

ADAPTIVE MPC WITH RBF NEURAL NETWORK COMPENSATION AND Q-LEARNING WEIGHT TUNING FOR VEHICLE ACTIVE SUSPENSION

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ABSTRACT. *With the advancement of the automotive industry, ride comfort and driving safety have become essential performance metrics. Traditional passive and semi-active suspensions can partly enhance performance but remain limited by adjustment range and comfort-stability trade-offs. To overcome these issues, this paper proposes a composite control strategy for active suspensions integrating model predictive control (MPC), radial basis function neural networks (RBFNN), and Q-Learning. MPC addresses multi-constraint, multi-objective optimization; RBFNN compensates actuator nonlinearities in real time; and Q-Learning adaptively tunes MPC weight matrices to improve robustness. Lyapunov-based analysis ensures asymptotic stability and boundedness of RBFNN weights. Simulations on a quarter-car model under speed bump excitation validate the approach. Results show that the QL-MPC-RBFNN controller outperforms conventional MPC, MPC-RBFNN and the distributed model predictive control (DMPC) in vehicle body acceleration, suspension deflection, and dynamic tire load, achieving superior comfort, safety, and robustness.*

Keywords: MPC, RBFNN, Q-Learning, Nonlinear compensation, Lyapunov stability analysis

1. Introduction. As essential vehicle performance indicators, ride comfort and safety are often compromised in passive/semi-active suspensions [1, 2]. Active suspensions overcome this by employing actuators to improve dynamics [3]. While classical controls (e.g., PID, and LQR) are widely used for their simplicity [4, 5, 6, 7, 8], their reliance on accurate models limits their adaptability to nonlinearities and complex conditions, motivating the shift to MPC and intelligent learning for superior robustness [9].

In the study of semi-active suspensions, Zhang et al. [10] applied explicit MPC to damper damping adjustment, achieving fast control law computation under actuator constraints while enabling real-time implementation on standard microcontrollers. Kim et al. [11] further proposed an MPC method that incorporates road preview information, which effectively compensated for gear-shift delays, significantly improving ride comfort

and demonstrating real-world effectiveness through vehicle experiments. For active suspensions, Bai and Sun [12] developed a disturbance-resilient MPC framework for active suspension systems (ASS) that incorporates perception error constraints from road preview sensors, ensuring stability and recursive feasibility under realistic conditions. Li et al. [13] addressed speed-dependent time delays by proposing a linear parameter-varying MPC, which integrated road preview information and an explicit control law lookup table for online optimization. Simulation results showed that its performance under variable-speed conditions was significantly better than that of passive suspensions. Overall, MPC determines control laws through receding horizon optimization and can effectively balance comfort, handling stability, and safety under explicit constraints, making it well-suited for suspension control in complex operating conditions. However, MPC is highly dependent on model accuracy, and its performance degrades in the presence of nonlinearities and uncertainties. Moreover, the weighting matrices Q and R remain fixed, lacking adaptability, which limits MPC's ability to consistently deliver optimal performance under varying road and vehicle conditions.

To overcome the limitations of conventional MPC, which relies heavily on accurate models and fixed weighting matrices under complex operating conditions, researchers have increasingly introduced intelligent methods into suspension control [14, 15]. Such approaches mainly include neural networks, fuzzy control, and reinforcement learning, which can enhance nonlinear compensation capability and adaptability while maintaining satisfactory performance.

In terms of nonlinear approximation, Papadimitrakakis and Alexandridis [16] embedded a radial basis function (RBF) model into a road-preview MPC framework to improve the modeling accuracy of suspension nonlinear dynamics, thereby significantly enhancing vehicle performance under complex excitations. Zhang et al. [17] developed a fast distributed MPC method based on multi-agent modeling, where graph theory and RBFNN approximation were introduced to balance system performance with computational efficiency. Maiworm et al. [18] employed Gaussian process models combined with MPC to achieve online learning and guaranteed constraint satisfaction, effectively mitigating the effects of model-plant mismatch. Al Aela et al. [19] proposed an adaptive neural network integrated with backstepping control for electrohydraulic active suspension systems, aiming to compensate for model uncertainties and ensure system stability. Sun and Zhao [20] designed a neural network-based adaptive sliding mode controller, in which the weight adaptation law was derived using Lyapunov theory, enabling precise tracking performance even in the presence of actuator nonlinearities and external disturbances.

