Ain Shams University
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Active Suspension System: Modern Control Techniques

BSc. Graduation Project (1)

MCT491s

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ABSTRACT

This thesis investigates the performance of various advanced control techniques applied to an active suspension system using a quarter-car model. The quarter-car model is widely used due to its simplicity and effectiveness in capturing the essential dynamics of a suspension system while allowing for efficient analysis and simulation. Simulation experiments are conducted to evaluate the effectiveness of these control algorithms.

The study focuses on the application of Linear Quadratic Regulator (LQR) for linear-time-invariant systems, Reinforcement Learning (RL), and Sliding Mode Control (SMC) to enhance suspension performance. LQR is particularly powerful for its ability to provide optimal control solutions by minimizing a defined cost function, balancing performance and energy efficiency. RL, on the other hand, offers a data-driven approach that adapts to system uncertainties and non-linearities, making it highly suitable for complex and dynamic environments. Additionally, the robustness of SMC makes it effective in handling system disturbances and parameter variations. Furthermore, the impact of state estimation using a Kalman filter is assessed, as it enables accurate estimation of unmeasured states, enhancing the overall control performance.

MATLAB/Simulink is employed to perform the simulations, beginning with the mathematical modeling of the system in state-space form, followed by the implementation of these modern control techniques. This research aims to contribute to a deeper understanding of control theory and its practical application in improving vehicle ride comfort and handling. By comparing the performance metrics of each control strategy, the study seeks to highlight the strengths and limitations of these advanced techniques, providing valuable insights into their applicability for real-world suspension systems.

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Nomenclature

Symbol	**Description**	**Unit**
b_s	Damper average damping coefficient	N.s/m
b_{tr}	Tire damping coefficient	N.s/m
e	Signal error	-
f	Frequency	Hz
f_{n-s}	Sprung mass natural frequency	Hz
f_{n-us}	Unsprung mass natural frequency	Hz
k	Stiffness of the Suspension Spring	N/m
k_t	Equivalent Spring Stiffness of the Tire	N/m
L	Lenght of Conecting rod	mm
M	Sprung Mass	kg
m	Unsprung Mass	kg
R	Lenght of Crank	mm
S_D	Sprung displacment	mm
STD	Static Tire Deflection	mm
T	Periodic Time	s
X	Position of the slider	mm
z	Vertical Position of The Car Body	mm
z_r	Road Excitation Displacement	m
z_t	Vertical position of Unsprung Mass	m
θ	Angle of the crank	degrees

Abbreviations

Symbol	Description
ASS	Active Suspension System
DOF	Degree-of-Freedom
DTD	Dynamic Tire Deflection
EMI	Electromagnetic Interference
FA	Actuator Force
FLC	Fuzzy Logic Control
IMU	Inertial Measurement Unit
LQR	Linear Quadratic Regulator
LVDT	Linear Variable Displacement Transducer
MPC	Model Predictive Control
MR	Magnetorheological
PI	Performance Index
PSS	Passive Suspension System
RF	Radio Frequency
RL	Reinforcement learning
RMS	Root Mean Square
RPM	Revolution per minute
SD	Sprung Mass Displacement
SMC	Sliding Mode Control
ST	Suspension Travel
STD	Static Tire Deflection
TR	Transmissibility Ratio
UD	Unsprung Mass Displacement

Chapter 1

Introduction

This chapter provides an introduction to vehicle suspension systems, outlining their fundamental characteristics and components. It begins by exploring various methods of classifying suspension systems and offers an overview of the terminology commonly used in suspension system technology. Detailed descriptions are included for several prevalent suspension components. It is important to highlight that this project specifically focuses on a prepared vertical test rig simulating a quarter-car model, which serves as the foundation for our study and analysis of suspension systems.

1.1 Importance of Suspension System

Suspension components, particularly spring, as the system elastic member, and damper have a profound effect as it serve a dual purpose contributing to the vehicle's handling and increasing the vehicle safety and improve the level of comfort of the passengers and keeping vehicle occupants comfortable and reasonably well isolated from road noise, bumps, and vibrations (better overall driving experience). It is important for the suspension to keep the vehicle wheel in contact with the road surface as much as possible, because all the forces acting on the vehicle do so through the contact patches of the tires. The suspension also helps protect the vehicle itself and any cargo or luggage from damage and wear. [8]

1.2 Suspension system components

This section provides brief overview of the essential components of suspension system, specifically springs and dampers, both of which have a profound effect on ride and handling performance. [9]

1.2.1 SPRING (Elastic member)

The suspension system incorporates an elastic link between the tires and the vehicle's body, enabling it to simultaneously press the tires onto the road surface to follow dips and absorb shocks or overloads. This system minimizes the transmission of impacts to the vehicle frame, ensuring both stability and comfort. There are three main types of springs commonly used in suspension systems: torsion bars, coil springs, and leaf springs.

