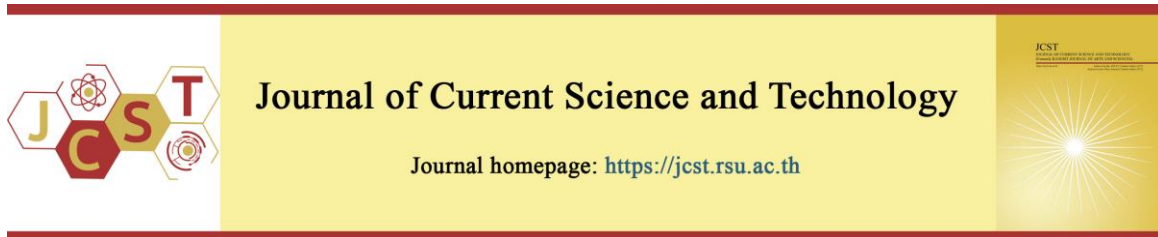


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Suspension Control Strategies for High-Speed Trains: A Comprehensive Review and Future Perspectives

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Abstract

The suspension system plays a crucial role in ensuring the smoothness, stability, and safety of high-speed trains. This paper provides a comprehensive overview of the development of passive, semi-active, and active suspension systems. Advanced intelligent control architectures, such as Proportional Integral Derivative (PID), Linear Quadratic Regulator/Gaussian (LQR/LQG), and Sliding Mode Control (SMC), are compared with modern approaches, specifically fuzzy logic control frameworks based on Particle Swarm Optimization (PSO), Adaptive Neural Networks (ANN), and Adaptive Nonlinear Control (ANC). The paper evaluates the advantages and disadvantages of each strategy by considering five core criteria: passenger comfort, vibration suppression capability, disturbance rejection, adaptability, and implementation complexity. The synthesis of results indicates that intelligent and adaptive controllers provide significant quantitative enhancements; for instance, a PSO-optimized hybrid Fuzzy-PID controller achieves a 42.8% reduction in root-mean-square (RMS) acceleration. Most notably, the ANC strategy attains the highest improvement, enhancing ride comfort by up to 68.2% compared with passive systems. Finally, future research directions are outlined, emphasizing the necessity of high-fidelity multi-physics modeling and the development of computationally optimized, data-efficient reinforcement learning frameworks directly integrated into fault-tolerant control loops.

Keywords: *adaptive and hybrid controllers, high-speed train suspension, intelligent control strategies, semi-active and active suspension, vibration suppression, reinforcement learning, magnetorheological damper*

1. Introduction

High-speed railway trains represent one of the most modern transportation systems, which are used extensively across numerous countries. **Figure 1** shows a 3D model of a typical high-speed train built by the authors using Inventor software. The development of high-speed rail is considered not only an indicator of national scientific and technological capability but also an important factor in promoting

economic growth and reducing urban traffic congestion (Shiao & Huynh, 2024). When operating at significantly high speeds, the ride quality is primarily compromised by vibrations induced by track surface irregularities, long-term damage from continuous wheel-rail interaction, and centrifugal forces during curve negotiation (He et al., 2020). Ensuring smoothness and comfort for passengers throughout the journey is an urgent requirement.

Several solutions have been proposed, such as improving track structure, maintaining a flat track surface, or selecting suspension systems equipped with appropriate damping components (Zhang et al., 2023). However, the key technology still mainly relies on the suspension system, which determines the ability to reduce multidirectional vibrations, maintain stability, and improve overall ride quality.

Railway suspension systems can be segmented into three types: passive, semi-active, and active systems (Liu et al., 2024). For a long time, passive systems were standard, relying on fixed spring and damper settings. While they provide reliability and cost-effectiveness, they are inflexible under different load and speed conditions. To address these concerns, research has shifted toward semi-active configurations, which provide adjustable damping forces. More recently, active suspension systems have emerged as the most advanced approach. Using an external energy source and an actuator, these systems can counteract positive and negative vibrations. With these advancements, it is possible to employ more advanced control systems to address the evolving requirements to increase speed and improve riding comfort.

The dynamic behavior of a train can be described in terms of three primary rotational motions, each affecting the vehicle's stability and passenger comfort in distinct ways.

- Yaw motion refers to the rotation of the train about its vertical axis, causing lateral deviation of the train nose. It is mainly influenced by aerodynamic forces (e.g., crosswinds) and track irregularities.

- Pitch motion is the rotation about the lateral axis, resulting in upward or downward movement of the front or rear of the train, typically affected by load distribution, acceleration/deceleration, and track profile variations.

- Roll motion is the rotation about the longitudinal axis, leading to lateral tilting of the train-body, primarily caused by lateral forces during curve negotiation, crosswinds, and centrifugal effects.

The selected active control approach is the primary determinant of the performance of contemporary suspension systems. These approaches involve control methods where sensor signal processing and the generation of corresponding command inputs for the actuators take place in both the semi-active and active suspension systems. While traditional control methods have established a reliable basis for vibration reduction, they often encounter limitations when applied to the strongly nonlinear dynamics of high-speed trains. To clarify these technical characteristics, particularly the distinction between model-based and model-independent strategies, active control methods investigated in recent years are summarized in **Table 1**.

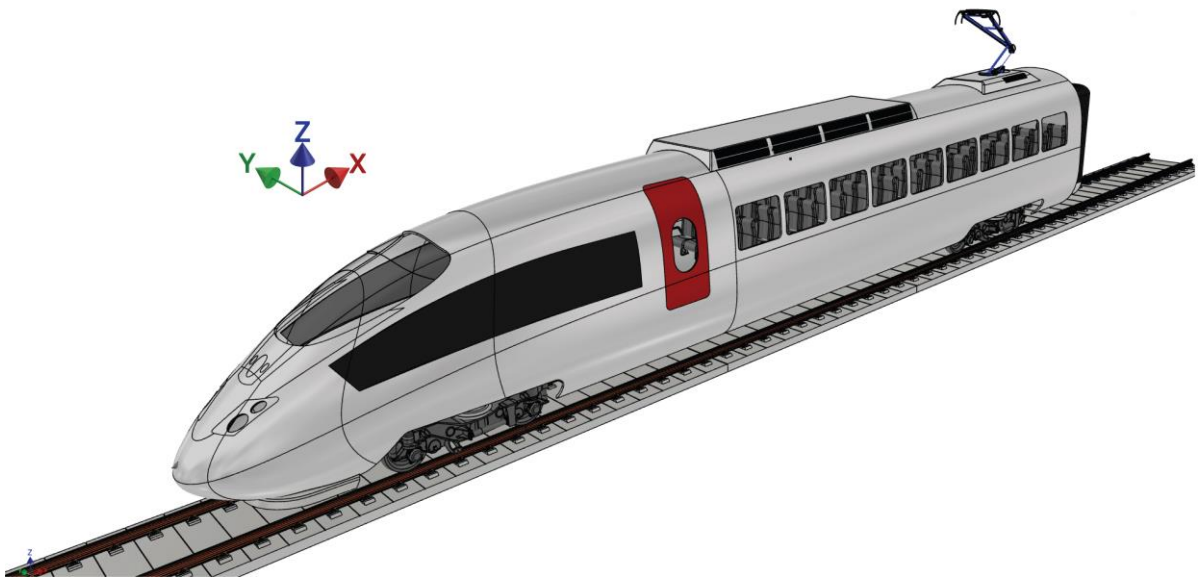


Figure 1 General 3D model of a high-speed train operating on a railway track

Table 1 Taxonomy of active control solutions and technical characteristics

Control Solution	References	Model Based	Model Independent	Nonlinear Handling	Adaptive Learning
Linear Quadratic Regulator/Gaussian (LQR/LQG)	Zhu et al. (2018)	√			
	Leblebici & Türkay (2018)				
	Zhao et al. (2026)				
Fuzzy Logic Control (FLC)	Koç (2020)		√	√	
	Sharma & Kumar (2018)				
	Tang & Ahmad (2025)				
Sliding Mode Control (SMC)	He et al. (2020)		√	√	
	Wijaya et al. (2024)				
	Tran et al. (2024)				
Fuzzy Proportional Integral Derivative (PID) based on Particle Swarm Optimization (PSO)	Jianjun et al. (2021)	√		√	√
	Qiu et al. (2021)				
Adaptive Neural Network (ANN) Control	Li et al. (2015)	√		√	√
	Peng et al. (2022)				
	Sun & Zhao (2020)				
Adaptive Nonlinear Control (ANC)	Zhang et al. (2024)	√		√	
	Qin et al. (2019)				
	Qin et al. (2021)				
Reinforcement Learning (RL)	Mou & Chen (2024)		√	√	√
	Dridi et al. (2023)				
	Deng et al. (2024)				

Recent years have witnessed extensive research into modern control strategies for high-speed train suspension systems. For semi-active suspensions, which are currently widely used in most high-speed trains, one notable example is the full-scale experimental study on ride comfort under lateral vibration in a CRH3 train equipped with a Magnetorheological (MR) damper, conducted by Alehashem et al. (2021). Their results demonstrated that replacing conventional dampers with MR dampers significantly reduces lateral train-body vibrations across all allowable speed ranges without causing instability. In addition, other studies have focused on analyzing and evaluating the reliability of semi-active suspension systems using MR dampers (Gutiérrez-Moizant et al., 2025; Tell et al., 2022). Other research has developed MR dampers integrated with machine learning techniques or additional mechanical support structures to further optimize vibration reduction in the train-body (Ferhath & Kasi, 2025; Hua et al., 2022). To improve control performance, He et al. (2020) proposed a Sliding Mode Control (SMC) strategy for semi-active suspensions and conducted simulations in MATLAB. The results indicated that this control method effectively handles vibrations induced by nonlinear disturbances. Overall, studies on semi-active suspension systems employing MR dampers show strong potential for improving and

stabilizing train-body vibrations under various operating conditions. However, because semi-active systems can only dissipate energy rather than actively inject it, their compensatory capacity remains inherently limited when mitigating severe, multidirectional vibrations caused by extreme track irregularities.

