

Article

Active Disturbance Rejection Control of an Active Suspension System Based on Fuzzy Extended State Observers

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Abstract

Through this paper, an active disturbance rejection control scheme is designed based on an extended state observer capable of estimating the system's internal variables and external disturbances without the need for expensive sensors and also attenuates sensor-induced noise, supporting cleaner measurements. The extended state observer is dynamically adjusted using fuzzy logic techniques. The proposed method is validated in Matlab/Simulink, with the results showing a significant reduction in both body displacement and acceleration compared to passive suspension systems, representing a direct improvement in vehicle stability and ride comfort; this demonstrates the robustness and adaptability of the proposed system. The evaluation covers three road excitations, sinusoidal, step, and trapezoidal, to broaden the analysis under both smooth and abrupt disturbances.

Keywords: vehicle suspension; active suspension; vehicle safety; vehicle comfort

1. Introduction

Safety and comfort are fundamental aspects that all vehicles must ensure to meet quality standards and provide the user with an optimal driving experience. To achieve this, mechanical engineers and the automotive industry work together to develop increasingly advanced solutions, among which the suspension system is one of the core components [1]. Vehicle suspensions connect the wheels to the chassis, and must absorb impacts, improve stability, and ensure uninterrupted tire-road contact under diverse road conditions [2]. Suspension systems can be classified into several categories according to their operation and degree of control:

- **Passive suspension:** This is the most common type, using mechanical components such as springs and shock absorbers [3].
- **Semi-active suspension:** This allows the modification of certain system properties (such as damper stiffness) in real time, through electronic valves or special materials [2,4,5].
- **Active suspension:** This includes actuators capable of actively generating forces to counteract disturbances, which are controlled by algorithms and can adapt to different driving situations [6–8].

Active suspensions promise a safer and more comfortable driving experience. This technology has traditionally been reserved for luxury vehicles, such as the BMW 7 Series, Tesla Model S, and Porsche Cayenne [9]. In recent years, its effectiveness and reliability



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have driven its gradual integration into mid-range models, such as the Audi Q5 and BMW X3. The global market for vehicles equipped with active suspension systems shows an exponential growth trend, with very positive forecasts for 2031, enabling its widespread implementation in the automotive sector [10]. In this context of technological expansion, improvements in suspension systems aim not only to increase safety and comfort, but also to optimize the overall vehicle performance. Active suspensions offer advantages such as greater stability and grip in corners, reduced risk of rollover, better shock absorption on uneven terrain, improved aerodynamics, and decreased wear on tires and other components [6].

The motivation for this work arises from the need to understand and apply advanced control algorithms that allow improving the behavior of active suspensions against road disturbances. Recent publications have advanced the field of active suspension control through active disturbance rejection control (ADRC) and extended state observers (ESOs), showing clear improvements over classical methods such as PID, particularly in robustness and disturbance rejection [11]. Additional studies explore advanced optimizations of ADRC using evolutionary algorithms to fine-tune its numerous parameters, highlighting the need for improved controller and observer tuning under varying road conditions [12]. Parallel research has proposed enhanced ESOs or Kalman-tuned ESOs to deal with noise and delays, although these approaches often require specific models or calibrations that are difficult to implement in real time. However, the existing literature shows several gaps: most works do not employ real-time adaptive tuning of the ESO, rely heavily on offline optimizations, and rarely present a dual-loop architecture that separates the generation of the desired control force from the actuator's force-tracking loop [13]. Furthermore, many studies validate their systems using only one or two excitation types, limiting objective comparison between different approaches [14]. This work addresses these gaps by proposing an ADRC with a dynamically fuzzy-tuned ESO, improving noise-robust state estimation without adding sensors; a dual-loop control structure that distinguishes between force reference generation and force tracking; and a thorough validation against a passive suspension using three distinct road profiles. The result is a controller that is more robust, adaptable, and rigorously evaluated than what is typically found in prior work.

The main contributions of this work are as follows:

- A dynamically fuzzy-tuned ESO that enhances noise-robust state and disturbance estimation without requiring additional sensors.
- A dual-loop control architecture that separates force reference generation from force-tracking control, improving clarity, stability, and adaptability.
- A comprehensive validation framework including three distinct road profiles (sinusoidal, step, and trapezoidal), enabling a more rigorous and comparable assessment than others presented in similar studies.

The remainder of this paper is organized as follows. Section 2 presents the active suspension model. Section 3 describes the methodology used for controller design. Section 4 provides several simulation results to demonstrate the feasibility of the proposed approach. The conclusions of this work are summarized in Section 5.

2. Active Suspension Model

In order to evaluate the vehicle suspension behavior, a mathematical model is presented [15]. This model has to include all the elements that describe how the suspension responds to different forces, both from the terrain and the vehicle's movement [16]. Therefore, a quarter-car suspension model will be considered through this work (see Figure 1), as it is one of the standards in the literature.

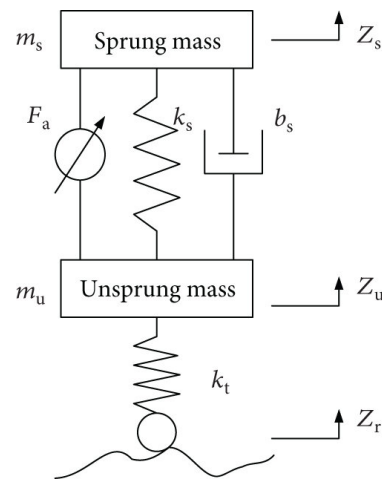


Figure 1. Simplified model of a quarter-car active suspension system.

The dynamics are expressed by aggregating spring, damper, tire, and actuator contributions on the sprung and unsprung masses as follows:

$$m_s \ddot{z}_s = k_s(z_u - z_s) + c_s(\dot{z}_u - \dot{z}_s) + F_{AS}, \quad (1)$$

$$m_u \ddot{z}_u = k_s(z_s - z_u) + c_s(\dot{z}_s - \dot{z}_u) + k_t(z_r - z_u) - F_{AS}, \quad (2)$$

where z_s and z_u denote the vertical displacements of the sprung and unsprung masses, respectively, and z_r is the road input.

The actuator dynamics are modeled as

$$\dot{F}_{AS} = \gamma_1 u(t) - \gamma_2 F_{AS} - \gamma_3 (\dot{z}_s - \dot{z}_u). \quad (3)$$

The parameters and terms employed in the quarter-car suspension model are defined as follows:

- m_s (sprung mass): car body and components supported by the chassis.
- m_u (unsprung mass): wheel, brake, and elements directly attached to the wheel assembly.
- k_s : suspension spring stiffness; elastic coupling between z_s and z_u .
- c_s : damping coefficient; viscous dissipation proportional to the relative velocity $(\dot{z}_u - \dot{z}_s)$.
- k_t : effective tire stiffness; elastic coupling between road elevation z_r and wheel displacement z_u .
- F_{AS} : active force applied by the actuator between the two masses.
- $\gamma_1, \gamma_2, \gamma_3$: actuator parameters.
- $u(t)$: electrical control input to the actuator.

The relative velocity term $(\dot{z}_s - \dot{z}_u)$ in the actuator dynamics (3) reflects typical physical behavior of hydraulic and electromechanical actuators, where force variation depends primarily on the rate of change of the actuator length. This modeling choice captures the intrinsic damping like interaction between the actuator and the suspension, consistent with widely used quarter car actuator formulations.