In terms of parameter adaptation, intelligent optimization and reinforcement learning have also been incorporated into suspension control. Manna et al. [21] employed an ant colony optimization algorithm to tune the Q and R weighting matrices of an LQR controller, significantly reducing vehicle body acceleration under irregular road conditions. Zhang et al. [22] proposed a two-layered learning MPC framework, in which Gaussian process regression was used to compensate for model mismatches and enable torque allocation, thereby improving vehicle stability. Bøhn et al. [23] introduced a reinforcement learning-based approach to automatically adjust MPC meta-parameters, achieving superior computational efficiency and closed-loop performance compared with manual tuning. Zarrouki et al. [24] combined deep reinforcement learning with Bayesian optimization to design a weight-varying safe MPC, which enables context-aware optimal parameter adaptation during operation.

As reviewed above, intelligent methods have been successfully applied either to approximating system nonlinearities [16, 17, 18] or to adaptively tuning control parameters [21, 22, 23, 24]. However, most existing studies that integrate intelligent methods with

MPC tend to focus on a single aspect – either compensating for system nonlinearities (e.g., [16, 17, 18]) or optimizing MPC parameters (e.g., [21, 22, 23, 24]) – rather than addressing both challenges simultaneously. The core contributions of this paper are as follows.

- 1) A multi-objective optimization framework centered on MPC is constructed, effectively handling various constraints and performance indices of the suspension system.
- 2) A nonlinear dynamic compensator based on RBFNN is designed to approximate and counteract actuator nonlinearities such as dead zones and saturation in real time, significantly enhancing model robustness.
- 3) A Q-Learning algorithm is introduced as an outer-loop adaptive mechanism to realize online adjustment of MPC weighting matrices, enabling the controller to actively adapt to varying operating conditions and maintain optimal performance.
- 4) Through rigorous Lyapunov stability analysis, it is proved that the composite closed-loop system achieves asymptotic stability and that the neural network weights are uniformly ultimately bounded, thereby ensuring the theoretical reliability of the proposed control scheme.

The rest of this paper is organized as follows. Section 2 presents the model and the preliminaries. Section 3 details the controller design and theoretical stability analysis. Simulation results are provided in Section 4, followed by the conclusion in Section 5.

2. System Modeling and Preliminaries.

2.1. System description. As a key component for enhancing vehicle ride comfort and safety, the performance of an active suspension system is directly related to the overall driving quality of the vehicle. For the purpose of analysis and controller design, the vehicle is commonly simplified into a quarter-car model, as illustrated by the ASS model on the right side of Figure 1.