In response to the growing need for higher stability and improved ride comfort, active suspension systems in high-speed trains have become one of the most extensively studied topics in recent years. A representative study aimed at improving the dynamic performance of high-speed trains using active suspension was conducted by Stichel et al. (2023), who designed and tested an active control system and reported promising results in terms of ride comfort under active control. In addition, Jianjun et al. (2021) applied a Fuzzy-Proportional Integral Derivative (PID) control strategy combined with the Particle Swarm Optimization (PSO) algorithm to optimize parameters in an active suspension system, and simulations performed in MATLAB demonstrated improved vibration performance compared with several other methods. The Linear Quadratic Gaussian (LQG) approach has also been explored as a control strategy for active suspensions by Zhu et al. (2018), showing favorable results in terms of ride quality and operational stability in high-speed trains.

In summary, studies on active suspension systems show significant improvements in ride comfort, highlighting the strong potential for adopting advanced control technologies in future high-speed train suspension applications. Nevertheless, traditional model-based active controllers and standalone intelligent algorithms still face critical challenges, such as vulnerability to unmodeled nonlinear disturbances, chattering phenomena, and computational delays.

Several studies have provided evaluations and overviews of control strategies for high-speed train suspension systems. Notable examples include the reviews conducted by Zhang et al. (2023) and Fu et al. (2020), in which the authors describe the main issues, generic solutions, and performance characteristics of various vibration control techniques related to train speed. However, these review studies primarily focus on traditional or standalone control strategies, and remain insufficient in providing effective solutions to the aforementioned limitations of semi-active and active systems. Specifically, the existing literature remains limited in providing a fully comprehensive, multi-criteria comparative analysis of hybrid intelligent controllers. To bridge this research gap, this paper provides a rigorous comparative evaluation of these advanced control strategies, explicitly analyzing their trade-offs across five critical criteria: passenger comfort, vibration suppression, disturbance rejection, adaptability, and implementation complexity. The remainder of this paper is organized as follows: Section 2 defines the research objectives. Section 3 formulates the main control problems for the passive, semi-active, and active suspension systems and presents the mathematical models. The

evolution of control solutions, from mechanical control for stabilization to advanced intelligent control, is addressed in Section 4. Section 5 compares and contrasts the methods reviewed in terms of ride comfort and stability. Finally, Section 6 summarizes the main conclusions and outlines potential directions for future research.

2. Objectives

The primary aim of this study is to provide a comprehensive review of control strategies for high-speed train suspension systems, addressing the limitations of previous studies that focused mainly on traditional or standalone controllers. As visually mapped in the structural flowchart in **Figure 2**, the specific and measurable objectives of this paper are as follows:

- Synthesizing and classifying specific control algorithms: Systematically trace the evolution from traditional mechanical systems to modern active controllers, specifically detailing the architectures of standalone methods and advanced intelligent approaches.
- Evaluating control performance: Comprehensively assess the effectiveness of these strategies across five primary criteria: passenger comfort, vibration suppression capability, disturbance rejection, adaptability, and implementation complexity.
- Identifying research gaps and proposing future directions: Build upon the synthesis and comparative analysis conducted in this review to highlight existing limitations and propose novel research directions for the development of future suspension systems.

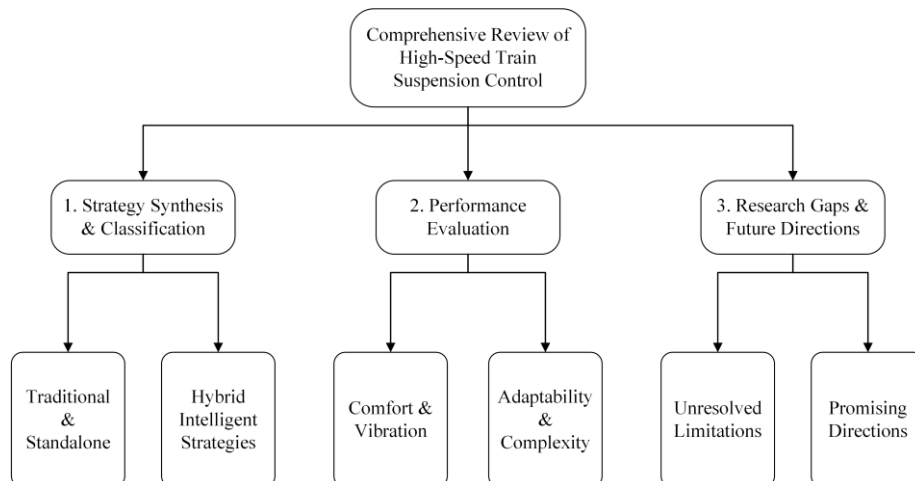


Figure 2 The overall framework and research objectives of this study

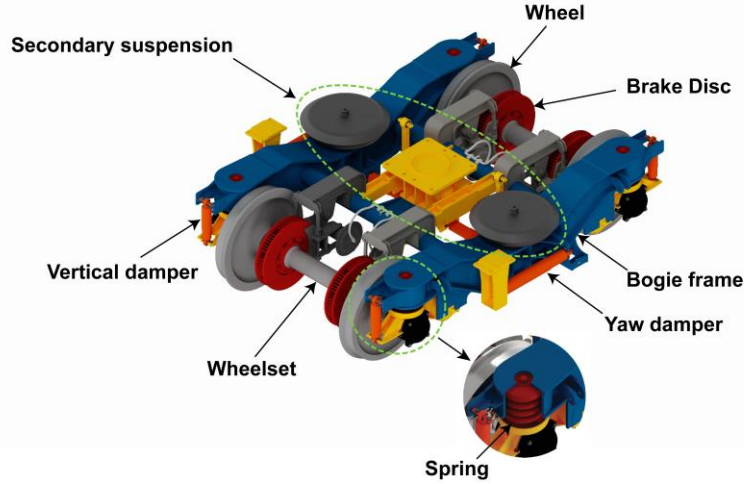


Figure 3 Overall structure of the suspension system integrated into the high-speed train bogie assembly

3. Suspension system and problem formulation

3.1 Suspension systems

The suspension system of a high-speed train is composed of two stages, as illustrated in the detailed component layout shown in **Figure 3**. The primary suspension connects the wheelset to the bogie through helical springs and vertical dampers, while the secondary suspension links the bogie to the train-body using air springs together with lateral dampers. Each suspension stage is designed with specific spring and damping characteristics to isolate vibration components at different frequency ranges (Fu et al., 2020). Based on their capability to adjust these characteristics in response to operating conditions, suspension systems are commonly classified into three categories: passive, semi-active, and active systems (Soliman & Kaldas, 2021).

Hunting stability in high-speed trains is significantly influenced by the interaction between the wheelsets, bogie, and train-body, which is typically mitigated by the combined effect of the primary and secondary suspension systems. In particular, the secondary suspension plays a crucial role in isolating the car-body from lateral and high-frequency vibrations. When the secondary suspension is removed, this isolation capability is significantly reduced, resulting in a more direct transmission of disturbances from the wheel–rail interface to the car-body. Consequently, the system becomes more sensitive to nonlinear disturbances such as track irregularities and aerodynamic effects, which may amplify lateral oscillations and induce hunting instability.

3.1.1 Passive Suspension System

The passive suspension system has the simplest structure, and its operating principle is based on the combination of a spring and a damper. Passive suspensions are not equipped with a controller and cannot adjust their parameters according to actual operating conditions. The spring and damper parameters are determined from the vibration equations derived using Newton's laws or the Lagrange method, in which the vertical motion of the suspended mass m , representing either the bogie or train-body is governed by the balance among the spring force, damping force, and base excitation displacement x_r originating from track irregularities or the lower suspension stage, as expressed in **Equation (1)** (Sun et al., 2022).

$$m\ddot{x} + c(\dot{x} - \dot{x}_r) + k(x - x_r) = 0 \quad (1)$$

Where $c(\dot{x} - \dot{x}_r)$ is the damping force, $k(x - x_r)$ is the spring restoring force, m is the sprung mass, c is the damping coefficient, k is the stiffness coefficient, x is the vertical displacement of the sprung mass, and x_r is the base excitation displacement.

The design and optimization of passive suspension systems based on track models have been investigated in several studies (Nguyen et al., 2008; Shieh et al., 2005). Because the spring and damper parameters are fixed according to the initial design, optimal vibration performance can be achieved only when actual operating conditions fall within the predefined range. Under crosswind effects, complex curved tracks, or uneven rail surfaces, the vibration stability of the train-body may be significantly

reduced. However, owing to their low cost and ease of maintenance, passive suspension systems are still widely used and are considered the foundation for the development of semi-active and active suspension systems (Jiang et al., 2015). The basic arrangement of these main components in both the primary and secondary stages is illustrated in **Figure 4a**.

3.1.2 Semi-active Suspension System

A more advanced version of the passive suspension is the semi-active suspension system. This system retains the structure of the passive suspension but is equipped with a controller that acts on the damper. As a result, the semi-active suspension can adjust the damping coefficient when the train operates under unfavorable conditions, thereby improving passenger ride comfort and enhancing train-body vibration stability during operation (Singh & Kumar, 2022). The damping force generated by this controllable component is expressed in **Equation (2)**, where the force varies according to the provided control signal. The detailed structural layout and arrangement of these components in the semi-active system are presented in **Figure 4b**.

$$F_d = c(i)(\dot{x} - \dot{x}_r) \quad (2)$$

Where F_d is the controllable damping force, and $c(i)$ is the variable damping coefficient governed by the control signal.

The variable parameters are crucial for maintaining train-body stability when the train encounters uneven tracks or enters curved sections. When an MR damper is integrated with control algorithms such as Skyhook or Linear Quadratic Regulator (LQR) in a semi-active suspension system, the resulting performance provides significantly better train-body stabilization than passive suspension systems. These improvements ensure that the train remains within safe operational limits and maintains high ride quality, even under varying and unpredictable track conditions.

3.1.3 Active Suspension System

The active suspension system has recently become a major focus of research, with many studies aiming to further develop and enable its practical application in the future (Dridi et al., 2023; Zhang et al., 2024). Unlike passive or semi-active suspension systems, this system actively generates control forces through an actuator, which directly influences the

vibration of the train-body. Accordingly, the dynamic equation of the active suspension system is expressed as follows:

$$m\ddot{x} + c(\dot{x} - \dot{x}_r) + k(x - x_r) = K_u \cdot u(t) \quad (3)$$

where $u(t)$ is the command signal generated by the controller, and K_u is the actuator gain.

