Research on the DDPG Algorithm for a Semi-active Suspension System for Improving Vehicle Ride Comfort on Uneven Roads*

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Abstract: The vibration control effectiveness for a vehicle using a controlled suspension system will outperform that of traditional passive suspension systems. The latter are limited with regard to their ability to adjust to varying road conditions, whereas the semi-active systems provide a higher flexibility and efficiency. This paper introduces a new approach for improving the ride comfort with regard to the semi-active suspension systems of vehicles by employing the Deep Deterministic Policy Gradient (DDPG)-based algorithm. The main objective of this research is to optimize the vertical control of a semi-active suspension system by using deep reinforcement learning (DRL), providing a dynamic, real-time adaptive solution to varying road conditions. By employing the DDPG-based algorithm, this paper addresses challenges such as continuous state spaces and action execution in semi-active suspension systems. The semi-active suspension system is modeled dynamically and its responses are evaluated across various road surfaces, including uneven and bump road conditions. The simulation results show that the DDPG-based suspension system significantly improves the suspension performance by reducing the vertical body acceleration, the suspension deflection, and the overall passenger discomfort in comparison with the passive suspension systems. The proposed approach features an excellent adaptability and efficiency in vehicle suspension control, highlighting the potential of AI in optimizing vehicle suspension systems for an enhanced ride comfort and stability.

Keywords: Quarter-car suspension, Semi-active suspension system, Car dynamics, DDPG, Deep reinforcement learning.

1. Introduction

The rapid advancement of autonomous driving technologies is revolutionizing the transportation systems, promising unprecedented intelligence. However, these systems face challenges, such as complex road structures and unpredictable events, which traditional control algorithms struggle to address. In this context, artificial intelligence, particularly DRL, offers promising alternatives to overcome the limitations of conventional control systems in dynamic environments (Hung et al., 2024; Petrescu et al., 2024).

DRL has shown great potential in areas such as vision, perception, planning, and control for autonomous vehicles (Tang et al., 2025). Its key strength lies in the ability to autonomously adapt and optimize vehicle behavior through continuous interaction with the environment, making it well-suited for complex, real-time control problems (Deng et al., 2023). Various DRL algorithms, including Deep Q-Network (Ban et al., 2024), Asynchronous Advantage Actor-Critic (Mnih et al., 2016), Proximal Policy Optimization (Haydari et al., 2020), DDPG and Soft Actor-Critic are effective for solving nonlinear, high-dimensional control challenges. While DRL applications in autonomous vehicle control have mostly focused on lateral and longitudinal control (Kuutti et al., 2020), in contrast, research into the vertical control of semi-active suspension systems remains underdeveloped, despite its significant importance in ensuring ride comfort.

Suspension systems are vital for shock absorption in vehicles, mitigating vibrations caused by uneven road surfaces, engine operations, and tire

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irregularities (Luu et al., 2025). These vibrations, primarily caused by road bumps and potholes, can severely affect passenger comfort (Turan et al., 2024). A key aspect of improving ride comfort is minimizing suspension deflection and body acceleration. Various suspension systems, including passive, active, and semi-active suspensions, have been developed to address these concerns (Wang et al., 2020). While passive suspension systems are simple and affordable, they lack the flexibility to adjust to varying road conditions and load disturbances (Kumar et al., 2020). On the other hand, active suspension systems, which generate control forces via actuators, provide a superior performance (Benhiba et al., 2025) but the complex structure and high energy consumption of active suspensions becomes the limitation for applying them to vehicles widely (Yu et al., 2024). Semi-active suspension systems, which adjust damping forces in response to road conditions, strike a balance by offering an improved ride comfort over passive systems, while being more energy-efficient and cost-effective than active systems (Liu et al., 2019). The challenge lies in developing high-performance controllers for semi-active suspensions that can adapt to changing conditions and optimizing their performance in real time. This research seeks to fill this gap by applying deep reinforcement learning, specifically the Deep Deterministic Policy Gradient (DDPG) algorithm to the vertical control of semi-active suspension systems.

The remainder of this paper is as follows. Section 2 introduces the related work and Section 3 presents the training environment, with the control signal being the basis of the semi-active suspension system. Further on, Section 4 sets forth the DRL algorithm design, while the effectiveness of the proposed controller is evaluated in Section 5. Finally, Section 6 presents the conclusions of this paper and sets forth possible future research directions.

