiffness coefficient in the pre-yield region, \(c\) is the damping coefficient in the post-yield region, \(f_c\) is the yield force, \(\alpha\) is the restoring coefficient, and \(I\) is the current.

The variable model parameters, \(k, c, f_c\), and \(\alpha\), are functions of the current and can be expressed as follows.

---

Figure 1. Co-simulation model of vehicle with semi-active lateral suspension control.
in which $f_a$, $f_b$, $c_a$, $c_b$, $k_a$, $k_b$, $b$, $a_a$, $a_b$ are parameters defined and initialized in Table 3.

The MRD was tested to determine its characteristics using an MTS 810 Material Testing Systems at Hong Kong Polytechnic University. The maximum and minimum length of the MRD was 587 mm and 433 mm, respectively, and the test conditions are listed in Table 4.

Figure 3(a) shows the analytical and experimental MRD force-velocity relationships for different currents, from which it can be seen that the force increases with the rise of control current $I$. The analytical results are similar to the experimental ones, which demonstrates that the model parameters are suitable for simulating the MRD. Figure 3(b) shows the VEP model can accurately describe the hysteresis loop characteristics of the MRD, in which the force increases with the rise in the excitation frequency.

In this work, a nonlinear autoregressive exogenous (NARX) neural network model is proposed to determine the MRD inverse model. The NARX is a dynamic neural network, which has several advantages compared to the static neural network, such as memory ability and capability to approximate nonlinear functions. The NARX neural network is composed of a time delay layer, input layer, hidden layer, and output layer, and can be expressed as follows

$$f(I) = f_{ca}I + f_{cb}$$
$$c(I) = c_{ca}I + c_{cb}$$
$$k(I) = k_a \tanh(bl) + k_b$$
$$a(I) = a_{ca}I + a_{cb}$$

The MRD force can be acquired for random normally distributed currents and piston displacements. The displacement and damping force of the damper are set as inputs, while the current is the output of the model. The maximum amplitude of the displacement is set as 2 mm, and maximum frequency and amplitude of the input current as 5 Hz and 2 A, respectively. The simulation time of VEP model is 30 s at 1000 Hz. The numbers of training, verification, and test samples are 21,000 (70%), 4500 (15%), and 4500 (15%), respectively. The input and output values are assumed from 0 to three and 0–2 unit time delays, respectively, and the number of hidden layer neurons is assumed from 3 to 15. The activation functions of the hidden and output layer are the Tansig and Purelin functions, respectively.

Table 2. Comparison of experimental and simulated modes of car body rigid motions.

| Modes       | Frequency (Hz) | Test | Simulation | Relative error, % |
|-------------|----------------|------|------------|-------------------|
| Lower swaying | 0.60          | 0.55 | 7.33       |
| Bounce motion | 0.76          | 0.75 | 1.97       |
| Pitch motion  | 1.05          | 1.04 | 1.52       |
| Yaw motion   | 1.14          | 1.06 | 6.68       |
| Upper swaying| 1.56          | 1.52 | 2.63       |

Figure 2. VEP model of an MRD.
Because random initial values are used in the neural network, 10 sets of displacements and forces from the VEP model are selected to assess the trained models. The correlation coefficient, \( R \), and RMSE are defined to evaluate the results

\[
R = \frac{\sum_{i=1}^{n} (y_i - \bar{y})(a_i - \bar{a})}{\sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2} \sqrt{\sum_{i=1}^{n} (a_i - \bar{a})^2}}
\]

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - a_i)^2}{n}}
\]

where \( y_i \) and \( a_i \) are the predicted and actual currents, and \( \bar{y} \) and \( \bar{a} \) are the average values of the predicted and actual currents, respectively. Model evaluation results are shown in Figure 4.

Figure 4(a) and (b) indicate that a larger input delay and a smaller output delay can be beneficial for accurate MRD modelling. Thus, the parameters of the MRD inverse model are selected as follows: input delay as 3, output delay as 0, and number of hidden layer neurons as 15. The maximum correlation coefficient, \( R \), of the 10 random datasets is 99.19%, while the minimum one is 98.83%. The predicted and actual currents are shown in Figure 5, which proves that the trained neural network agrees very well with the analytical MRD inverse model.