The active suspension system distinguishes itself by incorporating an external control force to strictly regulate the vibration of the train-body. In **Equation (3)**, this active intervention is represented by the control component $K_u \cdot u(t)$, which produces the required force. The structure of the active suspension system is derived from the passive suspension system but is differentiated by the integration of an external power supply and a force-generating actuator. Unlike passive or semi-active setups that merely dissipate vibratory energy, the actuator is positioned to inject external energy into the system, generating dynamic counterforces that help suppress rotational or translational motions of the train-body. These active forces are precisely regulated based on real-time sensor feedback processed by the central controller. The general configuration of the active suspension system is illustrated in **Figure 4c**. Overall, the use of diverse actuation mechanisms such as hydraulic, pneumatic, and electromagnetic technologies enables the active suspension system to effectively control vibrations in multiple directions, making this approach highly suitable when the train passes through curved tracks or is subjected to strong crosswind forces. However, the system involves high installation costs and requires a continuous energy supply throughout operation. Consequently, the selection of an active strategy must balance the trade-off between high-level stabilization and operational energy consumption.

3.2 Comparison of Suspension Systems

As analyzed above, suspension systems are fundamentally classified into three main groups based on control strategy and energy consumption, passive, semi-active, and active suspension systems. This section presents a detailed comparison of the advantages and limitations of each control strategy, aiming to identify the most suitable methods for analysis in this study.

Table 2 provides an overview of the key characteristics, highlighting the benefits and limitations of each type of suspension system for high-speed trains.

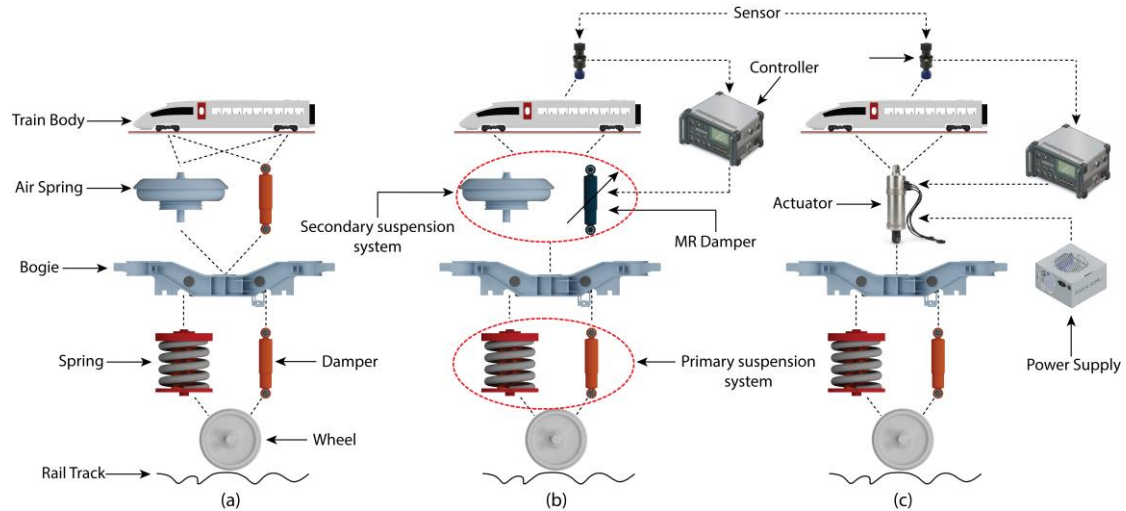


Figure 4 Schematic diagrams of suspension systems for high-speed trains: (a) Passive; (b) Semi-active; and (c) Active

Table 2 Comparison of suspension systems

Type	Control Strategy	Advantages	Limitations
Passive Suspension	Fixed spring and damper parameters (no control applied)	- Simple structure. - Low cost. - High reliability. - Easy maintenance.	- Unable to adapt to changing operating conditions. - Poor vibration-reduction performance at high speeds. - No real-time adjustability due to the absence of a control mechanism.
Semi-active suspension	Intelligent controllers that can vary damping characteristics (Magnetorheological (MR) damper, Electrorheological (ER) damper, SMC)	- Improved performance compared to passive suspension. - Lower energy consumption than fully active systems.	- Cannot generate active control forces. - Performance still depends on initial design conditions. - Difficult to optimize under strong nonlinear behaviors.
Active suspension	Fully controlled by actuators (Fuzzy-PID, PSO, SMC, LQG, ANN)	- Superior vibration-reduction capability. - Able to actively generate forces to stabilize the car-body. - Highly effective under harsh operating conditions (crosswind, curved tracks).	- Complex structure. - High installation and maintenance costs. - Requires high power input and advanced control algorithms.

As indicated in **Table 2**, passive suspension systems exhibit a high degree of reliability. However, their efficiency is not maximized when trains operate at elevated speeds. Owing to the fixed nature of the elasticity and damping parameters, optimal ride quality and train-body safety are not achieved in conditions involving curves or strong crosswinds. In contrast, active suspension systems are regarded as the ideal solution for high-speed trains because of their enhanced vibration control capabilities and their proficiency in actively mitigating random oscillations

produced during multidirectional operations, thus ensuring improved stability and operational safety. Nonetheless, considerable limitations remain regarding the extensive implementation of these systems in the future, primarily related to substantial energy demands as well as significant investment and maintenance expenses.

Currently, semi-active suspension systems are viewed as a compromise and are implemented extensively in contemporary rail vehicles. Through these systems, damping properties can be modified

based on operating conditions. Improved vibration mitigation, compared with passive systems, is achieved, while safety mechanisms are maintained during malfunctions. Nevertheless, optimal minimization of multidirectional vibrations affecting the train-body has not been accomplished by semi-active suspension systems, as is achievable with active systems. Consequently, this study synthesizes and analyzes advanced control strategies from earlier investigations into semi-active and active suspension systems, with an emphasis on assessing train-body stability and vibration-reduction effectiveness.

3.3 Problem Formulation

The introduction of passive, semi-active, and active suspension systems has been extensively researched and applied in high-speed trains to optimize operational efficiency. However, due to the unpredictable interactions between track perturbations and high-speed aerodynamic drag, it remains extremely difficult to fully and reliably control train-body vibrations. Contemporary engineering must overcome these nonlinearities in track parameters and other perturbations while maintaining a delicate balance between system stability and passenger comfort. Therefore, the primary challenges systematically analyzed in this study to overcome these technical barriers can be described as follows:

3.3.1 Problems of the Mechanical Structure

The dynamic behavior of high-speed train suspension systems is fundamentally governed by the interaction between mechanical components and external excitations. To formulate the control problem, the dynamic model is generally represented

in the form shown in **Equation (4)**, where F_a denotes the additional force associated with the suspension type. For passive suspension systems, this term is zero; for semi-active suspension systems, it is governed by a controllable damping coefficient $c(i)$ acting on the relative velocity between the train-body and track excitation; and for active suspension systems, it corresponds to the control force generated directly by the actuator.

$$m\ddot{x} + c(\dot{x} - \dot{x}_r) + k(x - x_r) = F_a \quad (4)$$

However, a single-degree-of-freedom model cannot fully capture the complex multidirectional vibrations of a high-speed train. To capture the coupling effects of lateral, rolling, and yaw motions, the complexity of the system dynamics is increased to a higher order in the state space. This complex spatial configuration is detailed in **Figure 5**, which depicts the dynamic model of a high-speed train. Specifically, based on the reference model, this transverse cross-sectional diagram establishes a four-degree-of-freedom (4-DOF) architecture to evaluate the coupled dynamic responses. To accurately reflect the system dynamics, the model assigns two independent DOFs to the train-body and two DOFs to the bogie. For the train-body, the designated DOFs are the lateral displacement along the horizontal axis and the roll angle around the longitudinal center of gravity. Similarly, the bogie is characterized by its own lateral displacement and roll angle DOFs. These four DOFs accurately capture the lateral and roll dynamics required for active control. Using the modeling approach presented by Li et al. (2015), the comprehensive kinematic model is expressed in matrix form in **Equation (5)** as follows:

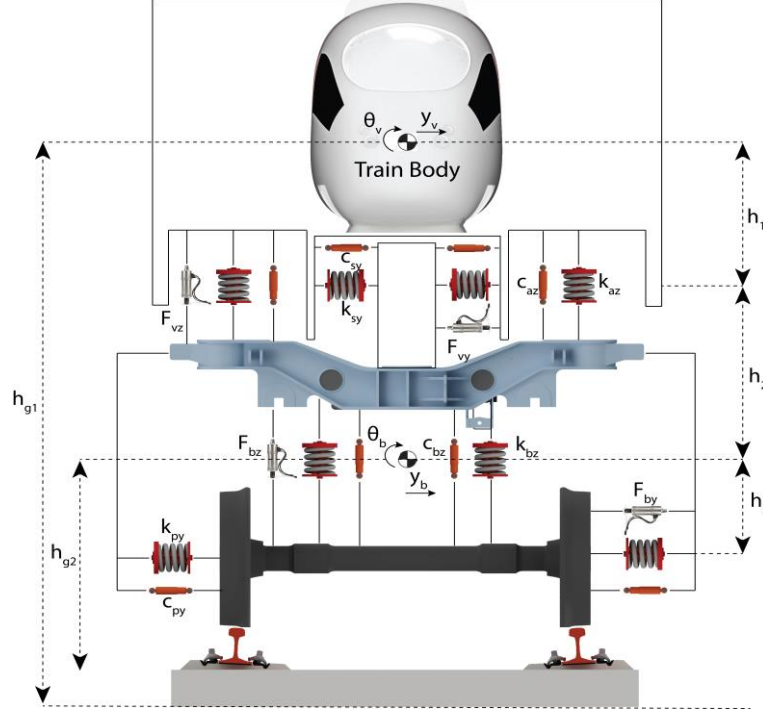


Figure 5 Dynamic model of a high-speed train

$$\begin{bmatrix} \dot{y}_v \\ \ddot{y}_v \\ \dot{\theta}_v \\ \ddot{\theta}_v \\ \dot{y}_b \\ \ddot{y}_b \\ \dot{\theta}_b \\ \ddot{\theta}_b \end{bmatrix} = A \begin{bmatrix} y_v \\ \dot{y}_v \\ \theta_v \\ \dot{\theta}_v \\ y_b \\ \dot{y}_b \\ \theta_b \\ \dot{\theta}_b \end{bmatrix} + B \begin{bmatrix} F_{vy} \\ F_{vz} \\ F_{by} \\ F_{bz} \end{bmatrix} + T(\cdot) + \omega(\cdot) \quad (5)$$

where y_v and θ_v are the displacement and angular displacement of the vehicle body, y_b and θ_b are the displacement and angular displacement of the bogie, F_{vy} and F_{vz} are the active control forces on the vehicle body, F_{by} and F_{bz} are the active control forces on the bogie, A is the system matrix of structural parameters, B is the input matrix for active control forces, $T(\cdot)$ represents the track characteristics, and $\omega(\cdot)$ represents the external aerodynamic forces.