2. Related Work

Semi-active suspension systems often employ magnetorheological dampers as actuators, adjusting the suspension damping by applying a magnetic field to the damper. Due to the limitations of passive suspension systems in maintaining vehicle body stability, many studies have focused on developing control strategies to dynamically adjust the damping coefficient, resulting in the creation of semi-active suspension systems (Luu et al., 2025). These systems are capable of adapting to varying road conditions, offering a significant improvement over passive suspensions. One widely used semi-active system is the skyhook damper, which controls damping by using a reference point to minimize body movement relative to road disturbances. Zhang et al. (2018) proposed a modified skyhook-inertance control strategy, incorporating a hydraulic device that allows the continuous adjustment of the inertance between the sprung and unsprung masses, enhancing the suspension performance.

In addition to the skyhook damper, several advanced methods for semi-active suspension have been developed. For instance, Sun et al. (2017) introduced a multi-mode switching damper, replacing the traditional continuous damping with four discrete modes controlled by solenoid valves. This approach, combined with model predictive control, improves the damping efficiency and reliability. However, combining continuous dynamics with discrete switching modes poses challenges in calculating the control signal. To address this, approaches such as fuzzy PID with sliding mode control (Dong & Duan, 2024), meta-heuristic algorithms (Liu et al., 2024), and neural networks (Huang et al., 2023) have been explored. Moreover, Takagi-Sugeno (T-S) fuzzy control has been applied to semi-active suspensions with MR dampers (Du et al., 2013), with further enhancements by Wang et al. (2021), who integrated a state observer with the T-S fuzzy model. Despite these advancements, these methods often fail to account for the uncertain factors in system modeling, which can lead to instability.

To address these challenges, DRL represents a promising alternative. Unlike traditional methods, DRL can learn complex, high-dimensional mappings directly from system states to control actions, without requiring precise vehicle models or road information. This ability enables a continuous learning and adaptation to actual road conditions and varying suspension parameters, offering a more flexible and robust control mechanism.

In this context, the DDPG algorithm is applied to semi-active suspension control. By using the DDPG training process, the control force is learned and optimized, resulting in the desired semi-active suspension force. This method automatically adjusts parameters in response to external changes in the environment, making it particularly well-suited for optimizing ride comfort and stability without relying on an exact system model.

The performance of the proposed method is evaluated through simulations of two road surface scenarios based on ISO 8608 standards (ISO, 2016), including uneven roads, bumpy roads, and pothole conditions. The simulation results demonstrate that the DDPG-based control approach outperforms passive suspension systems, particularly in terms of ride comfort. The main contributions of this paper are as follows:

1. A DDPG-based controller is proposed for semi-active suspension control, ensuring an improved ride comfort for autonomous vehicles. This represents a novel application of data-driven algorithms in vertical control for autonomous cars;

2. The control calculation process is simplified using DDPG to determine the virtual control forces for subsystems;

3. The simulation results confirm that, in comparison with the passive suspension systems, the DDPG-based method significantly improves the ride comfort across uneven and bumpy road surfaces. The proposed controller shows an exceptional adaptability across a variety of unpredictable parameters and road conditions.

3. Training Environment

The semi-active suspension system is a dynamic and intricate system, characterized by high order, nonlinearity, uncertainty, hysteresis, and vulnerability to failures. In order to analyze the impact of active suspension on car performance in a clear and efficient way, a two-degree-of-freedom quarter-car model with centralized parameters, based on Newton's law was created. This model, depicted in Figure 1 with the corresponding parameters outlined in Table 1, includes the primary components of a semi-active suspension system: sprung mass, unsprung mass, springs, dampers, and an actuator of the semi-active suspension system.