Although ride comfort optimization focuses on minimizing body accelerations and suspension travel, these objectives are enforced at the controller level rather than embedded in the actuator model itself. Using displacement or acceleration differences within the actuator dynamics would not reflect the physical principles governing force generation and would lead to inaccurate system representation.

In order to achieve a state-space representation, the state-vector is expressed as

$$\begin{aligned}x_1 &= z_s \\x_2 &= \dot{z}_s \\x_3 &= z_u \\x_4 &= \dot{z}_u \\x_5 &= F_A \\x_6 &= \dot{F}_A\end{aligned}\quad (4)$$

Then the state-vector is defined as

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} z_s \\ \dot{z}_s \\ z_u \\ \dot{z}_u \\ F_A \end{bmatrix}\quad (5)$$

From (5), we isolate $\dot{x}_2 = \ddot{z}_s$, $\dot{x}_4 = \ddot{z}_u$ and $\dot{x}_5 = \ddot{F}_A$

$$\begin{aligned}\dot{x}_2 &= -\frac{k_s}{m_s}x_1 - \frac{c_s}{m_s}x_2 + \frac{k_s}{m_s}x_3 + \frac{c_s}{m_s}x_4 + \frac{1}{m_s}x_5 \\ \dot{x}_4 &= \frac{k_s}{m_u}x_1 + \frac{c_s}{m_u}x_2 - \frac{k_s + k_t}{m_u}x_3 - \frac{c_s}{m_u}x_4 - \frac{1}{m_u}x_5 + \frac{k_t}{m_u}z_r \\ \dot{x}_5 &= -\gamma_3x_2 + \gamma_3x_4 - \gamma_2x_5 + \gamma_1u(t)\end{aligned}\quad (6)$$

Following Equations (4)–(6), the continuous-time state-space active suspension system is presented as

$$\dot{x}(t) = Ax(t) + Bu(t) + Ez_r(t)\quad (7)$$

where matrices A , B , and E are

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ -\frac{k_s}{m_s} & -\frac{c_s}{m_s} & \frac{k_s}{m_s} & \frac{c_s}{m_s} & \frac{1}{m_s} \\ 0 & 0 & 0 & 1 & 0 \\ \frac{k_s}{m_u} & \frac{c_s}{m_u} & -\frac{k_s + k_t}{m_u} & -\frac{c_s}{m_u} & -\frac{1}{m_u} \\ 0 & -\gamma_3 & 0 & \gamma_3 & -\gamma_2 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \gamma_1 \end{bmatrix}, \quad E = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{k_t}{m_u} \\ 0 \end{bmatrix}\quad (8)$$

The parameters employed in the quarter-car suspension model and those required for the ESO within the ADRC controller are presented in Table 1.

The parameter values selected for the quarter car model correspond to widely adopted benchmarks in suspension research. Typical sprung and unsprung masses (380 kg and 37 kg) fall within the standard ranges reported for mid-size passenger vehicles, while the suspension stiffness $k_s = 37,500$ N/m and tire stiffness $k_t = 174,000$ N/m reflect commonly used values in the literature for capturing realistic vertical dynamics. Similarly, the damping coefficient $c_s = 3260$ N·s/m represents a standard medium damping configuration appropriate for passenger car comfort studies. These parameters allow for meaningful comparison with prior works and ensure that the model reflects representative real-world behavior rather than an idealized or artificially tuned scenario.

Table 1. Suspension parameters.

Symbol	Units	Value
m_s	kg	380
m_u	kg	37
k_s	N m^{-1}	37,500
k_t	N m^{-1}	174,000
c_s	Ns m^{-1}	3260
γ_1	$\text{N}^{3/2} \text{kg}^{-1/2} \text{v}^{-1/2}$	7000
γ_2	s^{-1}	3
γ_3	N m^{-1}	200,000

3. ADRC Design

To regulate the dynamic behavior of the active suspension system, the design of the ADRC is presented in this section. This method is chosen due to its capability of handling external disturbances and uncertainties without requiring an exact system model [17]. The ADRC is structured in three blocks: an extended state observer (ESO), used to estimate the system's internal states and disturbances; an error feedback controller, which generates the control signal; and a tracking differentiator, which smooths the reference signals to improve the system's response [18]. In addition, a fuzzy logic controller is incorporated to dynamically adjust the ESO parameters, increasing its adaptability to different terrain profiles [11].

3.1. Extended State Observer Model

The ESO estimates the states of the suspension model (7) and an additional external disturbance $x_6 = z_r$ (path excitation), using only the measurement of the suspension deflection [19].

The first step in formulating the ESO is to define the observation error, that is, the difference between the measured signal and its estimated value. This error is essential, as it acts as a feedback mechanism that allows for real-time correction of the observer's estimates. In practice, the only directly measurable variable is the suspension deflection $z_s - z_u$, obtained from a relative displacement sensor between the chassis and the wheel [20]. The ESO assumes that the system is observable through measured suspension deflection, which is a standard requirement in quarter car formulations. Under this assumption, the observer is capable of estimating both the internal states and the lumped disturbance despite modeling uncertainties, consistent with the robustness principles of ADRC. The introduction of fuzzy tuned observer gains does not modify the observability structure of the system; rather, it enhances robustness by adapting the correction terms to varying disturbance levels and road profiles. This allows the observer to maintain estimation fidelity even under rapid or nonlinear excitation changes, reinforcing the ADRC philosophy of combining disturbance rejection with adaptive decision making. Therefore, the ESO is designed using suspension deflection as the measured output:

$$e_1 = (z_s - z_u) - (\hat{z}_s - \hat{z}_u) \quad (9)$$

where $\hat{x}_1$ is the estimate of the suspension deflection given by the ESO.

To take into account the external disturbances, a common practice is to augment the state-space vector [21], such that

$$\hat{x}_6 = \hat{z}_r \quad (10)$$

By doing this augmentation, $\hat{x}_6$ will capture the estimate of the path disturbance.

The next step is to construct the dynamic equations that estimate each of the internal variables of the system. This estimate is based on the system model and is corrected in real time using the observation error.

$$\dot{\hat{x}}_1 = \hat{x}_2 + l_1 e_1 \quad (11)$$

where l_1 is an observer gain to be designed [22]. The following equations are derived directly from the physical model of the suspension system, which includes the spring, damper, and actuator forces.

$$\begin{aligned} \hat{x}_2 &= -\frac{k_s}{m_s} \hat{x}_1 - \frac{c_s}{m_s} \hat{x}_2 + \frac{k_s}{m_s} \hat{x}_3 + \frac{c_s}{m_s} \hat{x}_4 + \frac{1}{m_s} \hat{x}_5 + l_2 e_1 \\ \dot{\hat{x}}_3 &= \hat{x}_4 + l_3 e_1 \\ \dot{\hat{x}}_4 &= \frac{k_s}{m_u} \hat{x}_1 + \frac{c_s}{m_u} \hat{x}_2 - \frac{k_s + k_t}{m_u} \hat{x}_3 - \frac{c_s}{m_u} \hat{x}_4 - \frac{1}{m_u} \hat{x}_5 + \frac{k_t}{m_u} \hat{x}_6 + l_4 e_1 \\ \dot{\hat{x}}_5 &= -\gamma_3 \hat{x}_2 + \gamma_3 \hat{x}_4 - \gamma_2 \hat{x}_5 + \gamma_1 u(t) + l_5 e_1 \\ \dot{\hat{x}}_6 &= l_6 e_1 \end{aligned} \quad (12)$$