The system's sensitivity to these uncertainties remains a key challenge in suspension control. To assess the robustness of advanced controllers, these random excitations must be mathematically represented. To this end, track irregularities are regarded as individual weakly stationary random processes, which are most effectively characterized using Power Spectral Density (PSD) functions (Zhai,

2020). Tracking these specific frequency intensities is essential for active control systems to identify and counteract critical periodic excitations, thereby preventing dangerous resonant shaking (Xin et al., 2026). Furthermore, PSD analysis is indispensable for ensuring the reliability of high-fidelity simulations when evaluating the vibration suppression performance of the train-body response. To illustrate the mathematical structure of a typical disturbance source, the unified European track spectra are expressed as follows (Wu et al., 2023; Xin et al., 2026):

- Vertical track irregularities:

$$S_v(\Omega) = \frac{A_v^* \times \Omega_c^{*2}}{(\Omega^2 + \Omega_r^{*2})(\Omega^2 + \Omega_c^{*2})} \quad (6)$$

- Lateral track irregularities:

$$S_a(\Omega) = \frac{A_a^* \times \Omega_c^{*2}}{(\Omega^2 + \Omega_r^{*2})(\Omega^2 + \Omega_c^{*2})} \quad (7)$$

- Track cross-level irregularities:

$$S_c(\Omega) = \frac{A_v^* \times b^{-2} \times \Omega_c^{*2} \times \Omega^2}{(\Omega^2 + \Omega_r^{*2})(\Omega^2 + \Omega_c^{*2})(\Omega^2 + \Omega_s^{*2})} \quad (8)$$

- Track gauge variation (distance between the two rails):

$$S_g(\Omega) = \frac{A_g^* \times \Omega_c^{*2} \times \Omega^2}{(\Omega^2 + \Omega_r^{*2})(\Omega^2 + \Omega_c^{*2})(\Omega^2 + \Omega_s^{*2})} \quad (9)$$

Table 3 Definition of parameters for track irregularity power spectra

Power Spectrum	Description	Unit
$S_v(\Omega)$	Vertical irregularity spectrum	$\text{m}^2/(\text{rad.m}^{-1})$
$S_a(\Omega)$	Lateral irregularity spectrum	$\text{m}^2/(\text{rad.m}^{-1})$
$S_g(\Omega)$	Track gauge variation spectrum	$\text{m}^2/(\text{rad.m}^{-1})$
$S_c(\Omega)$	Rail cant (cross-level) spectrum	$1/(\text{rad.m}^{-1})$
A_v^*	Amplitude coefficient for vertical spectrum	$\text{m}^2.\text{rad/m}$
A_a^*	Amplitude coefficient for lateral spectrum	$\text{m}^2.\text{rad/m}$
A_g^*	Amplitude coefficient for track gauge spectrum	$\text{m}^2.\text{rad/m}$
Ω_c^*	Primary cutoff frequency	rad/m
Ω_r^*	Secondary cutoff frequency	rad/m
Ω_s^*	High-frequency cutoff	rad/m
b	Half the distance between the rolling circles (half track gauge)	m

where Ω is the spatial frequency (rad/m). To apply **Equations (6)-(9)** for calculations, **Table 3** provides the detailed definitions and units of the specific spectral parameters. These coefficients quantify the stochastic track irregularities, serving as standardized disturbance inputs essential for evaluating and comparing the performance of different control strategies under high-speed operating conditions.

In summary, the high-order state-space model in **Equation (5)**, derived from the modeling approach of Li et al. (2015), reflects the inherent complexity of the suspension system and the limitations of purely mechanical designs. Although these equations provide an accurate description of train dynamics, the spring and damper coefficients (k and c) of the passive suspension systems are fixed and do not adjust to the stochastic disturbances $T(\cdot)$ and $\omega(\cdot)$. Additionally, mechanical clearances in interlinked system components contribute to an increasingly difficult-to-manage nonlinearity, particularly when the train is operating on curved tracks, exposed to crosswinds, or on uneven rails (Gao et al., 2021; Montenegro et al., 2022a; Montenegro et al., 2022b; Zhu et al., 2017). In such scenarios, the relative displacement increases and may even surpass the compensatory capacity of mechanical suspension systems. These limitations highlight the need to incorporate semi-active and active suspension strategies to improve vibration control performance under actual operating conditions (Wang, 2022).

3.3.2 Problem of the Electrical Control System

Issues originating from the control system occur only in semi-active and active suspension systems. The variation in oil-flow characteristics in a semi-active suspension is described by **Equation (2)**. In active suspensions, the balancing force is adjusted in response to vibrations through the actuator mechanism, as

represented by **Equation (3)**. For semi-active suspension systems, numerous studies have designed controllers for MR/ER dampers to optimize control performance and reduce vibrations (Leblebici & Türkay, 2018). However, during actual operation, the generated control force may not respond quickly enough to the input signal of the MR/ER damper, making vibration reduction challenging. In addition, the fluid properties of the damper oil may degrade over time, resulting in suboptimal performance and causing the altered flow characteristics to deviate from the intended design. This degradation leads to decreased control effectiveness and affects the overall stability of the vehicle.

The actuators in an active suspension system rely heavily on sensor signals; therefore, if these signals are noisy or inaccurate, the effectiveness of the controller is compromised. Moreover, in situations where the train experiences strong vibrations, the actuators may not receive the control signals in time to generate balancing forces instantaneously. From the issues discussed above, it is evident that each type of suspension system has inherent limitations. Therefore, this study requires a detailed evaluation of the control methods applied to each suspension type in recent years to identify more robust solutions.

3.3.3 Challenges in Modern Control Solutions

Numerous studies have applied modern control methods to suspension systems with the aim of mitigating the aforementioned limitations and optimizing train-body vibrations (Huang et al., 2020; Yang et al., 2020; Ye et al., 2022). However, each method encounters specific constraints; for instance, approaches such as LQR, LQG, and Fuzzy-PID require highly precise dynamic models to function effectively. In practice, nonlinear disturbances from track irregularities or turbulent crosswinds are unmodeled parameters and cannot be predicted in advance,

leading to reduced effectiveness when modeling errors occur. To bypass the need for precise modeling, SMC has been proposed, offering strong disturbance rejection without requiring an exact mathematical model (Wijaya et al., 2024). Nevertheless, the SMC approach can induce “chattering”, causing transient instability in train-body vibrations, which poses challenges for applications requiring high ride comfort.

For more advanced intelligent control methods such as Adaptive Neural Networks (ANN) and Fuzzy-PID combined with PSO optimization, significant challenges still exist. The control performance of these methods heavily relies on the quality and quantity of the training data; insufficient or biased data acquisition may lead to inaccurate models and suboptimal performance (Jianjun et al., 2021; Li et al., 2015). In addition, sensor signals play a critical role in these approaches; unreliable signals may result in considerable instability in train-body vibrations. Overall, despite these hurdles, modern control strategies remain a key focus of current research and show high potential for practical application. Therefore, in Section 4 of this review, the authors conduct a deeper analysis based on comparisons and the applicability of each control method for different types of suspension systems.

4. Development of Control Solutions for Suspension Systems

Currently, with continuous advancements in engineering technology, the control of stability and ride comfort in high-speed trains has shifted from passive devices to intelligent control strategies integrated with sensors. The application of intelligent control algorithms and monitoring techniques not only enables conventional stability control but also enhances adaptability and facilitates fault diagnosis, thereby improving reliability and effectively reducing vibrations to optimize ride quality. Consequently, minimizing and controlling vibrations in train components is crucial for passenger comfort, track adhesion, and operational safety (Han et al., 2012; Jin, 2020).

4.1 Stability through Mechanical Structure

In high-speed train suspension systems, the mechanical structural stability of the passive system serves as the foundation for operational safety. Theoretically, the design of this system requires the

establishment of complex multibody dynamics models, primarily based on the fundamental Newton-Euler or Lagrange formulations, to determine the dynamic correlations among the train-body, bogie, and wheelset. Based on vehicle-track interaction theories, most notably the coupled model of (Zhai & Sun, 1994), it is evident that the mechanical design process must consistently address a rigorous trade-off between stiffness (k) and the damping coefficient (c). High stiffness in the primary suspension is mandatory to maintain hunting stability and ensure safe guidance when the train operates at ultra-high speeds; however, this inadvertently compromises ride comfort by directly transmitting high-frequency vibrations from the track to the train-body. To mitigate this issue, modern mechanical structures have evolved into a specialized dual-stage suspension architecture: the primary stage focuses on maintaining stability and positioning the wheelset, whereas the secondary stage is fine-tuned with softer parameters to isolate car-body vibrations. This structural separation is not merely a technical solution but also the core mechanical foundation ensuring that the train operates within safe limits before any electronic intervention.

As the design speeds of high-speed trains have surpassed the 300 km/h threshold, modern mechanical design has evolved significantly from previous eras to address these emerging challenges. As summarized in **Figure 6**, this advancement encompasses three primary strategic criteria: optimization of elastic elements, improvement of geometric layouts, and application of next-generation materials. The replacement of traditional linear springs with components featuring nonlinear stiffness and hydraulic bushings has enabled the system to adapt more flexibly to variable dynamic loads and complex aerodynamic disturbances. Concurrently, the optimization of bogie geometry and the application of lightweight yet highly durable materials significantly minimize the unsprung mass, thereby reducing the wheel-rail interaction forces and ultimately extending the lifespan of railway infrastructure. A well-designed mechanical system with seamlessly coordinated components absorbs most fundamental disturbances. This robust foundation allows the intelligent control strategies discussed in subsequent sections to operate more effectively with reduced computational complexity, rather than constantly compensating for the deficiencies of an inherently unstable mechanical structure.