- **Coil springs** are essentially wound torsion bars, prized for their exceptional endurance, compact design, and ease of mounting.
- **Leaf springs** consist of long, thin members that are loaded in bending. They are typically assembled using multiple thin metal layers to achieve the desired spring rate. Beyond providing suspension, they also function as linkage and damping elements.
- **Torsion bars** rely on the twisting motion of a long bar to provide a spring rate that reduces shock loading on the vehicle. However, their placement across the lower portion of the car makes them more difficult to package compared to other types. [10]

Characteristics of spring is detailed in Appendix 1.

1.2.2 DAMPER (Energy dissipation member)

As a car passes over a bump, the springs deflect and then rebound. Without a mechanism to dissipate the energy stored in the springs, the car would continue to bounce up and down. Dampers, or shock absorbers, fulfill this critical role. A damper consists of a piston and a cylinder equipped with adjustable valves that control the flow of hydraulic fluid (oil). These valves regulate the damping force during both the retraction (bounce) and extension (rebound) phases. The damper allows oil to flow through one-way valves in the piston and small control passages from one chamber to another, but this flow is deliberately restricted, causing it to move very slowly.

This controlled fluid movement slows down the spring's oscillations, helping the car return to a stable, level ride. The damper converts the kinetic energy from the vehicle's bounce into thermal energy, effectively dissipating it. Dampers are designed to retract under a lower force than is required for extension. This asymmetry allows them to absorb road bump forces while effectively dampening spring oscillations, resulting in improved ride comfort, vehicle stability, and control. [8]

1.3 Suspension System Performance

The performance of an automotive suspension system refers to how well it functions in terms of providing balance between passenger comfort, vehicle stability during all driving conditions.

Suspension dynamic performance:

Vehicle Handling: Vehicle stability and road holding (i.e. providing grip for the driver of the vehicle to control direction).

Ride Quality: Passenger's comfort or discomfort during movement of the vehicle.

The preferred performance of a suspension system is defined by its ability to seamlessly blend vehicle handling and roadholding, evaluated through dynamic tire deflection (DTD), with ride quality assessed via the transmissibility ratio (TR). An ideal suspension system ensures that passengers enjoy a smooth and comfortable ride, free from excessive body vibrations, while also providing the driver with optimal control, stability, and responsiveness under various driving conditions.

A well-designed suspension system strikes the perfect balance, delivering a luxurious ride for everyday driving and dynamic handling for sporty driving. It excels in vibration isolation by effectively dampening road-induced disturbances and offers sufficient suspension travel and dynamic tire deflection to adapt to diverse terrains.

Performance characteristics are detailed in Appendix 2.

1.4 Effect of suspension Parameters

Achieving both a luxurious ride and dynamic handling for sport driving presents a significant challenge in passive suspension systems (PSS). This is due to the opposing suspension characteristics required to fulfill these two objectives simultaneously. The inherent trade-offs in automotive passive suspension systems result in compromises between comfort and performance. Explanation of these trade-offs is detailed in Appendix 3.

1.5 Motivation

The experience of oscillations during vehicle motion is a well-documented challenge that arises primarily due to irregularities and stimuli encountered on road surfaces. These oscillations have far-reaching implications, affecting passenger comfort, cargo stability, and vehicle durability. To mitigate these effects, suspension systems are engineered to regulate and attenuate oscillations, ensuring that they remain within acceptable limits.