The continuous-time state-space formulation of the ESO is expressed as [23,24]

$$\dot{\hat{x}} = \hat{A} \hat{x} + \hat{B} u + \hat{L} e_1 \quad (13)$$

with the state-space matrices

$$\hat{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -\frac{k_s}{m_s} & -\frac{c_s}{m_s} & \frac{k_s}{m_s} & \frac{c_s}{m_s} & \frac{1}{m_s} & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ \frac{k_s}{m_u} & \frac{c_s}{m_u} & -\frac{k_s + k_t}{m_u} & -\frac{c_s}{m_u} & -\frac{1}{m_u} & \frac{k_t}{m_u} \\ 0 & -\gamma_3 & 0 & \gamma_3 & -\gamma_2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \hat{B} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \gamma_1 \\ 0 \end{bmatrix}, \hat{L} = \begin{bmatrix} l_1 \\ l_2 \\ l_3 \\ l_4 \\ l_5 \\ l_6 \end{bmatrix} \quad (14)$$

3.2. Observer Adjustment Using Fuzzy Logic

The correct selection of the observer gain matrix $\hat{L}$ in the ESO is fundamental to ensure optimal performance [25]. These parameters determine the observer's ability to accurately estimate both the system's internal states and external disturbances. An additional advantage of fuzzy tuning is its ability to reduce the sensitivity of the ESO during abrupt variations in road excitation. Fixed gain observers tend to react strongly to sudden changes, which may amplify estimation noise or introduce sharp correction peaks. In contrast, the fuzzy mechanism adjusts the observer gains based on the instantaneous error and disturbance estimations, allowing smoother gain transitions. When rapid changes occur, the fuzzy rules prevent unnecessary overshoots in the correction term, thereby reducing high frequency sensitivity while maintaining responsiveness. This ensures that the ESO remains robust under sudden disturbances without sacrificing estimation fidelity.

Fuzzy rule sets offer a transparent and linguistically meaningful structure that aligns with recent advances in explainable fuzzy systems and fuzzy decision making. This perspective is consistent with works such as Trillo et al. [26], which enhance interpretability through hierarchical fuzzy exception rules, Morente Molinera et al. [27], who employ fuzzy ontologies to support transparent criteria management, and Trillo et al. [28], who survey current trends in interpretable fuzzy decision frameworks. By leveraging these principles,

the proposed fuzzy tuned ESO not only adapts to varying disturbances but also maintains a rule-based structure whose decision process can be readily examined and understood.

With the aim of improving the observer's adaptability to varying disturbances, this work proposes the design of a dynamic tuning algorithm based on fuzzy logic for the parameters l_1 and l_2 [29]. In particular, a first fuzzy controller is implemented to adjust the parameter l_1 , which is structured with two inputs and one output. The inputs correspond to the error between the measured signal and the observed signal e_1 , and to the road disturbance estimated by the observer $\hat{x}_6$ [30]. The second fuzzy controller, responsible for adjusting the parameter l_2 , shares the architecture of the first one, but incorporates as its second input the derivative of the path disturbance signal.

The system classifies inputs into five linguistic levels (see Figure 2): Negative Large (NL), Negative Short (NS), Zero (ZE), Positive Short (PS) and Positive Large (PL), allowing for a flexible and robust formulation of fuzzy rules [31].

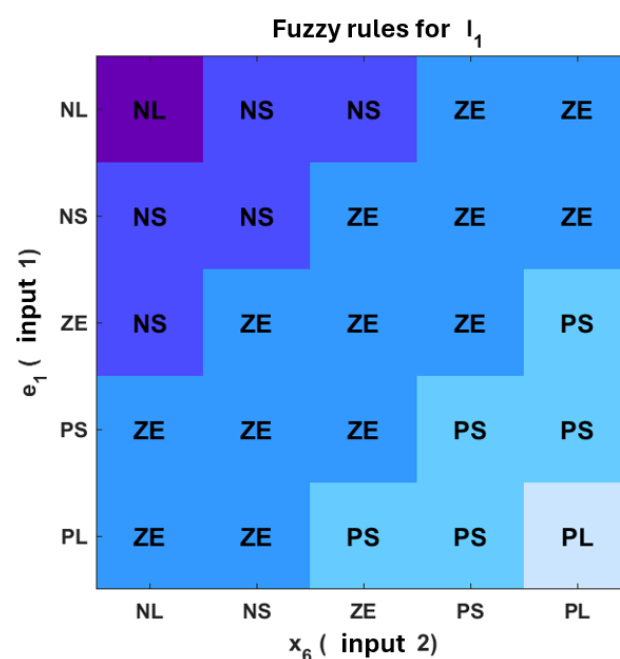


Figure 2. Visual representation chart of fuzzy logic membership rules for l_1 .

For the first fuzzy controller, the first input, which is the error between the measured and observed signal (e_1), is fused using triangular (TRIMFs) and trapezoidal (TRAPMFs) functions [32] as shown in Figure 3. On the other hand, the second input of the first controller, the estimated path disturbance $\hat{x}_6$ is represented by Gaussian (GAUSSMFs) and trapezoidal (TRAPMFs) functions, as shown in Figure 4.

In the second logic controller (l_2), the set of linguistic labels used in partitioning the input domain is expanded [33]. Two extreme levels are added to the five classic levels (see Figure 5): Very Large Negative (VLN) and Very Large Positive (VLP).

These IF–THEN rules in Figures 2 and 5 were formulated based on the physical behavior of the suspension and standard observer design intuition. The rules directly encode the expected relation between the inputs and desired observer aggressiveness: larger estimation errors or stronger disturbance variations require higher corrective gains, while small deviations call for reduced gain to avoid over-correction. This approach ensures smooth adaptive behavior and prevents discontinuities in the observer's response. The extended set of linguistic labels used for l_2 allows finer discrimination when the disturbance derivative becomes significant, improving robustness during sudden changes.

The resulting rule bases offer a transparent and physically interpretable structure that reinforces the adaptive tuning philosophy of the fuzzy ESO.

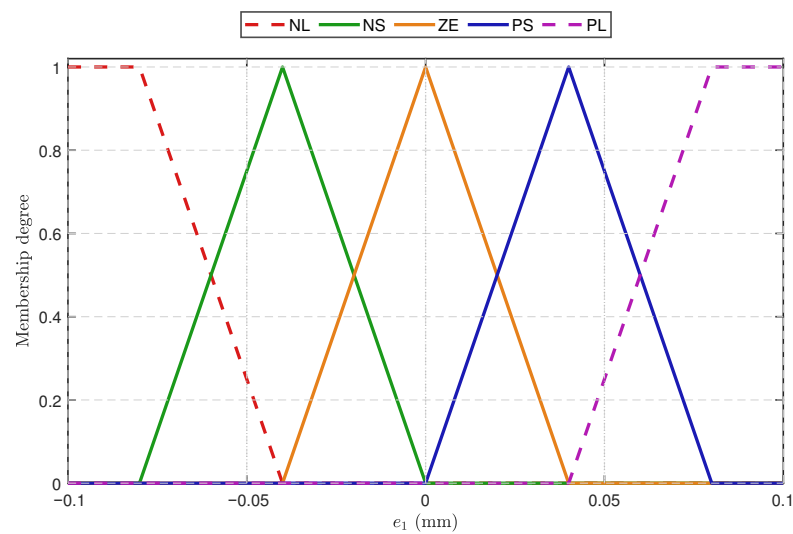


Figure 3. Membership degree functions of input e_1 for l_1 .