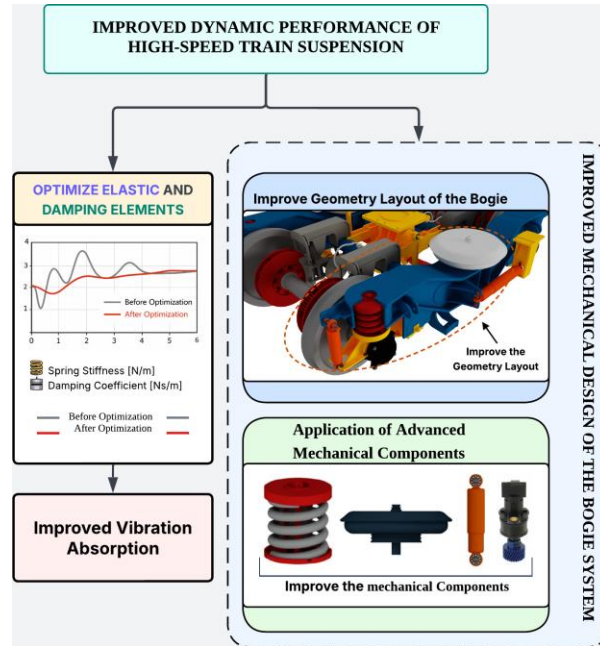


Figure 6 Overview of mechanical optimization strategies for high-speed train suspension systems

4.2 Development of Control Systems

In addition to efforts in mechanical optimization, the emergence of control strategies has marked a new turning point in regulating control forces to suppress vibrations in suspension systems. In the initial stages, linear optimization algorithms based on state-space models, such as LQR and LQG, were the primary focus of research. By establishing cost functions, these controllers determine the optimal balance between ride comfort and suspension travel limits; consequently, they achieve peak performance under linear conditions (Zhu et al., 2018). However, because of their reliance on idealized mathematical models, these methods lack flexibility when addressing real-world nonlinearities. This limitation has driven the development and widespread adoption of semi-active control strategies featuring the Skyhook damping law. By simulating a fixed virtual reference point in space, this strategy provides not only superior damping effectiveness but also high reliability and excellent energy efficiency. All of which are key factors that must be evaluated to enhance car-body vibration reduction in modern high-speed trains (Leblebici & Türkay, 2018).

Although linear and semi-active strategies have effectively addressed vibration issues under nominal conditions, actual operations are constantly subject to persistent model uncertainties and unpredictable complex nonlinear disturbances. To overcome these limitations, SMC has emerged as a highly robust

solution for handling system uncertainties and operational disturbances. By forcing the system state to track predefined trajectories on a stable sliding surface, SMC enables the suspension system to maintain consistent performance even under the most severe operating scenarios. Nevertheless, the challenge of chattering caused by abrupt changes in the control signal remains a major technical barrier, which can potentially induce structural fatigue and affecting component lifespan (He et al., 2020). The inherent trade-off between robustness and smoothness in these controllers serves as the primary motivation for integrating artificial intelligence to comprehensively resolve this issue. Consequently, these classical control methods serve as core logical frameworks and provide crucial sample data for the development of more advanced controllers in the modern era.

4.3 Intelligent Control for Suspension Systems

In recent years, numerous intelligent control methods have been developed globally, marking a significant breakthrough in the evolution of nonlinear control models. Unlike traditional nonlinear or semi-active control approaches, intelligent control systems can learn and adapt autonomously based on acquired data or direct system feedback. Through this capability, they enhance stability control and effectively suppress vibrations within the suspension system.

4.3.1 Hybrid Fuzzy Logic Control

In modern high-speed railway networks, a significant portion of the track is constructed on elevated viaducts and bridges, creating a highly complex and nonlinear operating environment. Consequently, Train-Bridge Interaction (TBI) emerges as a critical condition in which coupled vibrations severely affect the moving vehicle. Under such conditions, vibration mitigation can be achieved through self-adjusting suspension systems that adapt to varying track-bridge profiles (Valášek et al., 1998). When a bridge experiences excessive vibrations, these high-intensity excitations are directly transmitted back to the train, necessitating advanced active or semi-active control solutions to suppress the coupled dynamic responses and ensure system reliability (Gao et al., 2021; Wang et al., 2003). As operating speeds

increase, traditional passive systems are no longer sufficient to maintain train stability, making active controllers with feedback loops essential (Sharma & Kumar, 2018; Zhu et al., 2017). As illustrated in **Figure 7**, the physical model of TBI explicitly maps this dynamic environment, identifying the precise placement of auxiliary and main suspensions alongside the active control forces (U_1 to U_6) used to prevent these coupled vibrations. Within this multibody architecture, the sprung mass encompasses the train car-body and the bogie frames, which are dynamically isolated by the secondary and primary suspensions to ensure passenger comfort. Conversely, the unsprung mass consists of the wheelsets at the base, which remain in direct contact with the track and continuously experience the initial high-frequency excitations from the bridge.

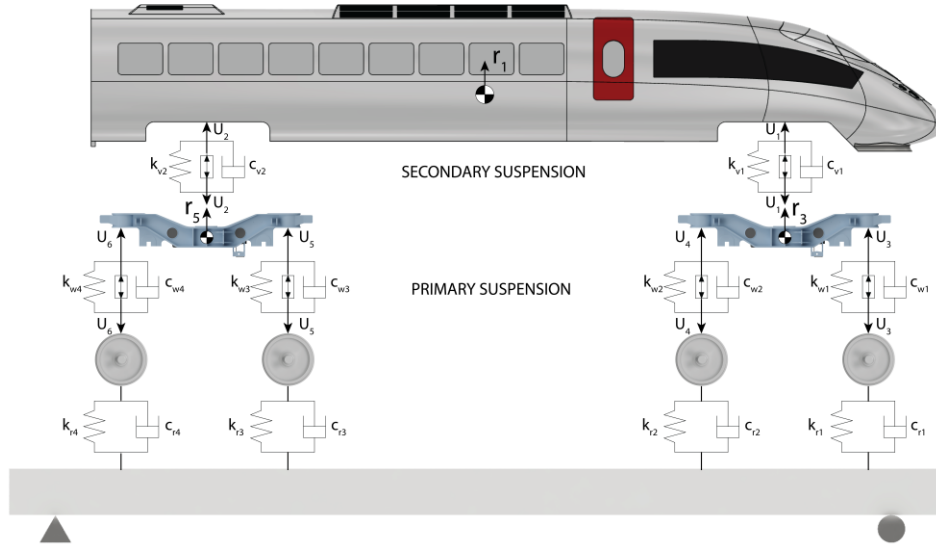


Figure 7 Physical model of Train-Bridge Interaction with Active Suspension System

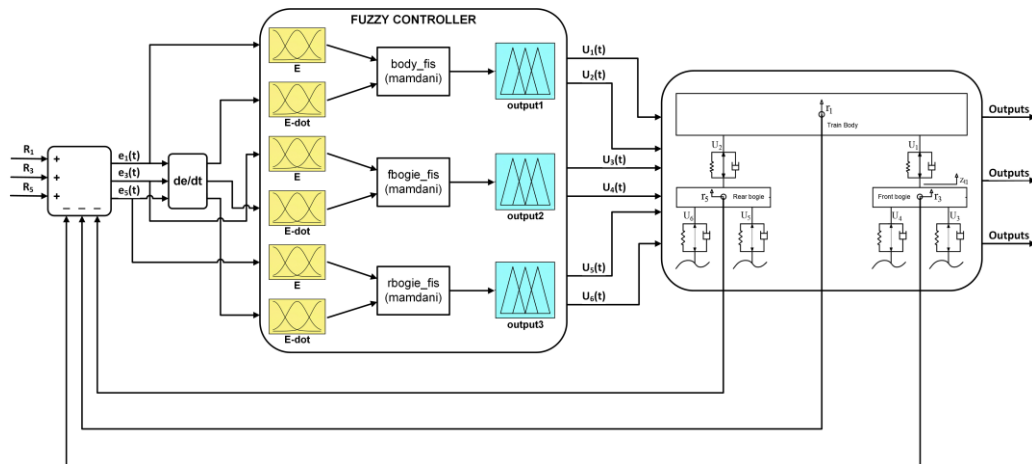


Figure 8 Structure of the Fuzzy Logic Controller for vibration suppression in the High-Speed Train system

The fuzzy logic controller shown in **Figure 8** is used to suppress vibrations in the components of the high-speed train (HST), including the train-body, front train, and rear train (Koç, 2020). In this context, the vertical displacement parameters r_1, r_3, r_5 of the train-body, front train, and rear train were selected as measured variables. Meanwhile, the reference inputs were defined as parameters R_1, R_2 and R_3 . The controller errors are then calculated using these reference inputs. After these error parameters are derived, the parameter errors and their derivatives are defined as inputs for the fuzzy logic controller. Additionally, auxiliary suspensions are placed between the train-body and the front and rear trains, as illustrated in **Figure 7**; similar to the main suspension, the auxiliary suspension prevents vibrations between the trains and the train-body. The fuzzy logic controller generates actuator forces, which are subsequently incorporated into the equations of motion provided in the model.

To further enhance system flexibility, modern strategies combine fuzzy control with a PID controller to form a hybrid Fuzzy-PID architecture (Jianjun et al., 2021). In the process of developing the Fuzzy-PID controller, the selection of initial PID parameters is mainly based on manual tuning, which relies heavily on experience and operator skill. Therefore, it is difficult to ensure that the suspension system remains consistently stable. To address this, PSO is employed to iteratively optimize the initial parameters of the controller. By generating a population of random particles with specific positions and velocities, the

algorithm gradually converges toward the global optimum to minimize the fitness function (Akgul & Unluturk 2023; Qiu et al., 2021; Singh & Prasad, 2019). As illustrated in **Figure 9**, the PSO algorithm is used autonomously to optimize the initial PID parameters K_{p0}, K_{i0}, K_{d0} . These base values are then integrated into the pre-designed Fuzzy-PID controller via a summation mechanism, enabling the suspension system model to achieve optimal vibration suppression under actual operating conditions.