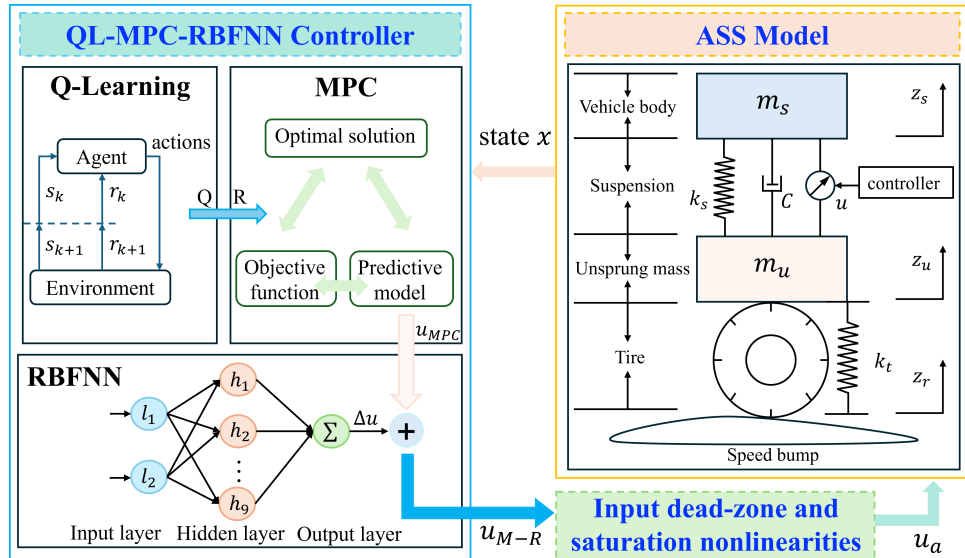


FIGURE 1. Overall framework of the QL-MPC-RBFNN controller and ASS model

The left side depicts the controller structure: the Q-Learning module adaptively tunes the MPC weights; the MPC core computes the optimal control command u_{MPC} ; the RBFNN provides compensation Δu for actuator nonlinearities. The combined signal $u_{M-R} = u_{MPC} + \Delta u$ is the total control command sent to the actuator. The right side

shows the ASS plant, where u represents the ideal control force in the dynamic equations, and u_a denotes the actual force applied after nonlinearities, such as dead-zone and saturation.

Considering the active suspension model shown in Figure 1, the dynamic equations of the ASS can be expressed as follows:

$$\begin{aligned} m_s \ddot{z}_s + k_s(z_s - z_u) + C(\dot{z}_s - \dot{z}_u) &= u, \\ m_u \ddot{z}_u - k_s(z_s - z_u) - C(\dot{z}_s - \dot{z}_u) + k_t(z_u - z_r) &= -u. \end{aligned} \quad (1)$$

The sprung mass m_s represents the vehicle body, while the unsprung mass m_u corresponds to the wheel and suspension. The tire is modeled as an equivalent stiffness element interacting with the road surface. The active suspension system introduces an additional control force as the control input, denoted by u , through the actuator to enhance vehicle dynamic performance. Here, k_s and k_t denote the stiffness coefficients of the suspension spring and the tire, respectively; C is the suspension damping coefficient; z_s , z_u and z_r represent the displacements of the vehicle body, the suspension, and the road disturbance, respectively.

Under this model, the primary control objectives of the suspension system can be summarized as follows:

- 1) Ride comfort – minimize the vertical acceleration of the sprung mass as much as possible;
- 2) Ride smoothness – constrain the suspension deflection within allowable limits to prevent mechanical damage to suspension components;
- 3) Driving safety – regulate fluctuations of the dynamic tire load to ensure continuous contact between the tire and the road surface.

Due to the presence of dead-zone and saturation nonlinearities in the ASS actuator, the actual actuator input is typically expressed as $u_a = \phi(u)$, where $\phi(\cdot)$ is an unknown function incorporating both dead-zone and saturation effects. Let the state vector be defined as $x = (z_s - z_u, \dot{z}_s, z_u - z_r, \dot{z}_u)^T$, the output vector as $y = (\ddot{z}_s, z_s - z_u, z_u - z_r)^T$, $\Delta u = u_a - u$ represents the unknown dead zone and saturation nonlinearities and $\omega = \dot{z}_r$ is road surface disturbance. Accordingly, the state-space representation of the ASS can be written as follows:

$$\begin{aligned} \dot{x} &= Ax + B(u + \Delta u) + E\omega, \\ y &= Cx + D(u + \Delta u), \end{aligned} \quad (2)$$

where

$$\begin{aligned} A &= \begin{bmatrix} 0 & 1 & 0 & -1 \\ -\frac{k_s}{m_s} & -\frac{C}{m_s} & 0 & \frac{C}{m_s} \\ 0 & 0 & 0 & 1 \\ \frac{k_s}{m_u} & \frac{C}{m_u} & -\frac{k_t}{m_u} & -\frac{C}{m_u} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ \frac{1}{m_s} \\ 0 \\ -\frac{1}{m_u} \end{bmatrix}, \quad E = \begin{bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{bmatrix}, \\ C &= \begin{bmatrix} -\frac{k_s}{m_s} & -\frac{C}{m_s} & 0 & \frac{C}{m_s} \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \quad D = \begin{bmatrix} \frac{1}{m_s} \\ 0 \\ 0 \end{bmatrix}. \end{aligned}$$

Therefore, it is necessary to introduce more flexible and intelligent control strategies to achieve effective control of such complex nonlinear systems.