### Control strategy and algorithm

#### Mixed SH-ADD control strategy

To analyze the performance of the proposed control strategies, a simplified quarter-car vehicle lateral dynamic model with two DOFs is formulated as depicted by Figure 6(a), whose mathematical model is as follows

\[
\begin{bmatrix}
    m_c & m_b \\
    \dot{y}_c & \dot{y}_b
\end{bmatrix}
\begin{bmatrix}
    \ddot{y}_c \\
    \ddot{y}_b
\end{bmatrix}
+ \begin{bmatrix}
    c_{xy} & -c_{xy} \\
    -c_{xy} & c_{xy}
\end{bmatrix}
\begin{bmatrix}
    \dot{y}_c \\
    \dot{y}_b
\end{bmatrix}
+ \begin{bmatrix}
    k_{xy} & -k_{xy} \\
    -k_{xy} & k_{xy}
\end{bmatrix}
\begin{bmatrix}
    y_c \\
    y_b
\end{bmatrix}
= \begin{bmatrix}
    0 \\
    k_{sp}y_c
\end{bmatrix}
\]

where \( m_c \) is the quarter-car body mass, \( m_b \) is the half-bogie mass, \( c_{xy} \) and \( k_{xy} \) are the damping and stiffness of the secondary lateral suspension respectively, \( k_{sp} \) is the stiffness of the primary lateral suspension, and \( y_c \) and \( y_b \) are the lateral displacements of the car body and bogie, respectively. The corresponding parameters can be seen in Table 1.

The SH, ADD, and mixed SHADD control strategies are commonly used control algorithms to suppress the car body vibrations. Mathematically, they can be described as follows:

\[
F_{SH} = \begin{cases}
    C_{\text{max}}(\dot{y}_c - \dot{\bar{y}}_b) \quad \dot{y}_c(\dot{y}_c - \dot{\bar{y}}_b) \geq 0 \\
    C_{\text{min}}(\dot{y}_c - \dot{\bar{y}}_b) \quad \dot{y}_c(\dot{y}_c - \dot{\bar{y}}_b) < 0
\end{cases}
\]

\[
F_{ADD} = \begin{cases}
    C_{\text{max}}(\dot{y}_c - \dot{\bar{y}}_b) \quad \dot{y}_c(\dot{y}_c - \dot{\bar{y}}_b) \geq 0 \\
    C_{\text{min}}(\dot{y}_c - \dot{\bar{y}}_b) \quad \dot{y}_c(\dot{y}_c - \dot{\bar{y}}_b) < 0
\end{cases}
\]

### Table 3. MDR VEP model parameters.

| Parameter | Value | Unit | Parameter | Value | Unit |
|-----------|-------|------|-----------|-------|------|
| \( f_{ca} \) | 5.008 | kN/A | \( f_{cb} \) | 0.482 | kN |
| \( c_a \) | 3.994 | kN s/(m A) | \( c_b \) | 9.796 | kN s/m |
| \( \alpha_a \) | 20.008 | 1/A | \( \alpha_b \) | 17.498 | - |
| \( k_a \) | 4.903 | MN/m | \( k_b \) | 6.212 | MN/m |
| \( b \) | 1.909 | 1/A | — | — | — |

1262 Journal of Low Frequency Noise, Vibration and Active Control 41(3)
Table 4. MRD test conditions.

| Test group | Frequency $f$ (Hz) | Displacement amplitude $D$ (mm) | Velocity amplitude $V$ (m/s) | Current $I$ (A) | No.of cycles |
|------------|-------------------|--------------------------------|-----------------------------|----------------|--------------|
| 1          | 1                 | 5, 10, 16, 32                 | 0.03, 0.06, 0.1, 0.2       | 0, 0.5, 1, 1.5, 2 | 20           |
| 2          | 2                 | 5, 8, 16, 24                  | 0.06, 0.1, 0.2, 0.3        | 0, 0.5, 1, 1.5, 2 | 20           |
| 3          | 3                 | 5, 10, 15                     | 0.1, 0.2, 0.3             | 0, 0.5, 1, 1.5, 2 | 15           |
| 4          | 4                 | 4, 8, 12                      | 0.1, 0.2, 0.3             | 0, 0.5, 1, 1.5, 2 | 15           |
| 5          | 5                 | 3, 6, 10                      | 0.1, 0.2, 0.3             | 0, 0.5, 1, 1.5, 2 | 15           |

Figure 3. Force-velocity relationships for (a) different currents and (b) various excitation frequencies.