Through comparative evaluations, this specific hybrid Fuzzy-PID controller optimized by PSO has been demonstrated to be highly effective in minimizing the root-mean-square (RMS) of train-body acceleration. It significantly outperforms conventional fuzzy control and traditional Skyhook methods, thereby confirming its exceptional effectiveness in improving ride comfort for high-speed trains (Jianjun et al., 2021). The superior stability of fuzzy controllers optimized by PSO has also been confirmed in heavy-duty offshore engineering. Studies on jack-up rig jacking systems show that this hybrid approach significantly reduces structural sway and adapts well to variable loads (Tran et al., 2022), reinforcing its applicability to high-speed train suspensions. In conclusion, the Fuzzy-PID controller with PSO optimization demonstrates superior vibration suppression capabilities while also reflecting strong adaptability to the nonlinear characteristics of high-speed train suspension systems.

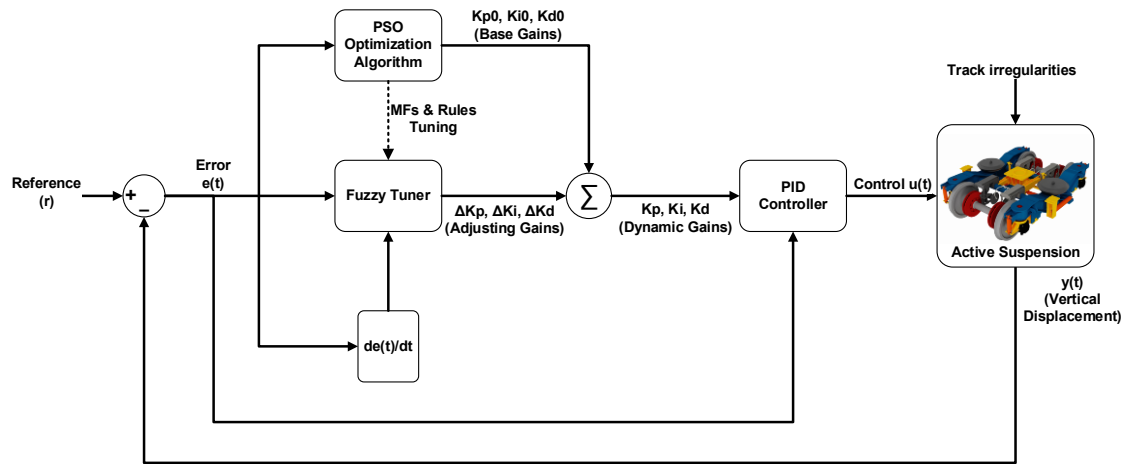


Figure 9 Fuzzy PID system block diagram based on PSO

4.3.2 Adaptive Neural Network Control

ANN control is considered an intelligent control method in which neural networks are used to approximate unknown nonlinear and uncertain components of the system. Instead of requiring a fully detailed model, the ANN learning process is guided by an adaptive law based on Lyapunov theory. In this framework, a Lyapunov function acts as a mathematical "energy function" representing the total system error. By designing update rules that ensure this error energy continuously decreases over time, the system is theoretically guaranteed to reach a stable state. This intuitive mechanism approximates deviations in real time, enabling the system to operate stably even under disturbances and parameter variations. Over the past decades, various active suspension systems for railway transportation have been developed (Bruni & Resta, 2001; Goodall, 1997; Metin & Guclu, 2011).

In high-speed train suspension systems, developing an efficient fault-tolerant control (FTC) scheme is crucial for handling model uncertainties and unpredictable actuator faults. To better reflect the dynamic behavior of the system, such as the coupling effects between lateral and rolling motions alongside external disturbances, a more realistic model is often considered in which the damping parameters are

treated as unknown and time-varying, rather than known and constant, as assumed in most previous studies. By extracting kernel information from the system's nonlinearities and integrating it with a neural network, an enhanced controller is formulated to compensate for concentrated uncertainties and internal faults. The architecture of this strategy is explicitly visualized in **Figure 10**, where the neural network acts as an adaptive compensator. By processing tracking errors to generate refined control signals, the controller can effectively suppress complex vibrations without requiring a precise mathematical model. As a strong testament to the high effectiveness of deep learning in complex oscillation control, integrating deep learning with Model Predictive Control (MPC) has shown remarkable results in minimizing sway in ship-to-shore crane operations (Dang et al., 2025). Although situated in the marine engineering domain, this inclusion serves as cross-domain validation for the algorithm's versatility. It demonstrates that learning-based predictors can effectively handle multibody nonlinearities and severe stochastic disturbances, which are mathematically analogous to the complex aerodynamic and track-induced oscillation dynamics found in rail vehicles.

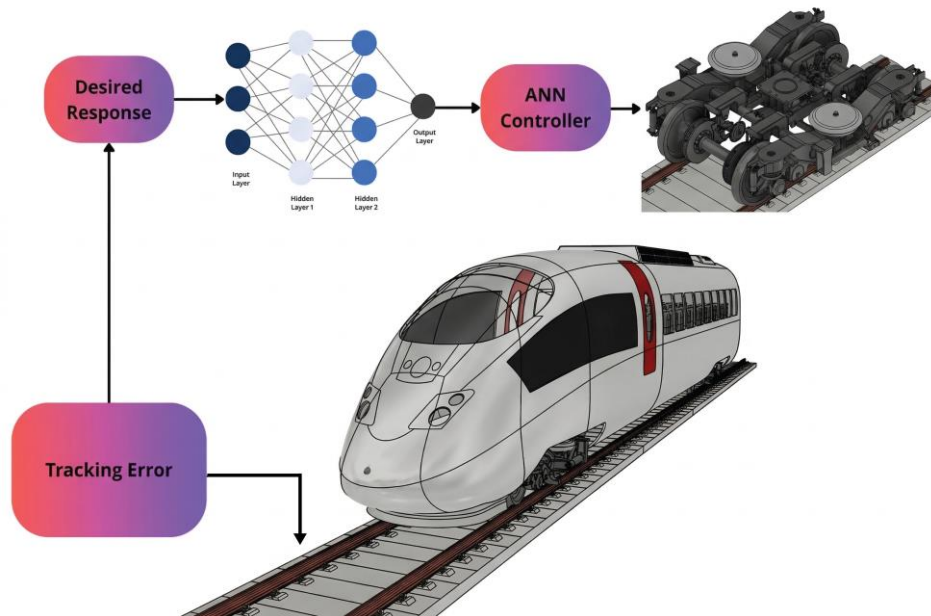


Figure 10 Adaptive Neural Network Control Suspension Model for High-Speed Train

Functionally, the ANN controller not only stabilizes both lateral and rolling vibrations but also demonstrates significant fault-tolerant capability when actuator performance degrades. The system can rapidly recover from internal failures to restore equilibrium through its nonlinear approximation mechanism and adaptive weight updating, which compensate for model deviations (Li et al., 2015). Overall, unlike traditional control strategies that require a separate Fault Detection and Isolation (FDI) mechanism, the ANN controller maintains effective control without the need for such explicit diagnostic steps.

4.3.3 Adaptive Nonlinear Control

The adaptive nonlinear control (ANC) method is a model-based control approach designed for systems with strong nonlinear dynamics, time-varying parameters, and uncertain external disturbances. Unlike traditional control methods, nonlinear adaptive control employs Lyapunov theory and backstepping techniques to construct control laws that can adjust in real time, providing stable compensation for the system without requiring an exact model. As

illustrated by the physical layout of the lateral quarter railway vehicle model in **Figure 11a** and its corresponding free-body diagram in **Figure 11b**, this capability is particularly important for managing the complex interactions between the vehicle body and track irregularities. Based on this dynamic configuration, the general governing equations of the system are established as follows:

$$\begin{cases} m_c \ddot{x}_c = -F_{AL} - F_{ML} - F_{nd} = -k_s(x_b - x_c) - k_n(x_n - x_c) - F_{nd} \\ m_b \ddot{x}_b = F_{AL} + F_{ML} + F_{nd} - F_p = k_s(x_b - x_c) + k_n(x_n - x_c) + F_{nd} - k_p(x_r - x_b) \end{cases} \quad (10)$$

in **Equation (10)**, F_{AL} denotes the linear air-spring force, F_{ML} represents the force transmitted through the Maxwell damper model, and F_{nd} defines the nonlinear damping force. Its application to high-speed train suspension systems has demonstrated high control effectiveness in compensating for model deviations, actuator delays, and environmental uncertainties. Consequently, nonlinear adaptive control ensures robust stability while simultaneously improving the ride comfort and smoothness of the train during high-speed operation.

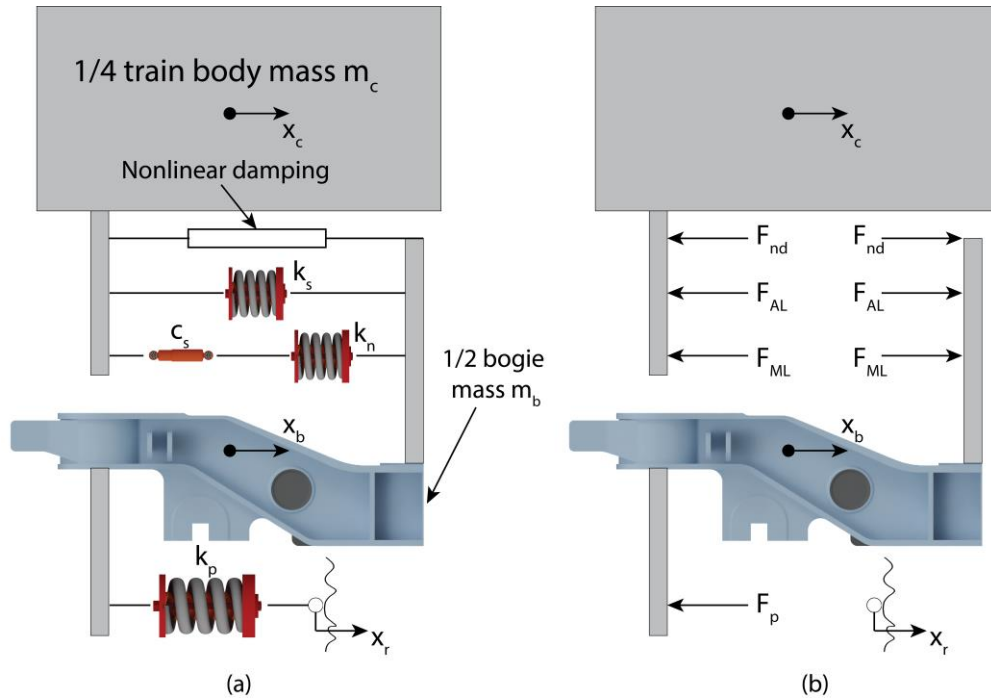


Figure 11 The lateral quarter railway vehicle model: (a) physical model; and (b) free-body diagram