2.2. Nonlinear disturbance compensation based on RBFNN. Within the proposed three-layer composite control framework, the inner-loop RBFNN is employed to dynamically compensate for actuator dead zones and saturation nonlinearities. Owing to its simple structure, global approximation capability, and fast local response, the RBFNN is well suited for real-time approximation of smooth nonlinear functions. The objective of the compensator is to provide an additional term $\Delta\hat{u}$ for the MPC controller, such that the actual control command received by the actuator becomes $u + \Delta\hat{u}$. In this way, the nonlinear deviation $\Delta\hat{u}$ can be effectively counteracted, thereby enhancing overall control accuracy.

To approximate the nonlinear deviation $\Delta\hat{u}$, the RBFNN is formulated as follows:

$$\Delta u = W^T \sigma(x) + \varepsilon, \quad (3)$$

where W denotes the weight matrix, and ε represents the bounded approximation error. $\sigma(x) = [\sigma_1(x), \dots, \sigma_9(x)]^T$ is the radial basis vector composed of Gaussian functions, where the i -th component is defined as

$$\sigma_i(x) = \exp - \frac{\|x - c_i\|^2}{\sigma_i^2}.$$

Here, c_i and σ_i denote the center vector and the width parameter of the i -th neuron.

In practical applications, since the ideal weight matrix W is unknown, the actual output of the RBFNN compensator is obtained using its estimated weight $\hat{W}$:

$$\Delta\hat{u} = \hat{W}^T \sigma(x). \quad (4)$$

To ensure effective compensation and stabilize the weight updating process, a weight adaptive update law is designed based on Lyapunov stability theory:

$$\dot{\hat{W}}(t) = \gamma \sigma(x(t)) (F^T P E(t)), \quad (5)$$

where $\gamma > 0$ is the learning rate that regulates the convergence speed of the weights; $F = [0 \ 1]^T$ is a constant vector mapping the compensation term to the acceleration channel; P is a symmetric positive-definite matrix that serves as the solution to the Lyapunov equation in the subsequent stability proof; and $E = [e_s \ \dot{e}_s]^T$ denotes the system error state vector. This update law ensures that the compensation term can be adjusted in real time according to the error information, thereby achieving online adaptivity and convergence.

Through this design, the RBFNN provides a data-driven nonlinear compensation mechanism for the active suspension system without relying on additional prior models, thereby effectively enhancing the robustness of the overall framework under complex operating conditions.

2.3. Model predictive control. MPC is an advanced control strategy based on modeling, rolling optimization, and feedback correction, particularly well-suited for optimal control of multivariable constrained systems.

First, the continuous-time model is discretized to construct the predictive model of MPC. Using the forward Euler method, the discrete state-space equation is obtained:

$$x(k+1) = A_d x(k) + B_d u(k), \quad (6)$$

where k denotes the current time step. x and u represent the state and input variables, respectively. A_d and B_d are coefficient matrices of appropriate dimensions. This model is then used to predict the state evolution of the system over a finite prediction horizon N .

At each sampling instant k , the MPC computes the control sequence by solving the following finite-horizon optimal control problem:

$$\min_{U_k} J = \sum_{i=0}^{N-1} [x(k+i|k)^T Q x(k+i|k) + u(k+i|k)^T R u(k+i|k)] + x(k+N)^T F x(k+N), \quad (7)$$

where $U_k = [u(k|k), u(k+1|k), \dots, u(k+N-1|k)]^T$ denotes the control sequence to be optimized. Q and R are the state and control weighting matrices, which are predefined constant matrices. The terminal cost term $x(k+N)^T F x(k+N)$, with terminal weight matrix F , is introduced to guarantee the stability of the system.