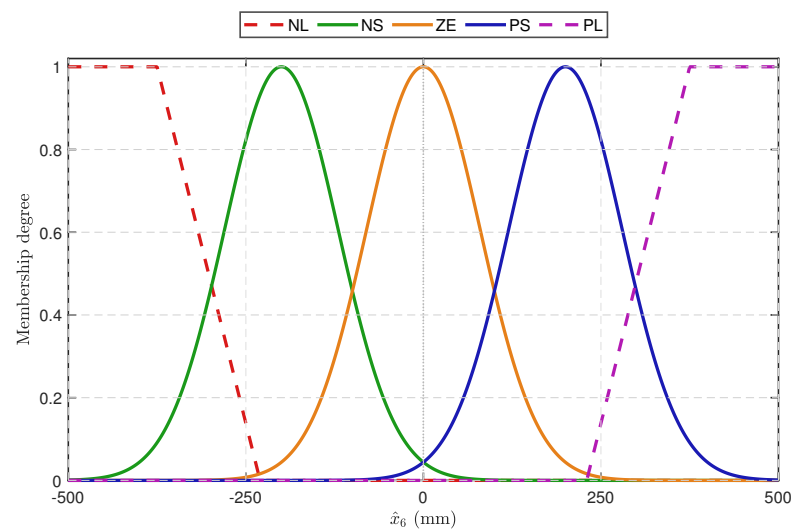


Figure 4. Degree functions of input $\hat{x}_6$ for l_1 .

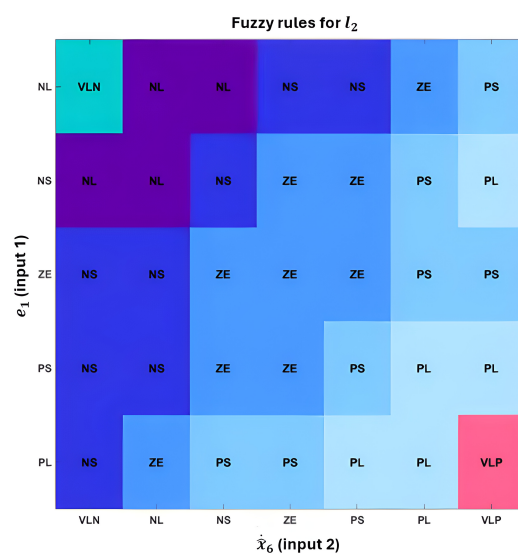


Figure 5. Visual representation chart of fuzzy logic membership rules for l_2 .

To dynamically adjust the parameter l_2 , two inputs are defined: the error between the measured signal and the observed signal (e_1) and the derivative of the path disturbance ($\hat{x}_6$) [34]. Gaussian functions (GAUSSMFs) are adopted instead of triangular functions to represent the controller's second input, corresponding to the derivative of the path disturbance, as presented in Figures 6 and 7.

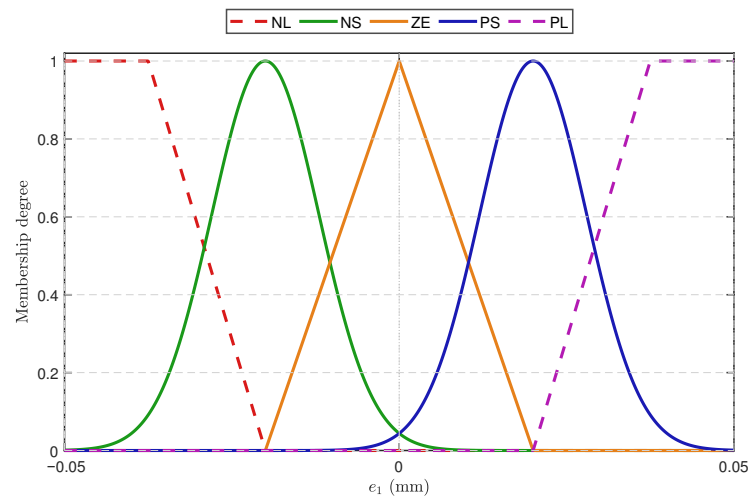


Figure 6. Membership degree functions of input e_1 for l_2 .

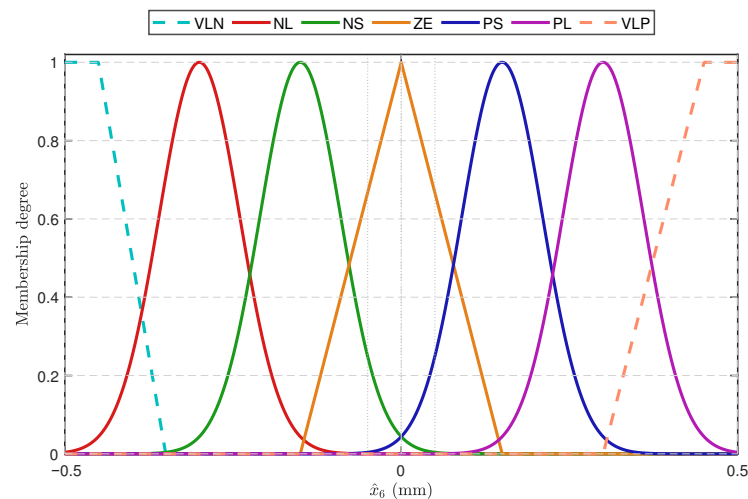


Figure 7. Membership degree functions of input $\hat{x}_6$ for l_2 .

3.3. Actuator Force Reference Generation

For the active suspension system to respond effectively to ground disturbances, establishing a reference force signal is essential [35]. This signal acts as a dynamic target that the controller must follow, representing the desired control force based on the estimated behavior of the environment [36]. The reference signal allows the current state of the system (measured or estimated) to be compared with the desired state. This comparison generates a control error, which the controller uses to calculate the corrective action to be applied to the system [37]. The proposed active suspension system design utilizes a PID controller to generate the reference signal due to its ability to provide a fast, stable, and easily adjustable response. Before the system can generate a useful reference signal for the controller, it needs to know how much the vehicle's behavior is deviating from the desired behavior [38]. Since both the disturbance and the displacement are estimated using the ESO, a reference

error e_2 can be calculated, indicating how much the disturbance is influencing the vehicle's motion [39].

$$e_2 = \hat{x}_6 - K_e \hat{x}_1 \quad (15)$$

Before generating the control signal, it is necessary to clarify the role of each variable in the ADRC structure. First, the reference error e_2 quantifies how much the estimated road disturbance $\hat{x}_6$ affects the vehicle body displacement $\hat{x}_1$. This error is then used to generate a desired reference force, denoted as $F_{A,ref}$, which represents the ideal force that the controller should apply to counteract the effect of the disturbance.

The reference force is computed through a PID controller according to

$$F_{A,ref} = K_{ref} \left(k_p e_2 + k_i \int e_2 dt + k_d \dot{e}_2 \right), \quad (16)$$

where K_{ref} is an amplification gain that adjusts the magnitude of the reference force. In this structure, $F_{A,ref}$ is not the control input itself, but a reference force that the actuator should try to follow.