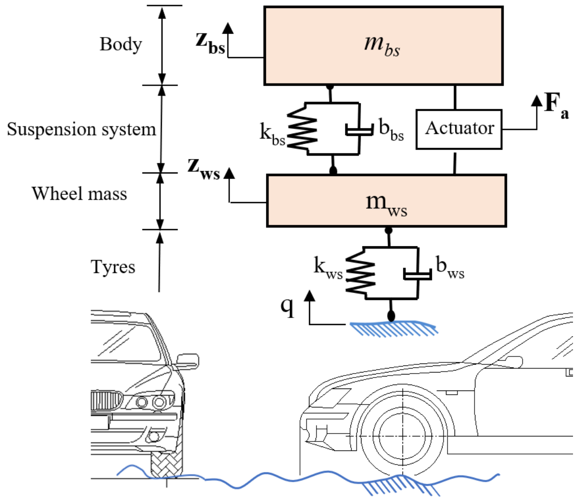

Figure 1. Quarter-car model of the semi-active suspension (Luu et al., 2025)

Depending on the actuator and damping configurations, it can simulate both passive and active suspension modes.

According to the definition above, the dynamics of the semi-active suspension system can be approximately represented in a linear form by the following equation:

$$\begin{cases} m_{bs}\ddot{z}_{bs} + b_{bs}\left(\dot{z}_{bs} - \dot{z}_{ws}\right) + k_{bs}\left(z_{bs} - z_{ws}\right) = F_a \\ m_{ws}\ddot{z}_{ws} - b_{bs}\left(\dot{z}_{bs} - \dot{z}_{ws}\right) - k_{bs}\left(z_{bs} - z_{ws}\right) \\ +k_{ws}\left(z_{ws} - q\right) + b_{ws}\left(\dot{z}_{ws} - \dot{q}\right) = -F_a \end{cases}, \quad (1)$$

The chosen system state variables and outputs are specified as follows:

$$Z = \begin{bmatrix} z_{ws} & z_{bs} & \dot{z}_{bs} & \dot{z}_{ws} \end{bmatrix}^T, \quad (2)$$

$$Y = \begin{bmatrix} \ddot{z}_{bs} & z_{bs} - z_{ws} \end{bmatrix}^T. \quad (3)$$

The definitions for the control input and road disturbance input are as follows:

$$U = \begin{bmatrix} q & F_a \end{bmatrix}^T, \quad (4)$$

By using equations (2) through (4), equation (1) can be expressed as the following state-space equation:

$$\begin{cases} \dot{Z} = AZ + BU \\ Y = CZ \end{cases}, \quad (5)$$

where: m_{bs}[kg] and m_{ws}[kg] are the sprung mass (body mass) and unsprung mass, respectively; k_{bs}[N/m] and k_{ws}[N/m] represent the suspension spring stiffness, tire stiffness, respectively; b_{bs}[N.s/m] and b_{ws}[N.s/m] are the damping coefficient and tire damper, respectively; F_a[kN] represents the semi-active suspension control force; z_{bs}[m] and z_{ws}[m] represent the body displacement and tire displacement, respectively; and q[m] denotes the road displacement.

$$A=\begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -\dfrac{k_{bs}+k_{ws}}{m_{\mathrm{w}}} & \dfrac{k_{bs}}{m_{\mathrm{ws}}} & -\dfrac{b_{bs}+b_{ws}}{m_{\mathrm{ws}}} & \dfrac{b_{bs}}{m_{\mathrm{ws}}} \\ \dfrac{k_{bs}}{m_{bs}} & -\dfrac{k_{bs}}{m_{bs}} & \dfrac{b_{bs}}{m_{bs}} & -\dfrac{b_{bs}}{m_{bs}} \end{bmatrix},$$

$$B=\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \dfrac{-k_{ws}}{m_{\mathrm{ws}}} & \dfrac{-1}{m_{\mathrm{ws}}} \\ 0 & \dfrac{1}{m_{bs}} \end{bmatrix},\ C=\begin{bmatrix} k_{bs} & -1 \\ -k_{bs} & 1 \\ b_{bs} & 0 \\ -b_{bs} & 0 \end{bmatrix}^T.$$

4. DRL Algorithm Application for Semi-active Suspension Control

The DDPG algorithm is a widely recognized method in the field of deep reinforcement learning. By combining the strengths of the deep Q-network and the Actor-Critic methodologies, DDPG is particularly effective for solving complex, high-dimensional problems requiring a continuous action space. As shown in Figure 2, the reinforcement learning environment for this approach is based on a back stepping-driven active suspension system. This structure employs an actor-critic off-policy method, which involves two distinct networks: the actor network and the critic network.