By defining the predicted state vector X_k and applying the predictive model (6), the above optimization problem can be transformed into a QP problem with respect to the control sequence U_k . Through standard expansion, this QP problem can be reduced to a quadratic form, yielding the optimal solution:

$$U_k = -Kx(k), \quad (8)$$

where the feedback gain matrix K is determined jointly by the predictive model parameters (A_d, B_d) and the weighting matrices (Q, R, F). MPC adopts a receding horizon strategy, in which only the first element of the optimal sequence, $u(k) = u(k|k)$, is applied to the system. At the next time step, the entire optimization procedure is repeated based on the updated state measurement, thereby achieving continuous optimization of system dynamics.

3. Main Results. The proposed QL-MPC-RBFNN control framework, illustrated in Figure 1, integrates three key components in a hierarchical structure: the MPC serves as the primary controller for constrained optimization; the RBFNN acts as a nonlinear compensator to counteract actuator imperfections; and the Q-Learning module operates as an outer-loop adaptive unit, tuning the MPC's parameters online. This framework, together with the quarter-car ASS model shown on the right side of Figure 1, forms a cohesive adaptive control system aimed at simultaneously improving ride comfort, handling stability, and safety under complex conditions. The following presents a rigorous analysis of this framework's stability.

Theorem 3.1. (*Asymptotic Stability of the MPC Closed Loop*) Consider the system described by the discrete predictive model (6). Let the state and control weighting matrices $Q > 0$ and $R > 0$ be given. If the terminal cost weighting matrix F in the MPC optimization problem (7) is chosen as the solution to the discrete algebraic Riccati equation:

$$F = Q + K^T R K + (A_d - B_d K)^T F (A_d - B_d K), \quad (9)$$

where K is the feedback gain defined in (8), then under the control law (8), the nominal closed-loop system is asymptotically stable in the absence of nonlinear disturbances.

Proof: Construct a discrete-time Lyapunov function $V(x_k) = J^*(x_k)$, i.e., the optimal cost function. By comparing the optimal cost $J^*(x_k)$ at step k with the cost of a specific feasible control sequence $J(x_{k+1}; \tilde{U})$ at step $k+1$, it can be shown that the Lyapunov difference is negative definite.

At step k , suppose the MPC yields the optimal input sequence

$$U^* = \{u_k^*, u_{k+1}^*, \dots, u_{k+N-1}^*\}.$$

For step $k+1$, define a feasible candidate control sequence as

$$\tilde{U} = \{u_{k+1}^*, u_{k+2}^*, \dots, u_{k+N-1}^*, \kappa(x_{k+N}^*)\},$$

where, according to (8), $\kappa(x) = -Kx$, and the state evolution satisfies $x_{k+1} = (A_d - B_d K)x_k$. Thus, the corresponding cost at step $k + 1$ is

$$J(x_{k+1}; \tilde{U}) = \sum_{i=1}^N (x_{k+i}^T Q x_{k+i} + u_{k+i}^T R u_{k+i}) + x_{k+N+1}^T F x_{k+N+1}.$$

Here, $Q = a_Q \cdot Q_0$, $R = a_R \cdot R_0$, with $a_Q = \rho m$ and $a_R = \frac{m}{\rho}$. The baseline weighting matrices Q_0 and R_0 are manually specified, while the two auxiliary variables ρ and m are updated by the Q-Learning algorithm (as shown in Algorithm 1).

TABLE 1. Q-Learning for MPC Q , R tuning

Algorithm 1: Q-Learning for MPC Q , R tuning

1. Initialize Q-table, parameters ρ , m and related variables.
 2. At each control step k :
 - 2.1. Construct state $s_k = (E_k, \dot{E}_k, u_{k-1})$.
 - 2.2. Select action a_k from action set $\mathcal{A} = \{-1, 0, +1\}^2$ using ε -greedy policy.
 - 2.3. Decode a_k into increments $(\Delta \log \rho, \Delta \log m)$; update ρ , m .
 - 2.4. Compute MPC weights: $a_Q = \rho m$, $a_R = \frac{m}{\rho}$.
 - 2.5. Observe next state s_{k+1} and compute reward.
 - 2.6. Update Q-table using temporal-difference rule.
 3. Output (a_Q, a_R) to MPC controller.
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According to (9), the candidate cost function at step $k + 1$ can be simplified as

$$J(x_{k+1}; \tilde{U}) = \sum_{i=1}^{N-1} (x_{k+i}^T Q x_{k+i} + u_{k+i}^T R u_{k+i}) + x_{k+N}^T F x_{k+N}.$$