Figure 4. Comparison of predicted and actual currents for different delays: (a) correlation coefficient $R$, and (b) RMSE.

Figure 5. Comparison of actual and predicted currents.
where $C_{\text{max}}$ (60 kNs/m) and $C_{\text{min}}$ (12 kNs/m) are the maximum and minimum values of damping coefficient, and $m=2\pi f$, in which $f$ is the SH-ADD crossover frequency. Symbols and and $\|$ represent logical AND OR operators, respectively. The SH, ADD, and mixed SH-ADD control strategies assume that a virtual damper connects the car body to the ‘sky’ (fixed wall) and reduces its vibrations. Because in reality there is no damper, its action is simulated indirectly by adjusting the damping value of a secondary lateral damper, and different adjustment criteria determine the effective operating frequency range of control strategies.

The variance gain is a conventional quantity used to verify the effectiveness of a control algorithm,\textsuperscript{14} and it is computed as follows

$$F_{\text{acc}}(j\omega) = \sqrt{\frac{1}{T} \int_{0}^{T} (\ddot{y}_c(t))^2 dt}$$

where $\ddot{y}_c$ is the car body acceleration, and $y_{cr}$ is the disturbance.

The car body variance gain under different control strategies are shown in Figure 7, which indicates that the SH control can effectively reduce the low-frequency vibrations, while the ADD control can provide a strong attenuation in the high-
frequency range. The mixed SH-ADD algorithm combines the advantages of the SH and ADD approaches and the car body vibrations can be further suppressed. Thus, the mixed SH-ADD control strategy is adopted to suppress the car body vibrations in this study.

**Modified hybrid control strategy**

As reported,\textsuperscript{17} the SH control strategy increases the bogie vibrations while restraining the car body vibrations, and the SH-ADD strategy has the same control characteristics. Thus, a modified hybrid control strategy is introduced to overcome this drawback. The SH-ADD and GH control strategies are naturally complementary and the car body vibrations can be reduced by the former while the bogie oscillations can be suppressed by the latter. The vehicle dynamic performance can be improved comprehensively by combining the two strategies, thus a modified hybrid damping control strategy combining the SH-ADD and GH algorithms is proposed as follows, which is shown in Figure 6(b)

\[
F_{\text{mix}} = \begin{cases} 
C_{\max} \left( \dot{y}_c - \dot{y}_b \right) & \left[ \dot{y}_c \leq m \dot{y}_c \wedge \dot{y}_c \left( \dot{y}_c - \dot{y}_b \right) > 0 \right] \lor \left[ \dot{y}_c > m \dot{y}_c \wedge \dot{y}_c \left( \dot{y}_c - \dot{y}_b \right) > 0 \right] \\
C_{\min} \left( \dot{y}_c - \dot{y}_b \right) & \left[ \dot{y}_c \leq m \dot{y}_c \wedge \dot{y}_c \left( \dot{y}_c - \dot{y}_b \right) \leq 0 \right] \lor \left[ \dot{y}_c > m \dot{y}_c \wedge \dot{y}_c \left( \dot{y}_c - \dot{y}_b \right) \leq 0 \right]
\end{cases}
\]

\[
F_{\text{gnd}} = \begin{cases} 
C_{\max} \left( \dot{y}_b - \dot{y}_c \right) \dot{y}_b \left( \dot{y}_b - \dot{y}_c \right) \geq 0 \\
C_{\min} \left( \dot{y}_b - \dot{y}_c \right) \dot{y}_b \left( \dot{y}_b - \dot{y}_c \right) < 0
\end{cases}
\]

\[
F_{\text{hybrid}} = a F_{\text{mix}} + (1 - a) F_{\text{gnd}}
\]

where \( \alpha \) is the hybrid damping coefficient, \( m \) is the empirical parameter, which can be found from the relationship \( k = \beta \ddot{y}_c + \gamma \) with \( \beta = 647.8 \) and \( \gamma = -18.3 \), and \( \ddot{y}_c \) is the car body lateral root mean square (RMS) acceleration in 10 s.\textsuperscript{22}