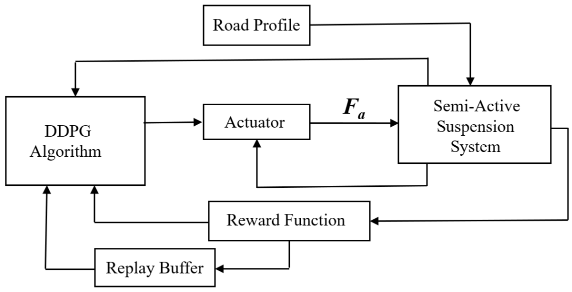

Figure 2. Reinforcement learning process

Since the samples generated by exploring the RL neural networks are not independently and identically distributed, a replay buffer is introduced to mitigate this issue. This buffer stores the control law, along with the system states and reward functions, providing a way for sampling and reusing experiences for a better learning.

The expected return function, according to Bellman's equation, after applying the control law u_i in state Z_i and following a deterministic policy, can be represented as:

$$Q(Z_i,u_i)=E\left(R_i(Z_i,u_i)+\gamma Q(Z_{i+1},u_{i+1})\right), \tag{6}$$

where Z_i is the state vector of the semi-active suspension system and γ is the discount factor for future returns. The reward function design is crucial for the DDPG strategy, and in this paper, the reward function is defined as:

$$R_i=-\left(k_1\ddot{z}_b{}^2+k_2(z_b-z_w)^2+k_3z_b{}^2\right), \tag{7}$$

where k_1, k_2 and k_3 represent the weight coefficients in the multi-objective optimization problem, respectively.

The architecture of the DDPG algorithm, shown in Figure 3, consists of two main parts: the actor network and the critic network. The actor network is employed for producing actions, with noise introduced to facilitate action exploration. The critic network, on the other hand, is used for assessing the long-term rewards of the actions, aiding the actor network in the learning process in order to achieve the optimal deterministic policy.

Therefore, the core of the DDPG algorithm is comprised of four networks: the main actor network μ, the target actor network μ', the main critic network Q and the target critic network Q'. Additionally, the DDPG algorithm employs the experience replay mechanism from the deep Q-network approach in order to reduce the correlations among samples. In this process, the fragments (Z_i,u_i,R_i,Z_{i+1}) are collected from the environment using an exploration policy and stored in a replay buffer with a limited capacity, where older samples are discarded as the buffer fills. It is important to note that the actor network of DDPG, denoted by u_t, is generated by adding Gaussian noise denoted by $\xi \sim N(0,\sigma_\tau)$ to the actor policy:

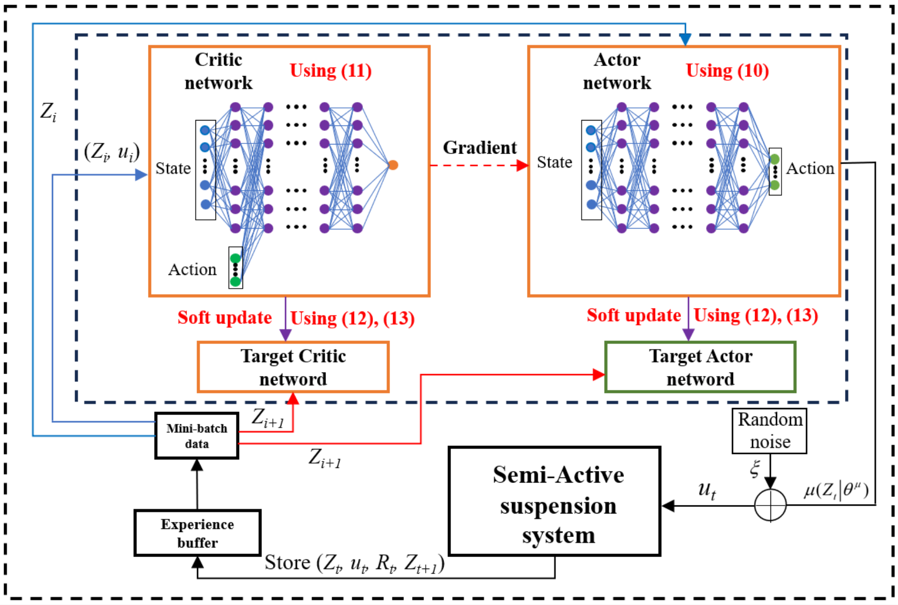

Figure 3. Semi-active suspension DDPG-based control algorithm architecture

$$u_t = \mu(Z_i|\theta^{\mu}) + \xi, \tag{8}$$

where, θ^{μ} refers to the weights of the actor network, t is the time step and ξ is the exploration noise. The main actor network generates actions aimed at maximizing the Q-value, with the corresponding objective function defined as:

$$J(\theta^{Q}) = -\frac{1}{N}\sum_{i=1}^{N} Q(Z_i, u), \tag{9}$$

where θ^{Q} denotes the weight parameters of the main critic network Q. For every update, a batch of N training samples is selected, and the gradient of the objective function is aligned with the expected gradient of the Q-value function. This leads to the main actor network being updated using the following function:

$$\nabla J(\theta^{\mu}) \approx \frac{1}{N}\sum_{i=1}^{N}[\nabla_a Q(Z_i, \mu(s_i|\theta^{\mu})|\theta^{Q})\nabla_{\theta}\mu(Z_i, \mu(s_i|\theta^{\mu})] \tag{10}$$

The critic network's objective is to minimize the error in the Q-value estimation, and the loss function for episodic environments is expressed as:

$$J(\theta^{Q}) = \left\{y_i - Q(Z_i, \mu_i(Z_i|\theta^{\mu})|\theta^{Q}\right\}^2, \tag{11}$$

where, $y_i = R_i + \gamma Q'(Z_{i+1}, \mu'(Z_{i+1}|\theta^{Q}))$ represents the output of the target network. However, the Q network may become unstable and diverge in certain environments if the critic network is updated using equation (11). To address this issue, this paper introduces an adaptive law for adjusting the weights of the target networks, defined as follows:

$$\tau\theta^{Q} + (1-\tau)\theta^{Q'} \to \theta^{Q'}, \tag{12}$$

$$\tau\theta^{\mu} + (1-\tau)\theta^{\mu'} \to \theta^{\mu'}, \tag{13}$$

where τ is a small parameter, typically set at 0.001, ensuring smooth updates for the target networks, thereby aiding the stability of learning.

The goal of training the critic network is to minimize the Q-value error. The overall objective function is then written as:

$$J(\theta^{Q}) = \left\{\begin{array}{l} R_i + \gamma Q'(Z_{i+1}, \mu'(Z_{i+1}|\theta^{Q'})) \\ -Q(Z_i, \mu_i(Z_i|\theta^{\mu})|\theta^{Q} \end{array}\right\}^2. \tag{14}$$

Ultimately, using the policy gradient, the actor network's policy can be updated as follows:

$$\nabla J(\theta^{Q}) \approx \frac{1}{N}\sum_{1}^{N}\left[\begin{array}{l} (y_i - Q(Z_i, \mu(Z_i|\theta^{\mu})|\theta^{Q}) \\ \nabla_{u_i} Q(Z_i, \mu(Z_i|\theta^{\mu})|\theta^{Q} \end{array}\right] \tag{15}$$

The DDPG algorithm updates both networks by randomly sampling a minibatch from a replay buffer, where past state-action pairs are stored. This experience replay enables the network to learn from previous interactions and improve both the actor's policy and the critic's value estimation.

Based on this idea, the model learning algorithm is shown below:

Algorithm 1. DDPG algorithm for the semi-active suspension system

Input: set the structural index of the model: the system parameters m_{bs}, m_{ws}, k_{bs}, b_{bs}, b_{ws}, k_{ws}, q, the sampling time t, the constraint sets F_a.