Since the sequence $\tilde{U}$ is a feasible solution at step $k + 1$, it follows that $J^*(x_{k+1}) \leq J(x_{k+1}; \tilde{U})$. Thus,

$$V(x_{k+1}) - V(x_k) \leq J(x_{k+1}; \tilde{U}) - J^*(x_k) = -x_k^T Q x_k - u_k^T R u_k.$$

In summary, by ensuring that the terminal weight satisfies the Riccati equation (9), the stability of the terminal region is guaranteed. Consequently, $V(x_{k+1}) - V(x_k) \leq 0$, and the inequality is strictly negative when $x_k \neq 0$. Therefore, the Lyapunov function decreases monotonically, and the closed-loop system is asymptotically stable. $\square$

Remark 3.1. Since Q-Learning adaptively adjusts the Q and R , the weights in the MPC cost function (7) become adaptive. However, the stability of the closed loop still relies on the Riccati condition (9); therefore, the conclusion remains valid.

Theorem 3.2. (Uniform Ultimate Boundedness of the RBFNN Compensator) For the error dynamics system subject to nonlinear disturbance Δu , when the adaptive weight update law (5) is applied, both the weight estimation error of the RBFNN, $\tilde{W} = W - \hat{W}$, and the system tracking error E are uniformly ultimately bounded (UUB).

Proof: Define the system error state as $E = [e_s, \dot{e}_s]^T = [z_s - z_u, \dot{z}_s - \dot{z}_u]^T$. From the error dynamics, it follows that $\ddot{z}_s - \ddot{z}_u = \ddot{e}_s = -KE + (\Delta \hat{u} - \Delta u)$. The error dynamics can thus be written in standard form as

$$\dot{E} = \Lambda E + F(\Delta \hat{u} - \Delta u),$$

where

$$F = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad \Lambda = \begin{bmatrix} 0 & 1 \\ -K_1 & -K_2 \end{bmatrix}.$$

Since $\tilde{W} = W - \hat{W}$, the error dynamics can be rewritten as

$$\dot{E} = \Lambda E + F \left(-\tilde{W}^T \sigma(x) - \varepsilon \right).$$

Consider the augmented Lyapunov function $V \left(E, \tilde{W} = \frac{1}{2} E^T P E + \frac{1}{2\gamma} \tilde{W}^T \tilde{W} \right)$, $\gamma > 0$, where $P = P^T > 0$ satisfies $\Lambda^T P + P \Lambda = -Q$, $Q = Q^T > 0$.

Taking the time derivative of $V \left(E, \tilde{W} \right)$ and substituting the error dynamics together with the weight update law (5), we obtain

$$\dot{V} = -\frac{1}{2} E^T Q E - E^T P F \varepsilon. \quad (10)$$

- 1) If $\varepsilon \equiv 0$, i.e., the RBF neural network perfectly approximates the system nonlinearity, then from (10) it follows that $\dot{V} \leq -\frac{1}{2} \lambda_{\min}(Q) \|E\|^2$. Therefore, the system error $E(t)$ converges asymptotically to zero.
- 2) If ε is bounded, i.e., $|\varepsilon| \leq \bar{\varepsilon}$, then by the Cauchy-Schwarz inequality and Yang's inequality, we have

$$|E^T P F \varepsilon| \leq \frac{1}{4} \lambda_{\min}(Q) \|E\|^2 + \frac{\|P F\|^2}{\lambda_{\min}(q)} \bar{\varepsilon}^2.$$

Substituting this into (10) yields $\dot{V} \leq -\frac{1}{4} \lambda_{\min}(Q) \|E\|^2 + \frac{\|P F\|^2}{\lambda_{\min}(q)} \bar{\varepsilon}^2$. Therefore, E is UUB, with the convergence radius proportional to $\bar{\varepsilon}$. $\square$

After establishing the stability and convergence of the closed-loop system, together with the online adaptive adjustment capability endowed by Algorithm 1, MPC is employed as a receding-horizon optimizer and embedded into the composite control framework to achieve real-time optimization of the active suspension system's performance objectives.