Once the reference force is computed, the ADRC architecture generates a preliminary control action u_o whose objective is to track the reference force. This is achieved by computing the tracking error:

$$e_3 = F_{A,ref} - \hat{x}_5, \quad (17)$$

where $\hat{x}_5$ is the estimated actuator force provided by the ESO. u_o is the preliminary control action that attempts to make the actuator follow x_{ref} . The preliminary control signal is then generated by a second PID controller:

$$u_o = k_{p2} e_3 + k_{i2} \int e_3 dt + k_{d2} \dot{e}_3. \quad (18)$$

Thus, u_o attempts to make the actuator force follow the desired force x_{ref} . However, ADRC does not use u_o directly. Instead, it incorporates disturbance compensation using the total disturbance estimated by the ESO, denoted as $\hat{d}$, obtaining $u(t)$ which is the final control electrical signal given to the actuator, obtained by correcting u_o with the estimated disturbance $\hat{d}$. The final control signal applied to the actuator is

$$u(t) = \frac{u_o - \hat{d}}{b_o} \quad (19)$$

where b_o is the control gain associated with actuator dynamics and ensures proper scaling of the control input. The estimated total disturbance is given by

$$\hat{d} = -\gamma_3 \hat{x}_2 + \gamma_3 \hat{x}_4 - \gamma_2 \hat{x}_5 + l_5 e_1 + (\gamma_1 - b_o) u(t), \quad (20)$$

where each term represents contributions from actuator dynamics, hydraulic effects, observer correction, and model mismatches. Inclusion of $\hat{d}$ in the control signal enables ADRC to cancel disturbances and uncertainties in real time, improving robustness. The PID parameters in Equations (16) and (18) were determined through a simulation based tuning process. Initial values were selected using classical tuning heuristics and subsequently refined through iterative closed loop simulations. The tuning objectives were to ensure rapid disturbance rejection and maintain stable behavior across all excitation profiles. No automatic optimization algorithm was employed; instead, the parameters were adjusted manually based on performance metrics such as peak displacement. This procedure aligns with standard practices in suspension system PID tuning and ensures a balanced compromise between responsiveness and comfort.

4. Results

A series of simulations using Matlab/Simulink 2024a were conducted to validate the proposed methodology. A fixed-step numerical solver (ode4) was employed with a simulation step size of 0.001 s, corresponding to a control and observer update frequency of 1000 Hz. The total simulation time was set to 10 s for all test scenarios. The same simulation parameters were used consistently for all road excitation profiles to ensure a fair comparison between the passive and active suspension configurations. The system's behavior was tested under different ground excitation conditions. Three types of signal of road disturbance were tested, each representing a different kind of terrain disturbance commonly encountered in real driving conditions.

- A sinusoidal signal emulates continuous undulating or wavy road profiles, such as corrugated surfaces or gentle repetitive bumps.
- A step signal represents abrupt height changes in the terrain, similar to driving over speed bumps, pothole edges, or sudden level transitions.
- A trapezoidal signal mimics smoother ramps or elevated platforms with defined ascent and descent phases, resembling long bumps, ramps, or gradual changes in road elevation.

Three fundamental output variables have been monitored to evaluate vehicle comfort and stability: suspension mass displacement $x_1 = z_s$, acceleration of this mass $\dot{x}_2 = \ddot{z}_s$, and suspension travel $x_1 - x_3 = z_s - z_u$. The overall control architecture implemented in this work is shown in Figure 8. The diagram illustrates the complete integration of the ADRC framework, including the extended state observer (ESO), the fuzzy tuning modules, the dual PID structure for reference and force tracking, and the dynamic model of the quarter-car. To strengthen the validation of the proposed control strategy, an additional benchmark based on a Linear Quadratic Regulator (LQR) has been incorporated into the results section. The LQR controller is widely used in suspension control due to its optimal state–feedback formulation and serves as a meaningful reference point between classical linear optimal control and the proposed ADRC approach. Therefore, the simulation results now include a three-way comparison among the passive suspension, the LQR controller, and the fuzzy-tuned ADRC. This expanded analysis enables a clearer assessment of the advantages and limitations of each method under identical excitation conditions and provides a more rigorous validation of the proposed framework. This scheme provides a comprehensive view of how the different components interact to estimate disturbances, generate the desired reference force, and apply the compensated control action to the active suspension system.

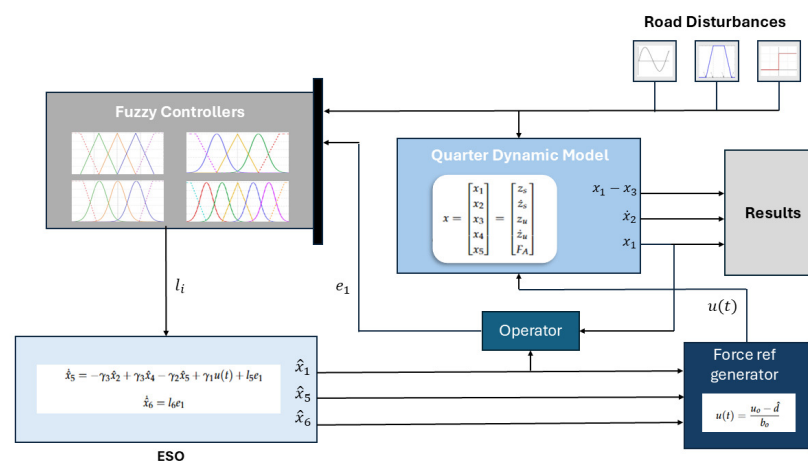


Figure 8. Block diagram of the proposed ADRC-fuzzy control framework in Matlab.

4.1. Sinusoidal Signal

The suspension system is excited with a road disturbance that corresponds to a sinusoidal wave, with an amplitude of 0.05 m and a frequency of 2 rad/s. This disturbance simulates a periodic irregularity in the road surface for 10 s. The objective is to evaluate the controller's ability to reduce vehicle body displacement and acceleration, as well as improve suspension travel, compared to the passive suspension system, as shown in Figure 9.

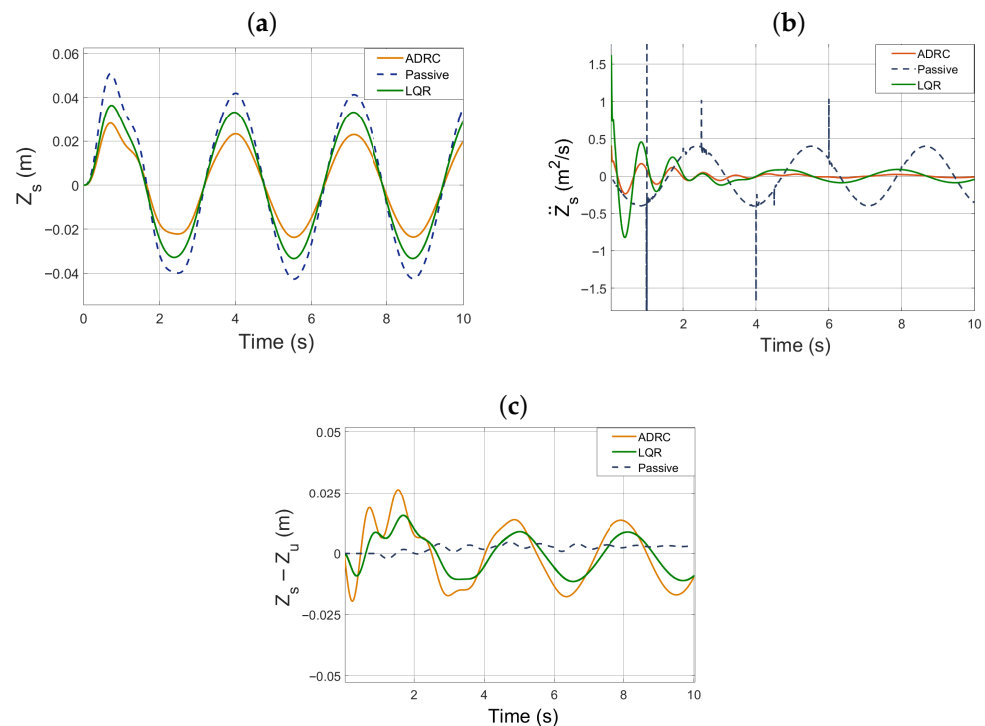


Figure 9. Simulation results under a sinusoidal excitation: (a) displacement, (b) acceleration, (c) relative displacement between sprung and unsprung mass.