Output: the control force F_a

Start loop to compute:

- Randomly initialize main critic network Q with weight θ^Q and main actor network μ with weight θ^μ.
- Initialize target networks Q' and μ' with weights $\theta^Q \rightarrow \theta^{Q'}$, $\theta^\mu \rightarrow \theta^{\mu'}$
- Initialize replay buffer.
- Generate empirical samples (Z_t, u_t, R_t, Z_{t+1}) to fill the buffer

for episode =1, M **do**

- Initialize N for action exploration
- Receive the initial observation state Z_1 of env

for $t=0$ to T **do**

- Output action $u_t = \mu(Z_t|\theta^\mu) + \xi$ based on actor policy and noise
- R_t, $Z_{t+1} \leftarrow$ env.step(u_t).
- Store sample (Z_t, u_t, R_t, Z_{t+1}) for R.
- Sample N samples (Z_i, u_i, R_i, Z_{i+1}) for R,

$$J(\theta^Q) = \begin{Bmatrix} R_i + \gamma Q'(Z_{i+1}, \mu'(Z_{i+1} \left| \theta^{Q'} \right.)) \\ -Q(Z_i, \mu_i(Z_i \left| \theta^\mu \right.) \left| \theta^Q \right. \end{Bmatrix}^2 .$$

- Upload θ^Q by minimizing $J(\theta^Q)$

$$J(\theta^\mu) = -\frac{1}{N}\sum_{i=1}^{N} Q(Z_i, \mu(Z_i \left| \theta^\mu \right.) \left| \theta^Q \right.) .$$

- Upload θ^μ by minimizing $J(\theta^\mu)$.
- Update the target networks:

$$\begin{cases} \theta^{\mu Q'} \leftarrow \tau\theta^{\mu Q} + (1-\tau)\theta^{\mu Q'} \\ \theta^{\mu\mu'} \leftarrow \tau\theta^{\mu\mu} + (1-\tau)\theta^{\mu\mu'} \end{cases} .$$

end for

end for

Update and go to step 1.

5. Numerical Simulations

To validate the proposed method, a quarter-vehicle semi-active suspension system model based on the nonlinear MacPherson suspension structure (as shown in Figure 1) is used. Ride comfort, a primary measure of the suspension system quality, serves as a key evaluation criterion. The performance and robustness of the proposed semi-active suspension control approach are tested through simulations and compared with those of passive suspension systems. Additionally, the simulations incorporate two types of road surface profiles - bumpy and uneven roads – for a quantitative analysis.

The agent's weights were trained using a single NVIDIA Tesla A100-40GB GPU. The training process took approximately 2.5 hours for the Policy Network to converge. The hyperparameters employed for training the DDPG are listed in Table 1.

Table 1. DDPG hyperparameters

Network configuration	**Value**
Input dimension (Q-Network)	8-D
Input dimension (Policy Network)	6-D
Hidden Layers (Q-Network)	2 layers
Hidden Layers (Policy Network)	2 layers
Training process	**Value**
Number of Episodes	800
Batch size	512
Buffer Size	10^5
Optimizer (Q-Network)	Adam
Optimizer (Policy Network)	Adam
Learning rate (Q-Network)	10^{-3}
Learning rate (Policy Network)	10^{-4}
Discount factor	0.99
Soft Update rate	0.99
Exploration noise: Episodes 1-10	0.5
Exploration noise: Episodes 100-200	0.3
Exploration noise: Episodes 200-500	0.15
Exploration noise: Episodes 500-700	0.05
Multi-objective weight k_1,k_2,k_3	0.7, 0.1, 0.1

5.1 Simulation for a Multi-bump Road Profile

The chosen bump road profile also illustrates the characteristics of transient response. The bump-road profile is defined as:

$$q(t) = \begin{cases} a\{1 - cos(\omega_q(t - 0,5))\} \\ 0, otherwise \end{cases} \tag{16}$$

The multi-bump road profile is shown in Figure 4. Figures 5 and 6 illustrate the body acceleration, and body displacement, respectively for the bump road profile. Passive suspension systems feature a poorer performance with a higher acceleration and bigger displacement. In comparison with the standard DDPG control, the semi-active suspension system using the DDPG strategy ensures an improved ride comfort with reduced and smoother vertical and pitch accelerations. Specifically, the body acceleration and body displacement are significantly reduced to *3,0 (m/s²)* and *0,075 (m),* respectively.

Furthermore, Figure 7 illustrates the suspension deflection of the quarter-vehicle model, showing that the proposed method maintains a strong performance. Notably, when compared with passive suspension, the DDPG-based approach obtains a smaller suspension deflection. Based on Figure 8, DDPG features a better performance in comparison with passive suspension systems in terms of peak amplitude.

In the next subsection, a different scenario is examined using an uneven road profile.