**Self-adjusting hybrid damping control strategy**

A previous study shows that larger values of the hybrid damping coefficient, \( \alpha \) (equation (10)) are beneficial for suppressing the motion of a sprung mass (car body), while smaller values of \( \alpha \) can effectively restrain the vibrations of an unsprung mass (bogie).\textsuperscript{23,24} However, the adjustment strategy of \( \alpha \) has not been studied. Due to time-varying nature of external excitation, a fixed \( \alpha \) cannot guarantee meeting the vibration suppression requirements when a high-speed train runs on an existing track, thus this paper proposes an adaptive hybrid damping control strategy utilizing a fuzzy controller.

The lateral acceleration RMS value of the car body and bogie frame are the inputs for the fuzzy controller and the value of \( \alpha \) can be obtained by a fuzzy rule. The universe of discourse of car body acceleration and bogie acceleration are [0.1,0.5] and [0.4,6.0], respectively, and both are quantified as NB (Negative Big), NM (Negative Middle), NS (Negative Small), ZO (Zero), PS (Positive Small), PM (Positive Middle), and PB (Positive Big). The universe of discourse of \( \alpha \) is [0,1], and is quantified into 11 levels: NU (Negative Ultra), NH (Negative High), NB, NM, NS, ZO, PS, PM, PB, PH (Positive High), and PU (Positive Ultra). The Mamdani method is adopted for fuzzy reasoning, in which the membership function is Gaussian and the back fuzzy control method is the centroid one. The fuzzy control rules are described in Table 5 and Figure 8.

| Bogie acceleration | Car body acceleration |
|-------------------|----------------------|
| NB                | ZO                   |
| NM                | ZO                   |
| NS                | ZO                   |
| ZO                | ZO                   |
| PS                | NB                   |
| PM                | NH                   |
| PB                | NU                   |

**Table 5. Fuzzy control rules.**
To verify the performance of the fuzzy controller, the relationships between acceleration, lateral Sperling index, and $\alpha$ are shown in Figure 9. The lateral accelerations of the car body and the bogie frame are normalized by multiplying the original data by 1/4 and 1/0.3, respectively.

Figure 9 shows that $\alpha$ is relatively large when the car body regular accelerations are larger than those of bogie, while $\alpha$ is relatively small when the opposite is true. This indicates that the fuzzy controller can efficiently adjust $\alpha$ based on the vehicle oscillations. The values of $\alpha$ when using the fuzzy controller is positively correlated to the ride index, which shows that the self-adjusting control algorithm can ensure the adequate suppression of frame lateral vibrations and improve the operating safety when the car body vibrations are small.

However, a high-speed train can be subjected to sudden lateral impacts while passing through existing track turnouts, because of the harder primary suspension used to ensure the vehicle stability. Nevertheless, the car body vibration is still small even if a small $\alpha$ is adopted when the turnout passing speed is low. Therefore, zero $\alpha$ value can be used when the speed is less than 50 km/h.

The SAHDC strategy, designed for the high-speed train running on existing tracks can be expressed as equation (11) and the following correction on the hybrid coefficient

$$
F_{\text{mix}} = \begin{cases} 
C_{\text{max}} \left( \ddot{y}_c - \ddot{y}_b \right) & \left[ |\dot{\ddot{y}}_c| \leq m |\dot{y}_c| & |\dot{\ddot{y}}_c - \ddot{y}_b| > 0 \right] \land \left[ |\dot{\ddot{y}}_c| > m |\dot{y}_c| & |\dot{\ddot{y}}_c - \ddot{y}_b| > 0 \right] \\
C_{\text{min}} \left( \ddot{y}_c - \ddot{y}_b \right) & \left[ |\dot{\ddot{y}}_c| \leq m |\dot{y}_c| & |\dot{\ddot{y}}_c - \ddot{y}_b| \leq 0 \right] \land \left[ |\dot{\ddot{y}}_c| > m |\dot{y}_c| & |\dot{\ddot{y}}_c - \ddot{y}_b| \leq 0 \right]
\end{cases}