The comparison between the two configurations showed in Figure 9a that the ADRC offers significantly superior vibration isolation, reducing the body displacement amplitude by approximately half and smoothing the initial transient. The orange signal (ADRC) in Figure 9b shows a considerably reduced amplitude, indicating a significant reduction in vertical vibration. Furthermore, the waveform is smoother and has less high-frequency content, suggesting that the controller not only reduces the amplitude but also filters out some noise and rapid oscillations, thus improving comfort. In terms of interpretation, the controlled increase in relative displacement in the ADRC in Figure 9c is an expected effect, as the controller uses the available suspension travel to isolate vibrations, sacrificing some wheel comfort to benefit occupant comfort.

4.2. Step Signal

This type of excitation allows us to evaluate the system's ability to respond to sudden changes in input and quickly stabilize the vehicle's dynamics. Figure 10 illustrates the results of this step signal simulation.

The response with ADRC in Figure 10a exhibits a particular behavior. After the step input, a series of damped oscillations appears before reaching a stable value. Overall, the ADRC manages to transform a permanent disturbance into a damped transient displacement, significantly reducing the final amplitude and improving vehicle comfort, although at the cost of a brief initial period of oscillations that are part of the compensation process. The case showed in Figure 10b is the system transforming the disturbance into a brief,

damped transient phenomenon, eliminating any permanent component of acceleration and improving dynamic comfort, although with a high initial peak inherent to the controller's fast response. The sharp acceleration peak observed at the onset of the step excitation reflects the idealized nature of the input, which introduces a discontinuous change in road elevation. Such instantaneous transitions generate high jerk values that are not typically present in real world road profiles but are widely used in suspension analysis as worst case disturbances. The initial oscillatory behavior results from the rapid corrective action of the ADRC combined with the transient settling of the ESO. As the observer stabilizes, the system quickly damps these oscillations. It is important to note that real excitations rarely present truly discontinuous steps, meaning that the magnitude of this spike would be significantly lower under physical road conditions. Finally, Figure 10c reflects the inherent trade-off of active control: improving comfort by reducing body vibrations, at the cost of momentarily increasing suspension travel.

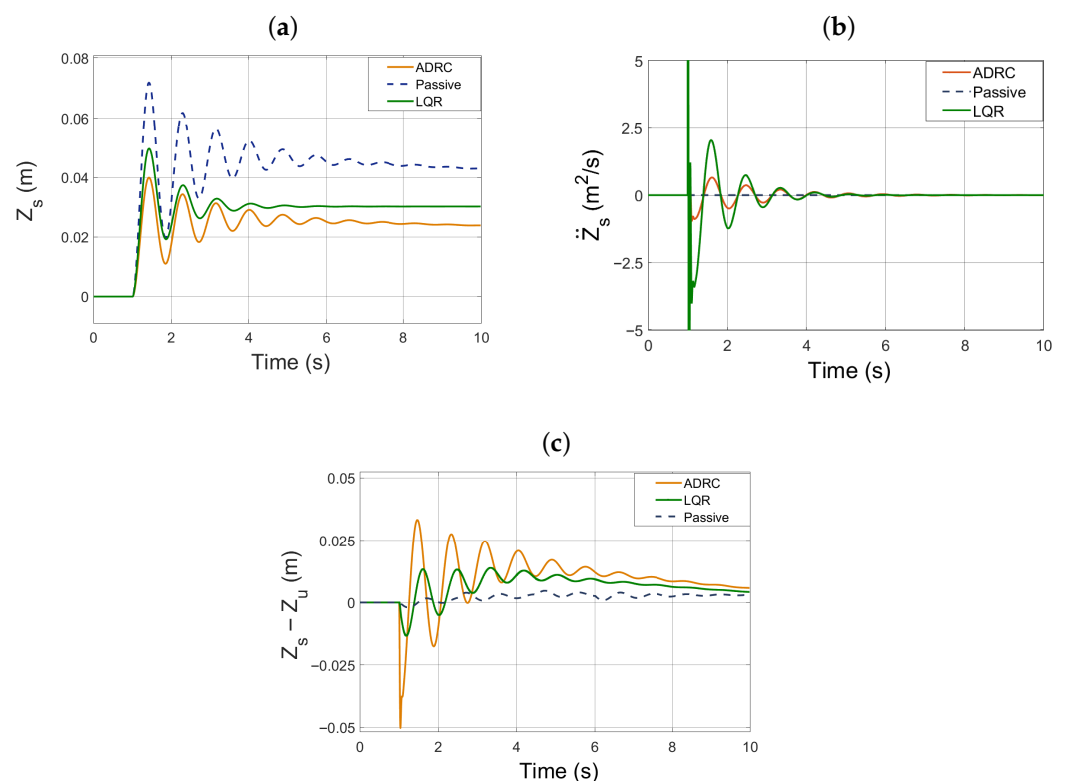


Figure 10. Simulation results comparing under a step excitation: (a) displacement of the suspended mass, (b) acceleration of the suspended mass, (c) relative displacement between the sprung mass and the unsprung mass.

4.3. Trapezoidal Signal

In this case, the response of the active suspension system to a trapezoidal disturbance is analyzed. This shape represents a rise or dip in the road with an incline and exit slope. Figure 11 presents simulation results with this type of signal excitation.

The system behavior in figure (a) shows how the active suspension transforms the trapezoidal disturbance into a more controlled response of lower amplitude, achieving effective filtering that improves comfort, although introducing slight oscillations inherent to the corrective action of the controller. In addition, Figure (b) highlights two key aspects. On the one hand, the practical limitation of calculating direct derivatives in Simulink when the input has discontinuities, and on the other, that ADRC manages to maintain acceleration within a moderate and stable range even in the face of abrupt disturbances, at the cost of introducing damped oscillations that are part of its compensation dynamics.

Finally, in Figure (c), the active system manages to improve comfort by reducing body roll, although it does so at the cost of a temporary increase in suspension travel, which highlights the inherent compromise between comfort and limiting relative movement.