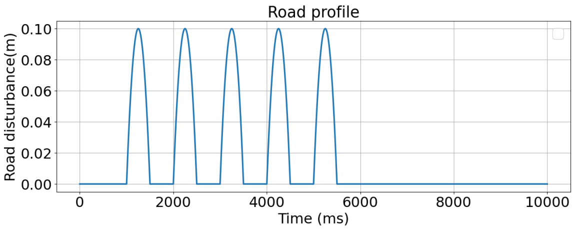

Figure 4. Bump Road surfaces

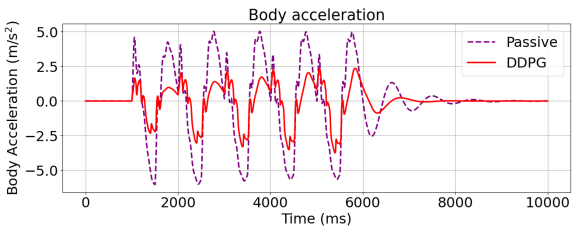

Figure 5. Simulation results under the bump road profile: body acceleration

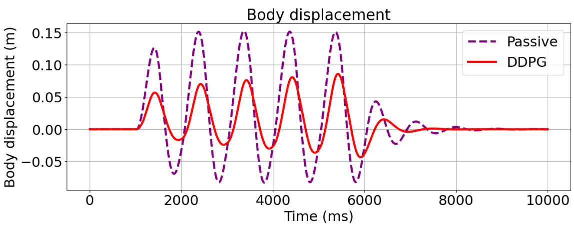

Figure 6. Simulation results under the bump road profile: body displacement

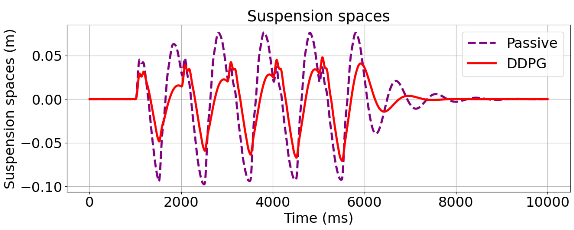

Figure 7. Simulation results under the bump road profile: suspension deflection

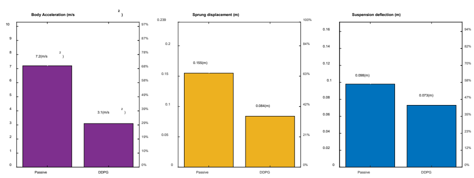

Figure 8. Simulation results under the bump road profile: maximum peak value

5.2 Simulation for an Uneven Road Profile

For further validation, a simulation experiment was carried out on an uneven road surface, selecting vertical and lateral profiles classified as level C uneven road surfaces in accordance with ISO 8608 (ISO, 2016), as depicted in Figure 9.

The simulation results shown in Figures 10 and 11 clearly indicate that, without any active actuator (i.e. in a passive suspension system), body acceleration and displacement reach their highest levels, leading to passenger discomfort. When the proposed control strategy is applied to the passive suspension system - transforming it into a semi-active suspension system based on the DDPG strategy - the suspension response improves. Specifically, with the DRL-based semi-active suspension system, body acceleration and displacement are reduced in comparison with the passive suspension system, demonstrating that the proposed method enhances ride comfort.

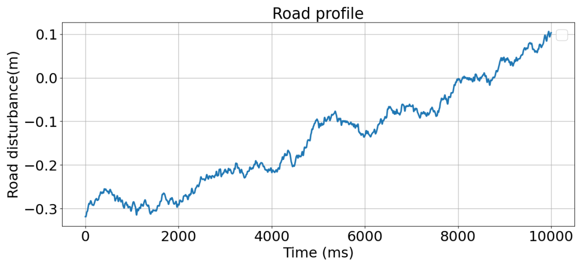

Figure 9. Uneven road profile

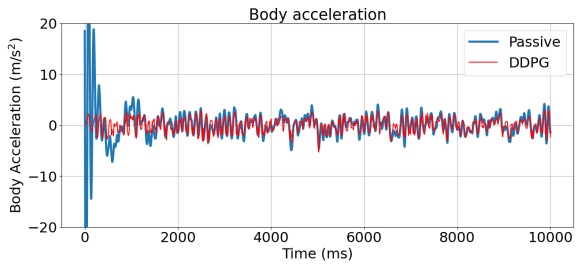

Figure 10. Simulation results under the uneven road profile (E): body acceleration