Instead of relying solely on traditional vibration isolation theory, the design of these advanced active suspension systems often involves a two-step framework. First, the control components are developed to enhance vehicle stability, directly based on nonlinear stability theory and bifurcation analysis. Second, these solutions are implemented using the Constraint-Following Control (CFC) approach, which treats the control problem as constrained servo control, allowing nonlinear control to be handled without linearization (Chen, 2009). The control objective is expressed as a quadratic constraint, enabling the determination of the minimal control force within the set of solutions satisfying the specified requirements and ensuring that the active suspension adheres to these constraints. This model-based control method has a simple structure, requiring neither Lagrange multipliers nor auxiliary variables (Feng & Jing, 2019; Qin et al., 2021; Zhang et al., 2022). By synthesizing this CFC methodology with a fourth-order “nonlinear damping” effect combined with a yaw-damper mechanism based on the Skyhook principle, this intelligent framework successfully eliminates lateral hunting motion under severe track conditions, thereby strongly demonstrating the robustness and high effectiveness of high-order

nonlinear damping mechanisms in active suspension systems (Zhang et al., 2024).

4.3.4 Reinforcement Learning Control

Reinforcement Learning (RL) is a novel algorithm that is currently receiving significant attention. This algorithm relies on data to learn optimal control laws without the need for traditional mathematical models. As illustrated by the general Twin Delayed Deep Deterministic Policy Gradient (TD3) architecture in **Figure 12**, the control process operates through continuous closed-loop interaction with the high-speed train suspension environment. Within this Actor-Critic structure, the Actor network observes the current suspension states to execute active control forces, whereas the Critic network evaluates these actions based on a defined reward signal to guide policy optimization. Furthermore, by integrating an experience replay mechanism and target networks, this framework ensures highly stable parameter updates (Mou & Chen, 2024). The transition toward such learning-based architectures is increasingly highlighted in recent surveys as a strategic solution to the inherent limitations of classical model-based suspension controllers (Kimball et al., 2024).

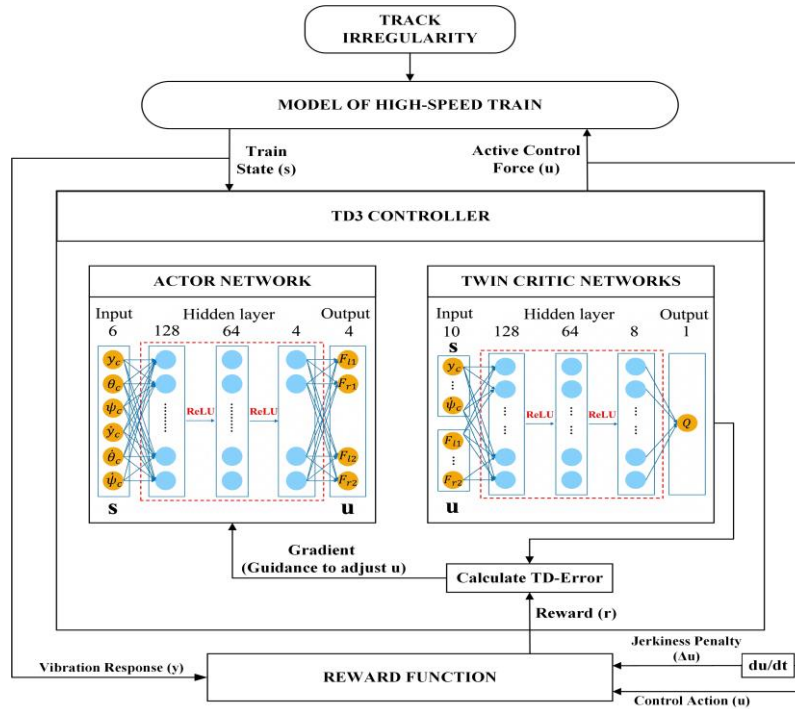


Figure 12 General TD3 control architecture for high-speed train active suspension systems

Within this domain, the TD3 algorithm has proven highly effective for managing complex, multi-degree-of-freedom train models (Mou & Chen, 2024). Based on this approach, time-domain and frequency-domain evaluations demonstrate that TD3 control significantly minimizes both peak and RMS lateral accelerations compared to conventional passive and Skyhook systems. Furthermore, this RL-based approach fundamentally alters the system's dynamic characteristics by suppressing critical low-frequency vibrations and shifting primary oscillation components to higher frequency bands, thereby enhancing overall ride stability.

Despite its theoretical optimality, the practical deployment of learning-based control in active suspensions must bridge the "sim-to-real gap", a challenge involving the transfer of models trained in simulation to physical vehicle systems (Kimball et al., 2024). Consequently, the current tendency to rely on overly broad and complex mathematical models often exacerbates this gap, severely hindering the computational optimization required for effective real-time intelligent control in practical high-speed train applications.

4.4 Fault Detection and Isolation for Control Support

With the rapid advancement of industry, increasingly sophisticated technology, and growing demand for high-speed rail transportation worldwide, the monitoring of high-speed trains has become an area of significant focus. In particular, the suspension system plays a critical role, as its condition directly influences train vibrations and oscillations during operation, and in extreme cases, faults may result in serious accidents such as derailments. Therefore, fault diagnosis of high-speed train suspension systems is of paramount importance. As train speeds increase, the reliability and safety requirements of the suspension system become particularly critical. In this context, fault monitoring plays a vital supporting role by providing real-time information, enabling the controller to autonomously switch to a safe mode or apply active fault compensation strategies to maintain vehicle stability.

To address these diagnostic challenges, advanced deep learning frameworks have been integrated into suspension monitoring systems. For instance, Ye et al. (2022) proposed a highly effective fault diagnosis procedure based on a 1-Dimensional Convolutional Neural Network (1D-CNN) architecture. This deep learning model is designed with five consecutive

feature extraction blocks, each containing a one-dimensional convolutional layer, an advanced activation layer, and a max-pooling layer to extract key vibration features from the input layer. The number of kernels increases progressively from 32 to 512 to generate deep and informative features. A global average pooling layer is then used to reduce the number of parameters and transfer the features to the classification stage. The final two blocks include 64 and 4 neurons, respectively, with the final Softmax layer classifying the signals into four states: Normal, Lateral Damper Fault (LDF), Yaw Damper Fault (YDF), and Yaw & Lateral Damper Fault (Y&LDF). This architecture allows the 1D-CNN to automatically learn temporal features and robustly distinguish faults despite noise from track irregularities and wheel wear. As train speeds increase, the reliability and safety requirements of the suspension system become particularly critical. Fault monitoring plays a supporting role by providing information for the controller to switch to a safe mode or apply fault compensation strategies. Ultimately, integrating these deep learning diagnostics with control algorithms is crucial for ensuring the safety and resilience of future high-speed trains.

5. Results and Discussion

The comparison results are based on the performance of the control strategies across five criteria: passenger comfort during train operation, vibration suppression capability, disturbance rejection, adaptability, and model implementation complexity. To provide a clear evaluation, the first two criteria, namely passenger comfort and vibration suppression capability, are systematically assessed through distinct methodological approaches. Specifically, the performance improvement metrics for conventional strategies are synthesized and normalized from the numerical simulation data of a CRH3 train operating at 288 km/h, as reported by Jianjun et al. (2021). This process extracts the RMS acceleration and the Sperling ride stability index (W_z). Conversely, the evaluation of modern control methods is constructed by synthesizing the ride comfort results from the respective research articles on each strategy. This approach helps standardize findings from diverse simulation environments into a unified comparative representation. Finally, to provide a holistic perspective, all five criteria are comprehensively evaluated and summarized as a qualitative comparative matrix.

5.1 Comparison of Conventional Control Method

The comparative performance of the conventional control methods, evaluated in terms of both vibration suppression and passenger comfort, is illustrated in **Figure 13**. The dual-axis plot demonstrates the clear advantages of the active control strategies over the passive suspension baseline. Specifically, the standalone Fuzzy control method achieves a notable 39.69% reduction in RMS acceleration and a 14.02% improvement in the

stability index. However, the hybrid Fuzzy-PID control optimized with PSO delivers the highest overall performance, improving RMS acceleration by 42.82% and the stability index by 22.80% compared with the passive baseline. These results indicate that PSO-optimized Fuzzy-PID control significantly outperforms individual methods, making it particularly suitable for complex systems such as electric multiple units.