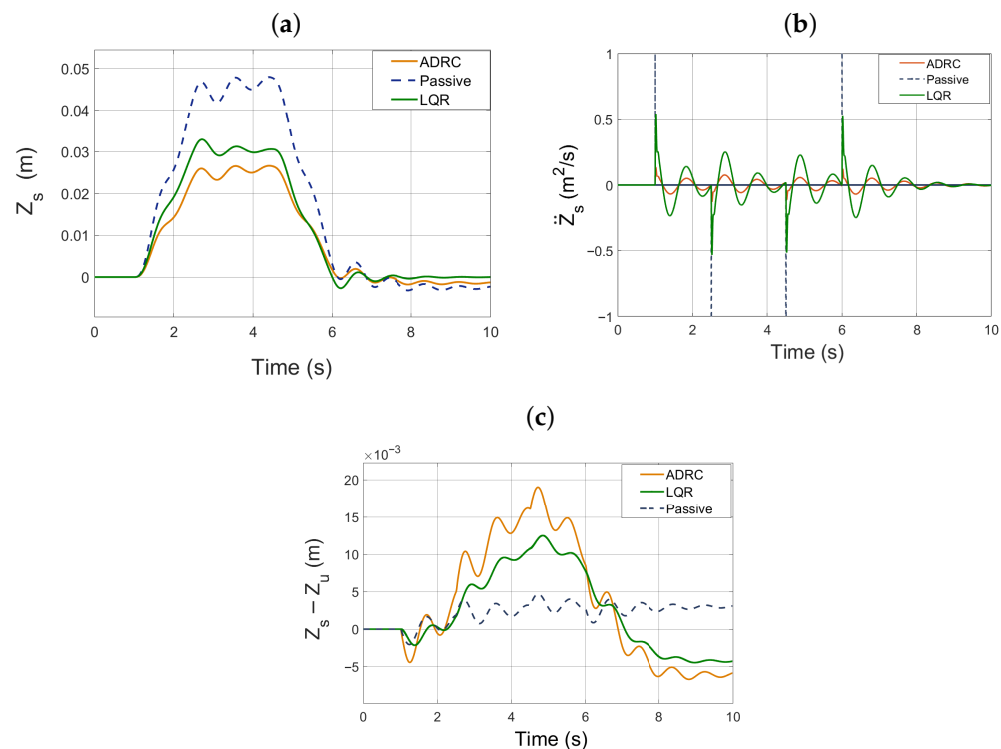


Figure 11. Simulation results under a trapezoidal excitation: (a) displacement of the suspended mass, (b) acceleration of the suspended mass, (c) relative displacement between the sprung mass and the unsprung mass.

5. Conclusions

In this work, a hybrid active suspension control strategy based on ADRC has been developed and evaluated, combining an ESO, a dynamic fuzzy tuning mechanism, and a dual PID structure. The purpose of this design was to significantly reduce body displacement and smooth acceleration under different road disturbances, while maintaining robustness to noise and changing operating conditions without requiring additional sensors.

The proposed approach was validated using three distinct road profiles: sinusoidal, step, and trapezoidal ramp, and its performance was compared with that of a conventional passive suspension. The results show clear improvements:

- Under sinusoidal excitation, the peak displacement is reduced to 24 mm, and the RMS to 21 mm, while the phase delay is practically eliminated.
- For a step input, ADRC cuts the peak displacement to 25 mm and limits acceleration to 0.1 m/s², although transient estimation errors appear in the observer during the abrupt rise.
- With a trapezoidal ramp, ADRC again provides the best containment of the sprung mass and delivers a cleaner acceleration signal, free from the saw-tooth effect caused by sensor noise in conventional schemes.

The improvements discussed above are directly supported by the simulation results presented in Figures 9–11. Under sinusoidal excitation (Figure 9), the proposed controller significantly reduces both displacement amplitude and acceleration peaks compared to the passive suspension. The step response plots (Figure 10) show that the fuzzy-ADRC system transforms the permanent disturbance into a damped transient, reducing the

steady-state displacement and limiting acceleration once the observer has settled. Similarly, the trapezoidal excitation results (Figure 11) confirm the controller's ability to attenuate body motion while maintaining acceptable suspension travel. These visual results validate the performance gains summarized in the conclusions.

These improvements arise from the control architecture: the ESO accurately estimates states and disturbances without additional sensors, the dynamic fuzzy tuning provides adaptability to changing conditions, and the dual PID contributes to stability and tracking. As a result, the approach mitigates chattering and phase lag typical of classical controllers, at the cost of greater actuator usage consistent with the increased suspension travel observed. Overall, the study confirms that ADRC is a strong candidate for active suspension control when the primary goal is minimizing sprung-mass displacement and ensuring robustness against noise and disturbances.

Potential future applications of this work include, but are not limited to, the following:

- Systematic optimization of the ADRC parameters through advanced or computational intelligence techniques to improve performance under varying load and road conditions.
- Experimental implementations to assess real-world limitations of actuators and sensors, bringing the design closer to practical scenarios.
- Integration of this type of active suspension into intelligent and connected vehicles, enabling systems capable of anticipating road irregularities through advanced perception technologies.

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Abbreviations

The following abbreviations are used in this manuscript:

ADRC	Active Disturbance Rejection Control
ESO	Extended State Observer
LQR	Linear Quadratic Regulator
PID	Proportional–Integral–Derivative

References

1. Viadero-Monasterio, F.; Boada, B.L.; Zhang, H.; Boada, M.J.L. Integral-Based Event Triggering Actuator Fault-Tolerant Control for an Active Suspension System Under a Networked Communication Scheme. *IEEE Trans. Veh. Technol.* **2023**, *72*, 13848–13860. [\[CrossRef\]](#)
2. Wang, Z.; Liu, C.; Zheng, X.; Zhao, L.; Qiu, Y. Advancements in Semi-Active Automotive Suspension Systems with Magnetorheological Dampers: A Review. *Appl. Sci.* **2024**, *14*, 7866. [\[CrossRef\]](#)