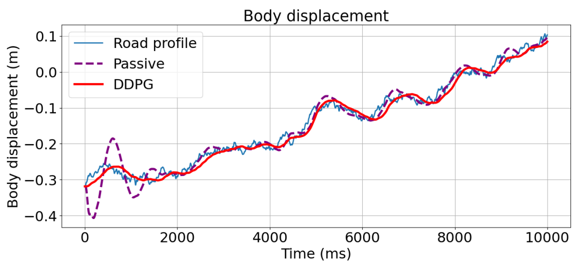

Figure 11. Simulation results under the uneven road profile (E): body displacement

Moreover, Figure 12 displays the suspension deflection of the quarter-vehicle model. The simulation results indicate that the semi-active system utilizing DDPG control effectively reduces suspension deflection. This demonstrates that the proposed model enhances ride quality while ensuring that suspension deflections remain within permissible limits on uneven road surfaces.

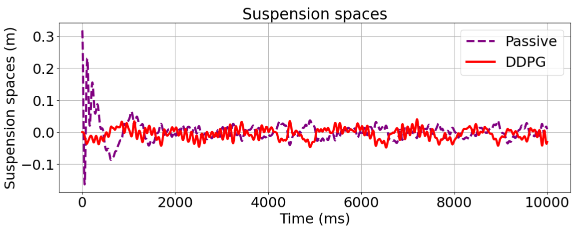

Figure 12. Simulation results under the uneven road profile (E): suspension deflection

The Root Mean Square (RMS)-based acceleration method can be applied in order to determine the average acceleration over a specific duration. The comfort reference values for public transport proposed by Dridi et al. (2023) and Kwon et al. (2020) as provided in Table 2 serve as a basis for quantitative assessment.

Table 2. Criteria for evaluating the ride comfort in public transport (Dridi et al., 2023; Kwon et al., 2020)

Acceleration RMS values	Comfort response
Less than 0.315 m/s^2	Not uncomfortable
0.315–0.63 m/s^2	A little uncomfortable
0.5–1 m/s^2	Fairly uncomfortable
0.8–1.6 m/s^2	Uncomfortable
1.25–2.5 m/s^2	Very uncomfortable
Greater than 2 m/s^2	Extremely uncomfortable

The RMS values for body acceleration in suspension systems indicate the vehicle's ride comfort performance (see Table 3). A lower index indicates a better performance.

Table 3. Evaluation of the ride comfort improvement based on RMS values

Road profile	Body acceleration (m/s^2)		Reduction (%)
	Passive suspension system	DDPG algorithm	
Multi-bump	0.6612	0.2542	61.55%
Uneven	0.5842	0.2981	48.97%

In comparison with passive suspension systems, the DDPG-controlled active suspension system reduced the body acceleration by 61.55% and 48.97% for multi-bump and uneven road profiles, respectively. This demonstrates that the proposed suspension control system effectively mitigates the overall vehicle vibration, enhancing the ride smoothness and ride comfort for the vehicle.

The DDPG algorithm paves the way for the practical implementation of artificial intelligence in autonomous vehicle control, providing valuable insights for the future evolution of the controlled suspension system for autonomous vehicles.

6. Conclusion

This paper proposed a novel method for optimizing semi-active suspension systems using the DDPG algorithm, applied to the vertical control of autonomous vehicle suspensions. The DDPG-based approach offers a data-driven solution that does not rely on detailed system models or road information.

The simulations results demonstrated that the proposed DDPG-based control method significantly outperforms the traditional passive suspension systems. Not only does the DDPG controller adapt to changing road conditions, but it also optimizes the suspension performance for an improved ride comfort, even in unpredictable environments. However, the limitation of this study that should be noted in future works is that the proposed method is only based on simulations, and while the results are promising, real-world testing is necessary for validating the effectiveness of the approach under actual driving conditions.

Future research should focus on evaluating the DDPG algorithm on a full vehicle model in order to assess its real-world performance with regard to autonomous vehicle suspensions.

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