Automotive suspension systems have evolved significantly, encompassing various designs such as passive (mechanical), semi-active, active, and pneumatic systems. Passive suspension systems, characterized by their simplicity and cost-effectiveness, dominate the market and are commonly integrated into mass-produced vehicles. They typically consist of components such as coil springs, leaf springs, torsion bars, dampers, lever arms, and stabilizer bars. While these systems perform adequately under standard conditions, their inherent limitations—such as fixed properties and lack of adaptability to dynamic external stimuli—can compromise ride comfort, particularly in challenging driving environments. To address these shortcomings, advancements in suspension technology have introduced systems with enhanced adaptability. Air suspension systems, for instance, employ air springs capable of modulating stiffness through internal pressure adjustments, offering improved responsiveness to varying road conditions. Semi-active systems, incorporating technologies like magnetorheological (MR) dampers, provide another layer of adaptability, enabling the system to better respond to road-induced oscillations.

Active suspension systems represent the pinnacle of suspension technology, capable of dynamically adjusting to changing road conditions in real-time. By actively controlling the forces applied to the suspension components, these systems offer unparalleled performance in mitigating oscillations, ensuring optimal ride comfort, and maintaining vehicle stability. This thesis aims to explore and further develop control strategies for active suspension systems, emphasizing their potential to redefine vehicle dynamics and enhance overall driving experiences. In active suspension system, a hydraulic actuator (or electromagnetic actuator) generates an impact force acting on both masses of the vehicle, gradually diminishing the vehicle's oscillation.[11]

1.6 Scope and Objective

The main focus of this study is to perform a comparative analysis for the most commonly used modern control techniques, including LQR, SMC, and RL. The evaluation will focus on their effectiveness in reducing vertical acceleration and displacement of the sprung mass, and the suspension travel. The pros and cons of each technique will be assessed based on these results.

- **Objectives:**
  - Conducting various simulations using MATLAB/SIMULINK on the quarter car model to understand its behavior.
  - Compare between the response of the PSS and ASS for various road profiles
  - Implement the selected control algorithms on MATLAB/SIMULINK environment for different conditions.
  - Conduct comparative analysis to determine the suitable control algorithm for which case.

1.7 Limitations

- Simplified Model: The use of a quarter-car model represents a simplification of the actual vehicle dynamics. A full-vehicle model would provide a more accurate representation of real-world behavior, considering interactions between different axles and body motions.
- Limited Scope: The research focuses on a limited set of control strategies (LQR, RL, and SMC). Exploring other advanced control techniques, such as adaptive control and predictive control, could provide further insights into optimal suspension performance.
- Simulation-Based: The study relies entirely on simulations. Experimental validation on a physical test rig would be necessary to further validate the findings and assess the practical feasibility of the proposed control strategies.
- Idealized Assumptions: The simulations may involve idealized assumptions, such as perfect actuator dynamics and the absence of noise and disturbances in the measurements. Real-world implementations may encounter challenges due to these factors.
- Computational Cost: Some control algorithms, such as Reinforcement Learning, can be computationally expensive, especially for complex models or real-time applications.

1.8 Thesis contribution

This work contributes to the field of vehicle dynamics by:

- Demonstrating the effectiveness of advanced control techniques: The study provides a comparative analysis of LQR, RL, and SMC controllers in enhancing the performance of an active suspension system. This analysis will shed light on the strengths and weaknesses of each approach under different operating conditions.
- Validating the use of simulation tools: The research leverages MATLAB/Simulink for the design, implementation, and evaluation of control strategies. This demonstrates the effectiveness of simulation tools in developing and testing control systems for complex dynamic systems like vehicle suspensions.
- Providing insights into control system design: The findings of this research will contribute to a better understanding of how to design and implement effective control systems for active suspensions, considering factors such as ride comfort and handling.
- Establishing a foundation for future research: The results and insights gained from this research can serve as a foundation for further investigations into more advanced control techniques, such as adaptive control and predictive control, for improving vehicle suspension systems.

1.9 Thesis Organization

The content of thesis is as follows:

- **Chapter 1: Introduction**
  - Provided background on vehicle suspension systems, motivation for the research, research objectives, scope and limitations, and an outline of the thesis structure.
- **Chapter 2: Literature Review**
  - Reviews existing research on vehicle suspension systems, control theory fundamentals, active suspension control, simulation and modeling techniques, and state estimation methods.
- **Chapter 3: Methodology**
  - Derives the equations of motion for the quarter-car model, develops the state-space representation.
- **Chapter 4: Modern Control Techniques**
  - Focuses on the design and implementation of LQR, RL, and SMC controllers in MATLAB/Simulink, including simulation setup, and analysis.
- **Chapter 5: Conclusion and Future Work**
  - Summarizes the key findings and conclusions, discusses the research contributions, acknowledges limitations, and suggests potential areas for future research.