The primary control objective is to suppress the vertical vibration of the sprung mass. Setting the reference trajectory as $y_d = 0$, the state tracking error becomes $e(k) = x(k)$. Based on the discrete system model defined in (6), the following finite-horizon optimal control problem is solved at each sampling instant k :

$$\begin{aligned} \min_{U_k} J = & \sum_{i=0}^{N-1} \{x(k+i|k)^T Q x(k+i|k) + u(k+i|k)^T u(k+i|k) R\} \\ & + x(k+N)^T F x(k+N). \end{aligned}$$

In this problem, the weighting matrices Q and R are not fixed but are provided online in real time by Algorithm 1. This enables the optimization objective of MPC to dynamically adapt to varying operating conditions, which is the key to achieving intelligent adaptive performance. The terminal weighting matrix is designed in strict accordance with the stability condition given in Theorem 3.1, thereby ensuring the asymptotic stability of the closed-loop system during the receding-horizon optimization process from a theoretical perspective.

By solving the above quadratic programming problem, the optimal control sequence U^* is obtained. Subsequently, the receding-horizon strategy is applied:

$$u_{MPC}(k) = u^*(k|k),$$

that is, only the first element of U^* is applied to the plant. At the next sampling instant, the entire “prediction-optimization-execution” process is repeated based on the updated state measurements.

In summary, Theorems 3.1 and 3.2 jointly constitute the stability foundation of the proposed composite controller. Although the controller integrates online adaptive Q-Learning and nonlinear compensation via RBFNN, under the given design, the entire QL-MPC-RBFNN closed-loop system is proven to be UUB in the Lyapunov sense. When the neural network approximation is sufficiently accurate, the system performance can approach asymptotic stability. This conclusion theoretically guarantees the core reliability of the highly adaptive intelligent control framework.

4. Simulation Example. To validate the effectiveness of the proposed QL-MPC-RBFNN controller, a quarter-car ASS model was established on the MATLAB/Simulink platform and compared with conventional MPC, MPC-RBFNN, and the DMPC controller from [17]. The system was subjected to a speed bump excitation, as illustrated in Figure 2(a), under a constant vehicle speed, and the car parameters are listed in Table 2.