F_{\text{gnd}} \begin{cases} 
C_{\text{max}} \left( \dot{\ddot{y}}_b - \ddot{y}_c \right) & \ddot{y}_b \left( \dot{\ddot{y}}_b - \ddot{y}_c \right) \geq 0 \\
C_{\text{min}} \left( \dot{\ddot{y}}_b - \ddot{y}_c \right) & \ddot{y}_b \left( \dot{\ddot{y}}_b - \ddot{y}_c \right) < 0
\end{cases}

F_{\text{hybrid}} = \alpha F_{\text{mix}} + (1 - \alpha)F_{\text{gnd}}

\alpha = \begin{cases} 
\alpha_{\text{fuzzy}} & v > 50 \\
0 & v \leq 50
\end{cases}

in which $\alpha_{\text{fuzzy}}$ comes from the fuzzy control algorithm to balance the level of vibrations of the car body and the bogie frame. Furthermore, the strategy also considers the turnout operation to restrain the wheelset lateral force and bogie lateral vibration.

**Numerical simulations and discussion**

The following numerical vehicle simulations use the SIMPACK model explained in *Multibody model of high-speed vehicle system*.

**Track geometry and irregularity**

There are three typical existing track geometries that need to be considered in simulations: tangent and curved track and the turnout. The tangent track has a length of 5000 m, and it is 300 m for the curved track. The radius of the circular track is
1500 m (referred as R1500) with a superelevation 175 mm on the outer rail. A transition track connects the tangent and curved track and has a length of 300 m. For the specific curve, its balancing passing through speed shall be 180 km/h. The turnout is type SC330, as shown in Figure 10. The passing speed is 45 km/h, and radius of turnout transition is 350 m. The track irregularities were measured on the Jinan-Qingdao line, one of the typical existing lines in China.

Tangent track case

The Sperling index, $W$, also referred to as the ride index, is widely used to evaluate the ride quality of railway vehicles. It is defined as follows

$$W = 3.57 \times 10^{-10} \frac{A^3}{f^2} F(f)$$

where $A$ is the vibration acceleration in m/s$^2$, $f$ is the vibration frequency in Hz, and $F(f)$ is the frequency weighting coefficient. The Chinese National Standard GB/T 5599-2019 declares that the Sperling index shall be calculated every 5 s. Its thresholds are 2.5, 2.75, and 3.0 for excellent, medium, and satisfactory ride comfort, respectively.

To examine the vehicle vibrations while running on an existing railway, the vehicle speed was set as 200 km/h and worn wheel profiles were used. In numerical simulations, four cases are compared, namely the passive suspension (no control), SH-ADD, GH and SAHDC control strategy on the lateral damper. Figure 11(a) shows that the Sperling index is reduced from 2.79 to 2.21 when the SH-ADD control strategy is adopted, both the peak and mean values are reduced by nearly 20%, and the ride comfort is improved from satisfactory to excellent. When the GH control is used, the peak value rises to 2.87 and exceeds that when passive suspension (no control) is applied. Using the SAHDC control, the ride index drops from 2.79 to 2.46, which proves that the SAHDC strategy can improve the ride quality significantly. Figure 11(b) shows that the car body lateral accelerations with SH-ADD damping control experiences the lowest and the RMS of acceleration is reduced by nearly 53% from 0.288 m/s$^2$ to 0.135 m/s$^2$. The improvement provided by the SAHDC is between SH-ADD and GH.
Figure 11. Comparisons between passive, SH-ADD, GH and SAHDC controls, (a) lateral Sperling index, (b) RMS of acceleration on car body and bogie frame, and (c) wheelset force and derailment coefficient on the tangent track.