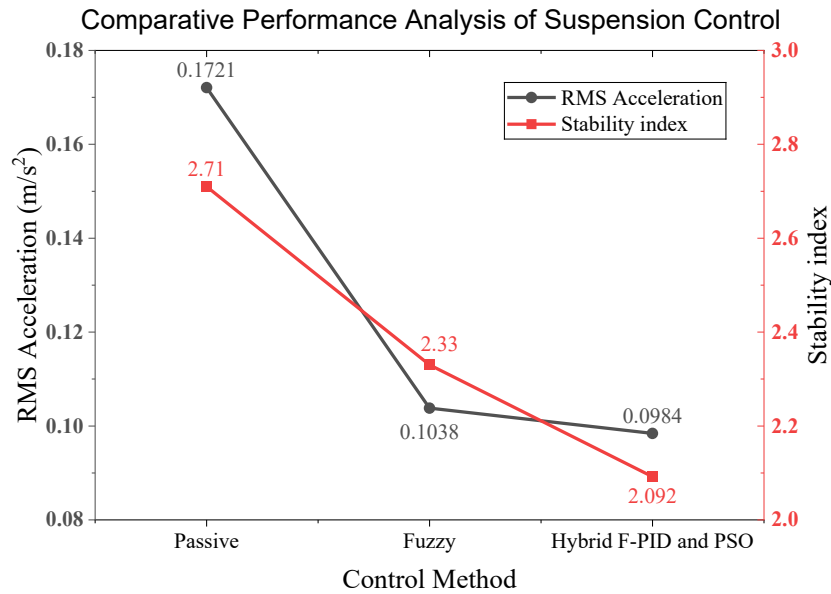


Figure 13 Comparison of RMS acceleration and stability index among conventional control methods

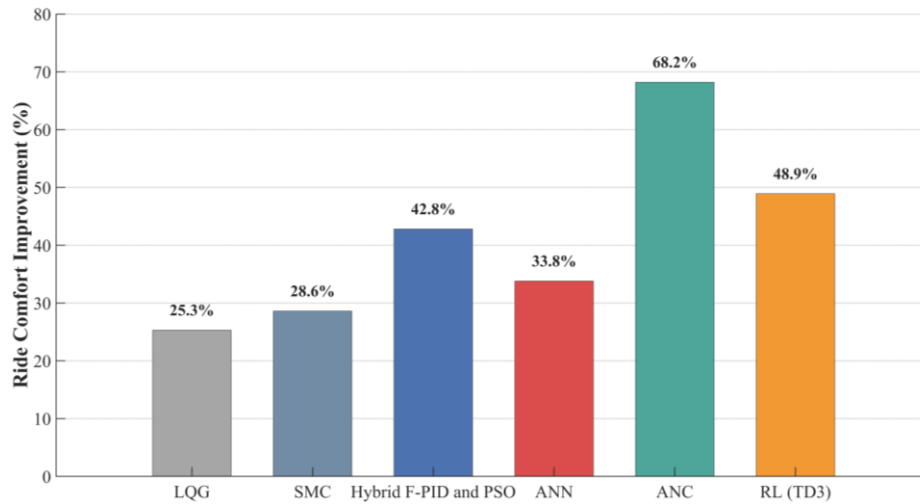


Figure 14 Comparison of ride comfort improvement (%) among modern control methods for high-speed train suspension systems

Table 4 Qualitative comparative matrix of suspension control strategies

Control Strategy	Passenger Comfort	Vibration Suppression	Disturbance Rejection	Adaptability	Implementation Complexity
LQG	Moderate	Moderate	Good	Moderate	Moderate
SMC	Moderate (Chattering)	Moderate	Very High	Moderate	Moderate
Hybrid F-PID and PSO	High	High	Good	Moderate	Moderate
ANC	High	Very High	High	Very High	High
ANN	High	Moderate	High	Very High	Very High
RL (TD3)	Very High	High	High	Very High	Extremely High

5.2 Comparison of Modern Control Methods

Figure 14 illustrates the comparison of ride comfort improvement among the evaluated modern control methods, achieved through cross-normalization of relative performance by extracting the percentage reduction in RMS acceleration compared with the corresponding passive suspension baseline of each study. The results demonstrate a clear performance hierarchy: conventional controllers such as LQG (Zhao et al., 2026) and SMC (Tran et al., 2024) provide foundational improvements of 25.3% and 28.6%, respectively. Intelligent and hybrid methods exhibit enhanced effectiveness, with ANN (Sun & Zhao, 2020) achieving 33.8%, followed by the PSO-optimized hybrid Fuzzy-PID (Jianjun et al., 2021) at 42.8% and RL-TD3 (Mou & Chen, 2024) at 48.9%. Notably, the ANC strategy (Zhang et al., 2024) attains the highest improvement level of 68.2%, underscoring its superior potential for advancing high-speed train stability and comfort.

5.3 Multicriteria Qualitative Assessment of Control Strategies

Table 4 clearly illustrates the trade-off between control performance and structural complexity. Conventional linear methods, such as LQG, offer the advantage of low computational complexity and ease of implementation, but they critically lack the adaptability required to handle unmodeled track irregularities. Robust strategies such as SMC excel in disturbance rejection against external uncertainties; however, the inherent switching mechanism often induces chattering effects, which limits overall passenger comfort.

Conversely, hybrid and adaptive control architectures, specifically the PSO-optimized Fuzzy-PID and ANC, strike an exceptional balance between advanced performance and implementation feasibility. Consistent with its quantitative superiority, ANC emerges as the most comprehensive solution; it

consistently achieves “Very High” qualitative ratings in vibration suppression, passenger comfort, and adaptability. This mathematically grounded approach is exceptionally effective in mitigating complex phenomena such as high-speed hunting instability, albeit requiring a sophisticated nonlinear update law. Finally, although artificial intelligence frameworks such as ANN and RL offer unparalleled adaptability by continuously learning from dynamic track environments, their “Very High” implementation complexity presents a significant operational bottleneck. The practical real-time deployment of these data-driven models is heavily constrained by computational latency, hardware limitations, and rigorous training requirements, which explains why mathematically rigorous adaptive methods currently outpace them in immediate practical efficacy. Nevertheless, RL remains a highly promising novel control paradigm, offering significant potential for future self-optimizing intelligent suspension systems as onboard computational capabilities advance.

6. Conclusions and Future Research Directions

6.1 Conclusions

As high-speed trains become a leading global development trend, ensuring passenger comfort and vehicle stability in real-world environments is increasingly critical. Previous review studies have primarily focused on standalone or conventional controllers, failing to provide a comprehensive analysis of hybrid and learning-based architectures under severe nonlinear conditions. The findings indicate that the integration of intelligent controllers has gained increasing attention among researchers in recent years, highlighting the strong potential for development and the high practical applicability of suspension systems equipped with advanced control technologies in the future (Li et al., 2024; Zhang et al., 2026; Umar et al., 2025).

This review addresses these issues by systematically synthesizing and evaluating the

performance of suspension control strategies from traditional to modern approaches. The established objectives were fulfilled through rigorous comparative analysis across five core criteria: passenger comfort, vibration suppression, disturbance rejection, adaptability, and implementation complexity. The comparative results demonstrate a clear performance hierarchy among modern control methods. Conventional methods such as LQG and SMC provide foundational improvements in ride comfort (25.3% and 28.6%, respectively) but face severe limitations regarding adaptability and chattering effects. Artificial intelligence frameworks, including ANN (33.8%) and RL-TD3 (48.9%), offer high adaptability by learning from dynamic environments; however, their real-world deployment is currently constrained by extremely high implementation complexity, computational latency, and rigorous training requirements. In contrast, hybrid and adaptive architectures strike a highly effective practical balance. Specifically, the PSO-optimized Fuzzy-PID delivers a solid 42.8% improvement despite its reliance on heuristic tuning. Most notably, the ANC strategy exhibits the highest vibration suppression capabilities, reaching a peak improvement level of 68.2%. Although ANC necessitates a sophisticated nonlinear update law, its mathematically rigorous framework currently stands as the most comprehensive and effective solution for mitigating high-speed hunting instability and ensuring passenger comfort.

Ultimately, this review provides a robust reference framework for selecting optimal suspension control strategies. It also highlights the limitations of each modern algorithm, which are also considered significant research gaps for future researchers to address.

6.2 Future Research Directions

Although many in-depth studies have been conducted on advanced control strategies in recent years, the literature has yet to resolve the complex issues that arise during practical implementation. Therefore, future research should focus on the following areas:

- Multi-physics modeling and TBI: Current studies often employ simplified structural models of suspension systems. There is a need to shift toward higher-fidelity models such as 12-DOF or 28-DOF structures. At the same time, deeper analyses are necessary of the influence of severe stochastic disturbances such as multidirectional winds, aerodynamic effects, track curvature, and TBI at high speeds.

- Real-time intelligent control and computational optimization: Intelligent control approaches such as RL and ANN are considered promising development trends, with results demonstrating improved vibration suppression and adaptability to complex operating conditions. However, a major limitation of these approaches is their requirement for large volumes of training data. Therefore, future research should focus on optimizing existing machine learning algorithms or developing hybrid control strategies to reduce data requirements while ensuring reliability.

- FTC through deep diagnosis: Instead of implementing fault diagnosis module and the FTC separately, future studies may integrate deep learning-based fault diagnosis models, such as 1D-CNN, directly into the FTC control loop. This integrated approach can help develop intelligent suspension systems capable of timely fault detection and automatic signal compensation, thereby ensuring operational safety even when actuators or sensors fail.

- Validation through Hardware-in-the-Loop (HIL) Simulation: To bridge the gap between theoretical control algorithms and practical implementation, controllers need to be evaluated through HIL experiments. This is an essential validation step for confirming the feasibility and reliability of complex control algorithms under operating conditions close to those of real high-speed railway systems.

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8. CRediT Statement

Tien-Dat Tran: Conceptualization, Writing – Original Draft, Formal Analysis, Software.

Cong-Son Doan: Software, Investigation, Data Curation, Formal Analysis, Visualization, Writing.

Thanh-Dat Le: Resources, Laboratory Experiments, Data Curation.

Viet-Dung Do: Statistical Analysis, Review & Editing.

Xuan-Kien Dang: Methodology, Supervision, Review & Editing, Funding Acquisition, Project Administration.

9. Abbreviations

Abbreviation	Full Term
PID	Proportional Integral Derivative
LQR	Linear Quadratic Regulator
LQG	Linear Quadratic Gaussian
SMC	Sliding Mode Control
PSO	Particle Swarm Optimization
ANN	Adaptive Neural Networks
ANC	Adaptive Nonlinear Control
RMS	Root-Mean-Square
FLC	Fuzzy Logic Control
RL	Reinforcement Learning
MR	Magnetorheological
ER	Electrorheological
DOF	Degree-of-Freedom
PSD	Power Spectral Density
TBI	Train-Bridge Interaction
HST	High-Speed Train
FTC	Fault-Tolerant Control
MPC	Model Predictive Control
FDI	Fault Detection and Isolation
CFC	Constraint-Following Control
TD3	Twin Delayed Deep Deterministic Policy Gradient
1D-CNN	1-Dimensional Convolutional Neural Network
LDF	Lateral Damper Fault
YDF	Yaw Damper Fault
Y&LDF	Yaw & Lateral Damper Fault
HIL	Hardware-in-the-Loop

10. Declaration of Competing Interest

The authors declare no conflicts of interest.

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