3. Mei, Y.; Wang, R.; Ding, R.; Jiang, Y. Classification Evolution, Control Strategy Innovation, and Future Challenges of Vehicle Suspension Systems: A Review. *Actuators* **2025**, *14*, 485. [\[CrossRef\]](#)
4. Viadero-Monasterio, F.; Meléndez-Useros, M.; Jiménez-Salas, M.; López Boada, M.J. Avoiding Lyapunov-Krasovskii Functionals: Simple Nonlinear Sampled-Data Control of a Semi-Active Suspension with Magnetorheological Dampers. *Machines* **2025**, *13*, 512. [\[CrossRef\]](#)
5. Viadero-Monasterio, F.; Meléndez-Useros, M.; Jiménez-Salas, M.; Boada, B.L. Robust static output feedback control of a semi-active vehicle suspension based on magnetorheological dampers. *Appl. Sci.* **2024**, *14*, 10336. [\[CrossRef\]](#)
6. Huang, C.; Liu, Y.; Sun, X.; Wang, Y. Intelligent Active Suspension Control Method Based on Hierarchical Multi-Sensor Perception Fusion. *Sensors* **2025**, *25*, 4723. [\[CrossRef\]](#)
7. Viadero-Monasterio, F.; Boada, B.; Boada, M.; Díaz, V. H_∞ dynamic output feedback control for a networked control active suspension system under actuator faults. *Mech. Syst. Signal Process.* **2022**, *162*, 108050. [\[CrossRef\]](#)
8. Viadero-Monasterio, F.; Jimenez-Salas, M.; Meléndez-Useros, M.; Boada, B.L.; Boada, M.J.L. Event-triggered fault-tolerant control for vehicle rollover avoidance based on an active suspension with robustness against disturbances and communication delays. In *Proceedings of the IFToMM World Congress on Mechanism and Machine Science*; Springer: Cham, Switzerland, 2023; pp. 795–805.
9. *Automotive Active Suspension System Market Size Report*; Global Market Insights: Selbyville, DE, USA, 2024.
10. *Automotive Active Suspension Market Report 2024–2034*; Emergen Research: Surrey, BC, USA, 2025.
11. Nguyen, T.A. Active Disturbance Rejection Control for an automotive suspension system based on parameter tuning using a fuzzy technique. *PLoS ONE* **2025**, *20*, e0313104. [\[CrossRef\]](#)
12. Tang, Z.; Zhao, Q.; Pham, D.T.; Zhang, X. Enhancing Active Disturbance Rejection Control for a Vehicle Active Stabiliser Bar with an Improved Chicken Flock Optimisation Algorithm. *Processes* **2024**, *12*, 1979. [\[CrossRef\]](#)
13. Michalski, J.; Mrotek, M.; Pazderski, D.; Kozierski, P.; Retinger, M. Improving Performance of ADRC Control Systems Affected by Measurement Noise Using Kalman Filter-Tuned Extended State Observer. *Electronics* **2024**, *13*, 4916. [\[CrossRef\]](#)
14. Orkisz, P.; Sapiński, B. Hybrid Vibration Reduction System for a Vehicle Suspension under Deterministic and Random Excitations. *Energies* **2023**, *16*, 2202. [\[CrossRef\]](#)
15. Abut, T.; Salkim, E. Control of Quarter-Car Active Suspension System Based on Optimized Fuzzy Linear Quadratic Regulator Control Method. *Appl. Sci.* **2023**, *13*, 8802. [\[CrossRef\]](#)
16. Abbas, S.B.; Youn, I. Performance Improvement of Active Suspension System Collaborating with an Active Airfoil Based on a Quarter-Car Model. *Vehicles* **2024**, *6*, 1268–1283. [\[CrossRef\]](#)
17. Ho, C.M.; Ahn, K.K. Extended State Observer-Based Adaptive Neural Networks Backstepping Control for Pneumatic Active Suspension with Prescribed Performance Constraint. *Appl. Sci.* **2023**, *13*, 1705. [\[CrossRef\]](#)
18. Song, D.; Chen, S.; Xue, W.; Zhao, Z. On the Stability Condition of Active Disturbance Rejection Control with Time-Varying Bandwidth Observer. *Control Theory Technol.* **2025**, *23*, 464–478. [\[CrossRef\]](#)
19. Li, Y.; Tan, P.; Liu, J.; Chen, Z. A Super-Twisting Extended State Observer for Nonlinear Systems. *Mathematics* **2022**, *10*, 3584. [\[CrossRef\]](#)
20. Li, G.; Yan, Y.; Liu, Y.; Wang, S. Research on Active Control of X-Type Interconnected Hydropneumatic Suspensions for Heavy-Duty Special Vehicles via Extended State Observer-Model Predictive Control. *Appl. Sci.* **2025**, *15*, 3041. [\[CrossRef\]](#)
21. Azar, A.T.; Smaït, D.A.; Muhsen, S.; Jassim, M.A.; Al-Salih, A.A.M.M.; Hameed, I.A.; Jawad, A.J.M.; Abdul-Adheem, W.R.; Cocquempot, V.; Sahib, M.A. A New Approach to Nonlinear State Observation for Affine Control Dynamical Systems. *Appl. Sci.* **2023**, *13*, 3300. [\[CrossRef\]](#)
22. Mai, G.; Wang, H.; Wang, Y.; Wu, X.; Jiang, P.; Feng, G. Nonlinear Extended State Observer and Prescribed Performance Fault-Tolerant Control of Quadrotor Unmanned Aerial Vehicles Against Compound Faults. *Aerospace* **2024**, *11*, 903. [\[CrossRef\]](#)
23. Shi, S.; Zeng, Z.; Zhao, C.; Guo, L.; Chen, P. Improved Active Disturbance Rejection Control (ADRC) with Extended State Filters. *Energies* **2022**, *15*, 5799. [\[CrossRef\]](#)
24. Bueno-Lopez, J.L.; Cardenal, J.; Deibe, A.; Garcia de Jalon, J. Potential and Limitations of an Improved Method to Produce Dynamometric Wheels. *Sensors* **2018**, *18*, 541. [\[CrossRef\]](#)
25. Gonzalez, A.; Balaguer, V.; Garcia, P.; Cuenca, A. Gain-Scheduled Predictive Extended State Observer for Time-Varying Delays Systems with Mismatched Disturbances. *ISA Trans.* **2019**, *84*, 206–213. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Trillo, J.R.; Fernandez, A.; Herrera, F. HFER: Promoting Explainability in Fuzzy Systems via Hierarchical Fuzzy Exception Rules. In *Proceedings of the 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Glasgow, UK, 19–24 July 2020; pp. 1–8. [\[CrossRef\]](#)
27. Morente-Molinera, J.A.; Cabrerizo, F.J.; Trillo, J.R.; Pérez, I.J.; Herrera-Viedma, E. Managing Group Decision Making Criteria Values Using Fuzzy Ontologies. *Procedia Comput. Sci.* **2022**, *199*, 166–173. [\[CrossRef\]](#)

28. Trillo, J.R.; Herrera-Viedma, E.; Higuera-Ruiz, M.J.; Alonso, S.; Morente-Molinera, J.A.; Cabrerizo, F.J. Challenges in Fuzzy Decision Making for Future Research. In *New Trends in Intelligent Software Methodologies, Tools and Techniques*; Frontiers in Artificial Intelligence and Applications; IOS Press: Amsterdam, The Netherlands, 2022; Volume 355, pp. 374–384. [\[CrossRef\]](#)
29. Chen, X.; Zhong, W.; Peng, X.; Du, P.; Li, Z. An Improved Adaptive Dynamic Programming Algorithm Based on Fuzzy Extended State Observer for Dissolved Oxygen Concentration Control. *Processes* **2022**, *10*, 2618. [\[CrossRef\]](#)
30. Shen, S.; Li, J.; Chen, Y.; Lv, J. Fuzzy Extended State Observer-Based Sliding Mode Control for an Agricultural Unmanned Helicopter. *Agriculture* **2025**, *15*, 306. [\[CrossRef\]](#)
31. Torrens-Urrutia, A.; Novák, V.; Jiménez-López, M.D. Describing Linguistic Vagueness of Evaluative Expressions Using Fuzzy Natural Logic and Linguistic Constraints. *Mathematics* **2022**, *10*, 2760. [\[CrossRef\]](#)
32. Le, V.H. Extending Fuzzy Linguistic Logic Programming with Negation. *Mathematics* **2022**, *10*, 3105. [\[CrossRef\]](#)
33. Lima-Junior, F.R. Advances in Fuzzy Logic and Artificial Neural Networks. *Mathematics* **2024**, *12*, 3949. [\[CrossRef\]](#)
34. Lima, J.F.; Patiño-León, A.; Orellana, M.; Zambrano-Martinez, J.L. Evaluating the Impact of Membership Functions and Defuzzification Methods in a Fuzzy System: Case of Air Quality Levels. *Appl. Sci.* **2025**, *15*, 1934. [\[CrossRef\]](#)
35. Cai, C.; Wang, G.; Wang, Z.; Li, R.; Li, Z. Research on Control Strategy of Semi-Active Suspension System Based on Fuzzy Adaptive PID-MPC. *Appl. Sci.* **2025**, *15*, 9768. [\[CrossRef\]](#)
36. Zhao, D.; Gong, M.; Wang, Y.; Zhao, D. A Position–Force Feedback Optimal Control Strategy for Improving the Passability and Wheel Grounding Performance of Active Suspension Vehicles. *Processes* **2025**, *13*, 1241. [\[CrossRef\]](#)
37. Yang, J.; Wang, S.; Bai, F.; Wei, M.; Sun, X.; Wang, Y. Prior-Guided Residual Reinforcement Learning for Active Suspension Control. *Machines* **2025**, *13*, 983. [\[CrossRef\]](#)
38. Han, S.Y.; Dong, J.F.; Zhou, J.; Chen, Y.H. Adaptive Fuzzy PID Control Strategy for Vehicle Active Suspension Based on Road Evaluation. *Electronics* **2022**, *11*, 921. [\[CrossRef\]](#)
39. Habibi, H. Control of Active Suspension Systems Based on Mechanical Wave Concepts. *Actuators* **2025**, *14*, 230. [\[CrossRef\]](#)

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