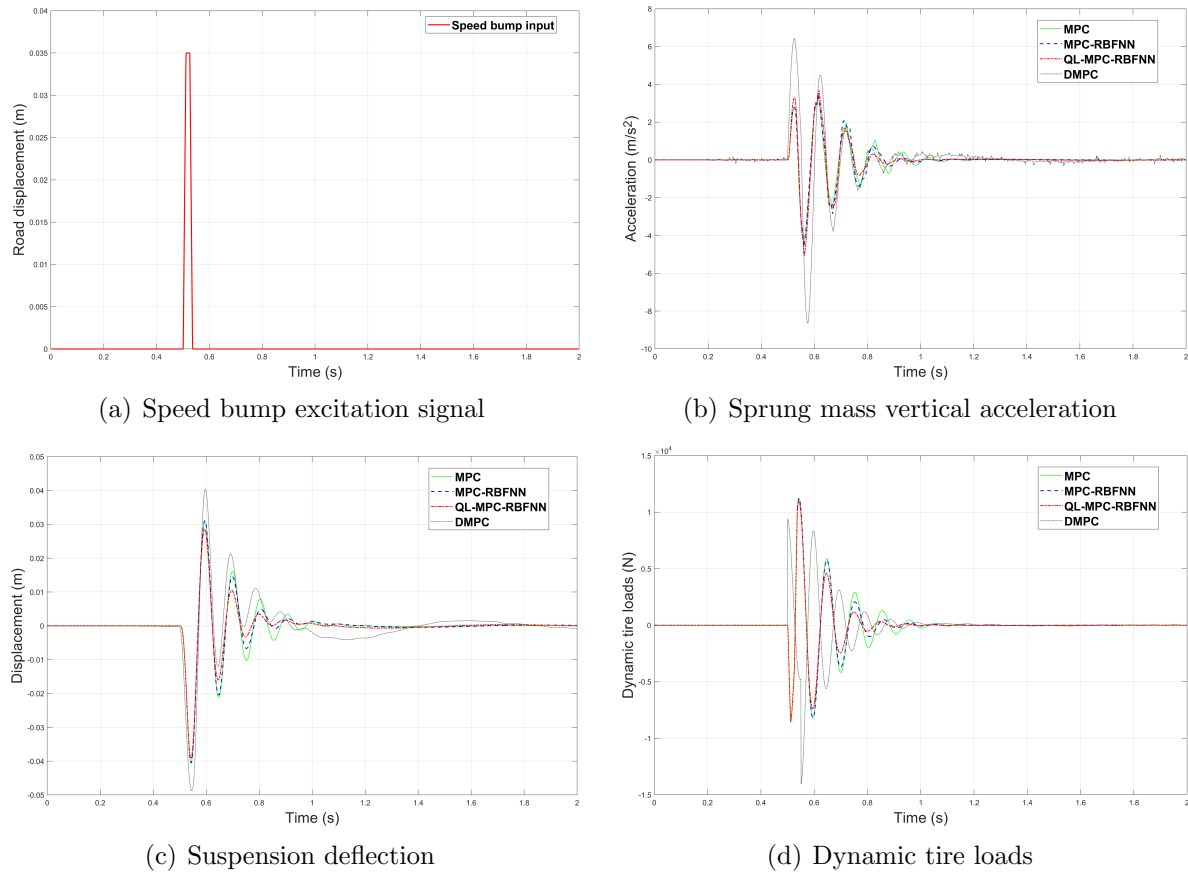


FIGURE 2. Comparative dynamic response of active suspension systems under speed bump excitation

Figure 2 compares the dynamic responses of the three controllers in terms of ride comfort, safety, and road holding. The results demonstrate that the proposed method offers significant advantages.

In terms of ride comfort, Figure 2(b) shows that the QL-MPC-RBFNN controller most effectively suppresses impact peaks and accelerates convergence. Although MPC-RBFNN performs better than conventional MPC, the incorporation of Q-Learning provides the

TABLE 2. The parameter of ASS model

Name	Value	Unit
m_s	500	kg
m_u	66.7	kg
k_s	27000	N/m
k_t	268000	N/m
C	1500	Ns/m

controller with stronger transient adaptability, thereby achieving the best comfort. As illustrated in Figures 2(c) and (d), the proposed controller also demonstrates competitive performance in suspension deflection and dynamic tire load regulation. It is observed that the DMPC strategy exhibits a slightly lower peak dynamic tire load within a short transient interval in Figure 2(d), which is consistent with its conservative multi-agent coordination and constraint-oriented design philosophy.

In contrast, the QL-MPC-RBFNN framework dynamically adjusts the MPC objective via Q-Learning, prioritizing rapid impact attenuation and fast recovery. Although this may result in a marginally higher instantaneous tire load peak, the overall oscillation decays faster and the steady-state behavior is smoother. Therefore, considering ride comfort, suspension travel, and dynamic tire load jointly, the proposed method achieves a superior overall performance trade-off. The RBFNN compensator effectively mitigates nonlinearities, while the Q-Learning layer dynamically optimizes the MPC objective, jointly endowing the system with stronger impact resistance and faster recovery capability.

5. Conclusion. This paper addresses the nonlinearities and uncertainties of active suspension systems by proposing a Q-Learning-based MPC-RBFNN composite control method. The framework enhances system performance through the three-layer integration of RBFNN nonlinear compensation, MPC rolling optimization, and Q-Learning-based online adaptation. The main contributions include the design of an adaptive RBFNN compensator capable of stably compensating for unknown actuator dynamics, and the introduction of a data-driven mechanism to optimize MPC weights online. Simulation results under speed bump excitation confirm that the proposed controller achieves a superior overall balance among ride comfort, safety, and road holding. Its lower response peaks and faster convergence significantly outperform conventional methods, providing an effective solution for high-performance suspension control under complex operating conditions. Future research will focus on validation with full-vehicle models and more complex road scenarios.

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