Figure 12. Comparisons between passive, SH-ADD, GH and SAHDC controls, (a) lateral Sperling index, (b) RMS of acceleration on car body and bogie frame, and (c) wheelset force and derailment coefficient on the curve negotiation scenario.
strategies with a value of 0.209 m/s². The bogie lateral acceleration without control is 0.790 m/s² and the RMS rises from 0.697 m/s² to 1.093 m/s² when applying the GH and SH-ADD controls, while it is 0.907 m/s² for the SAHDC. The safety indices, wheelset lateral force and derailment coefficient, are shown in Figure 11(c). Among the four simulated cases, the SH-ADD control case has the maximum wheelset lateral force of 10.04 kN, and GH control experiences the minimum of 8.23 kN. While it is 9.46 kN for the SAHDC case, which is slightly larger than that for the passive case as 9.37 kN. The derailment coefficient is 0.112 for the SH-ADD control, and it falls by 16% from 0.112 to 0.094 when the $\alpha$ is reduced from one to 0. The derailment coefficient under SAHDC case is 0.105, close to that under passive case.

Based on the above comparisons, the SAHDC strategy can not only efficiently improve the ride quality but suppresses the aggravation of oscillations of the bogie frames and wheelsets as well when a high-speed train runs on existing tracks.

**Curve negotiation scenario**

Refer to the curved track geometry defined in *Track geometry and irregularity*, the vehicle speed is set as 180 km/h in the curve negotiation scenario and the simulated results are presented in Figure 12. Figure 12(a) demonstrates that the lateral Sperling index can be obviously enhanced by the SH-ADD control. However, when the GH is used the ride quality deteriorates to only satisfactory, while the index is also excellent for the SAHDC strategy. Figure 12(b) illustrates that, with respect to the RMS of acceleration of 0.232 m/s² under passive case, it drops by 44.2% to 0.129 m/s² by the SH-ADD control, rises to 0.254 m/s² under GH control, reduces to 0.178 m/s² for SAHDC. Whereas the acceleration on bogie rises by 22.5% from 0.620 m/s² under passive case to 0.760 m/s² under the SH-ADD control, while it is reduced to 0.547 m/s² by the GH control. The SAHDC has a value of 0.665 m/s², close to that under passive case. As plotted in Figure 12(c), The SH-ADD slightly deteriorates the wheelset lateral force and derailment coefficient compared to passive suspension, from 16.02 kN to 17.75 kN and 0.245 to 0.254, respectively. While they are reduced to 15.24 kN and 0.220 by the GH control. The SAHDC case shows similar but better results than that under SH-ADD control.

![Figure 13. Vibrations of vehicle passing through turnout with different control strategies: (a) derailment coefficient, (b) bogie frame lateral accelerations, and (c) car body accelerations.](image-url)
Vehicle running through turnout

Vehicle passage through a turnout is simulated and analyzed in this section using the previously introduced turnout geometry.

Two peaks in the derailment coefficient for passive suspension, 0.49 and 0.46, can be seen in Figure 13(a). The first peak of the derailment coefficient increases to 0.52 for the SH-ADD control but the second peak can be effectively suppressed. For the SAHDC control, as $\alpha$ decreases the first peak of derailment coefficient gradually decreases to 0.35, while the second peak gradually increases. The peak in the derailment coefficient caused by the impact of the strike against check rails at around 17.5 s is between 0.62–0.65, indicating that changing $\alpha$ values has no apparent effect on this peak. Furthermore, this spike in the derailment coefficient here is caused by the inner side of the right wheel striking the check rail and it will not lead to derailing during actual operation. Figure 13(b) shows that the bogie lateral acceleration is 6.459 m/s$^2$ when the vehicle with passive suspension enters the turnout, while the peak value rises to 7.464 m/s$^2$ for the SH-ADD control and decreases to 5.742 m/s$^2$ for the SAHDC. Figure 13(c) shows that the car body lateral acceleration peak caused by the impact of switch blade can reach 1.056 m/s$^2$, but can be suppressed by the SH-ADD control. For the SAHDC, when $\alpha$ is reduced to 0.5 the value increases to 0.851 m/s$^2$ and the peak reaches 1.103 m/s$^2$, which exceeds the value for the uncontrolled system. On the other hand, the car body lateral acceleration caused by the impact against the check rail is larger than the value when the vehicle enters the turnout. The lateral acceleration peak is 2.391 m/s$^2$, but can be reduced to 1.517 m/s$^2$ by the SH-ADD control. However, as $\alpha$ decreases, the peak value of the car body lateral accelerations can increase and even exceed the peak value without control, reaching 2.470 m/s$^2$ for the SAHDC.

This analysis shows that the SAHDC can also effectively reduce the derailment risk and partly suppress the lateral impact of the bogie frame compared to the other control strategies. However, the car body vibrations will worsen. While the turnout negotiation scenarios usually occur at low speed, 45 km/h for the examined case, the car body vibration is still acceptable.

Conclusions

Because the new high-speed and the existing tracks differ a lot, this paper developed a novel adaptive hybrid damping control strategy for the high-speed trains to satisfy the running vehicle performance requirements on different types of tracks. Compared to the previous approaches or control algorithms, the proposed SAHDC can adjust the value of hybrid damping coefficient and reduce the car body vibrations to an acceptable level. This algorithm works effectively on straight and curved tracks, without worsening the bogie and wheelset vibrations, and can adequately reduce the derailment coefficient when passing through a turnout. The novel control strategy can guarantee achieving the vibration suppression targets of the bogie frame while meeting the ride quality requirements. The following conclusions can be drawn from the presented work:

1. The VEP model can accurately describe the force-velocity relationship of the MRD. Compared to the conventional phenomenological model, the VEP model has fewer parameters with clear physical meanings. The NARX neural network model with appropriate parameters can simulate the MRD inverse model.
2. The SAHDC control strategy is proposed combining the mixed SH-ADD (instead of the conventional SH) and GH algorithms which adjusts the hybrid damping coefficient using a fuzzy controller to guarantee the vehicle running performance, such as vibrations of car body, bogie frame, and wheelset for high-speed vehicles running on existing tracks.
3. A high-speed vehicle model is formulated and verified. Using the model, the SH-ADD, GH and SAHDC strategies are studied. Compared to the other strategies, the SAHDC can effectively adjust the hybrid damping coefficient based on vehicle vibrations and can balance the high-speed vehicle ability to negotiate curves and turnouts on existing tracks while satisfying the ride comfort.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Natural Science Foundation of China (Grant No.U2034210), and the Independent Research and Development Project of the State Key Laboratory of Traction Power (Grants No. 2021TPL-T05).
References

1. Yang JL, Liu LY, and Kou DH. Wu Guang High-Speed rail track irregularity power spectrum analysis. *Appl Mech Mater* 2014; 638–640: 1224–1228.

2. Goodall RM and Kortum W. Active suspensions for railway vehicles. An avoidable luxury or an inevitable consequence? In: *Proceedings of the 11th Triennial World Congress of the International Federation of Automatic Control*. Tallinn, USSR: Publ by Pergamon Press Inc; 1991, pp. 465–471.

3. Sinha PK, Wormley DN, and Hedrick JK. Rail passenger vehicle lateral dynamic performance improvement through active control. *J Dynamic Syst Meas Control* 1978; 100: 270–283.

4. Williams RA. Active suspensions classical or optimal? *Vehicle Syst Dyn* 1985; 14: 127–132.

5. Chen CJ and Wang KY. Study on modeling of lateral semi-active suspension system of high-speed train. *J Vibration Shock* 2006; 25: 151–154+169.

6. Zong LH, Gong XL, Xuan SH, et al. Semi-active $H_{\infty}$ control of high-speed railway vehicle suspension with magnetorheological dampers. *Vehicle Syst Dyn* 2013; 51: 600–626.

7. Karnopp D, Crosby MJ, and Harwood RA. Vibration control using semi-active force generators. *J Eng Industry* 1974; 96: 619–626.

8. Sharma SK and Kumar A. Ride performance of a high speed rail vehicle using controlled semi active suspension system. *Smart Mater Structures* 2017; 26: 055026.

9. Ahmadian M and Pare CA. A quarter-car experimental analysis of alternative semiactive control methods. *J Intell Mater Syst Structures* 2000; 11: 604–612.

10. Guo KH, Sui JK, and Guo YH. Semi-active control method for a high-speed railway vehicle lateral damper based on skyhook and groundhook hybrid damping. *Zhendong Yu Chongji/Journal of Vibration and Shock* 2013; 32: 18–22.

11. Tan QX. Research on identification method of NARX model. *Diss Master Thesis*. Huazhong University of Science & Technology, 2019.