Chapter 2

Literature Review

This chapter provides a brief overview of suspension system history and development, followed by reviewing the most recent studies concerned with modern control techniques in Active suspension system.

2.1 Suspension system history

Suspension is the term given to the system that connects a vehicle body to its wheels and allows relative motion between them. This Relative motion between the wheel and the body is necessary to isolate the vehicle's body from the road irregularities that are fed into the tire at the road/wheel interface. In general, some kind of linkage system that combines damping and stiffness controls this motion. We refer to this process as a suspension. This Damping and stiffness are fed to the system through the dampers, springs (shock absorbers) and the linkages that transmit motion or forces between various parts of the suspension system. [12], [8]

In the 15^{th} century, people understood that suspensions were crucial for making passengers feel comfortable. Back then, coaches had bodies that hung from a set of leaf springs attached to a strong chassis. This chassis held the wheel hubs. The loose ends of the springs were linked to the coach's body using leader belts. Figure 2.1 shows a coach[13] from around 1650 with this kind of suspension setup, providing a fascinating example. [1] [14]

Figure 2.1: This coach, built around 1650, shows a suspension made by four leaf springs and leader belts (National Automobile Museum of Torino). [1]

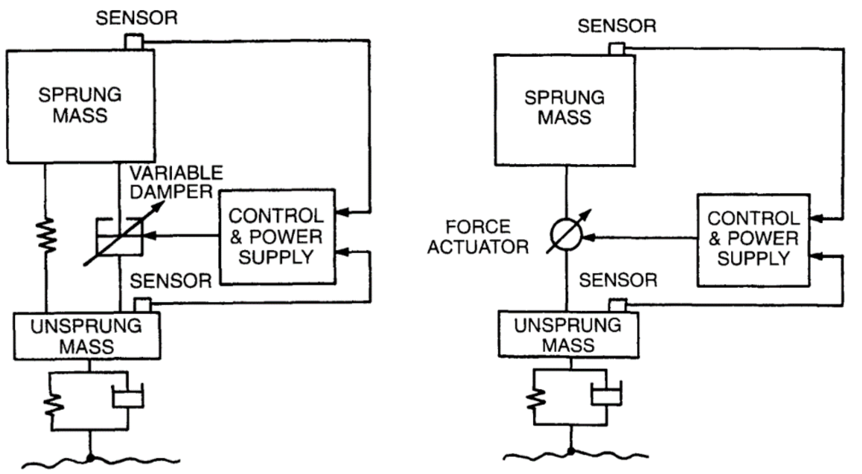
2.1.1 Suspension system evolution

1. **Passive Suspension Systems (Before 1980s):**
   - Early automotive suspension systems were mostly passive, relying on mechanical components such as springs and dampers to absorb shocks and vibrations.
   - These systems were simple and cost-effective but offered limited adaptability to varying road conditions.
2. **Active Suspension Systems (1980s - 1990s):**
   - The concept of active suspension, which actively adjusts the suspension settings in response to changing road conditions, gained popularity in the 1980s.

- One of the pioneering examples was the development of the Lotus Active Suspension in Formula 1 in the late 1980s.
- Some high-end road cars began to incorporate active suspension systems in the late 1980s and early 1990s, including models from manufacturers like Citroën and Cadillac.
- Active suspension systems used sensors to monitor various factors, and electronic control systems adjusted the suspension settings in real-time to optimize ride comfort and handling.

3. **Semi-Active Suspension Systems (1990s - Present):**
   - Semi-active suspension systems represent a middle ground between passive and active systems.
   - In a semi-active system, the suspension settings are adjusted in real-time, but they typically do not provide as much active control as fully active systems.
   - Popular semi-active systems include electronically controlled shock absorbers (e.g., Delphi's MagneRide) that can adjust damping rates based on driving conditions.
   - These systems offer improved ride quality and handling without the complexity and cost associated with fully active systems.
4. **Recent Developments (2000s - Present):**
   - Advancements in sensor technology, computing power, and materials have allowed for more sophisticated suspension systems.
   - Active and semi-active suspension systems continue to evolve, with a focus on enhancing performance, safety, and comfort.
   - Some modern high-performance and luxury vehicles feature advanced adaptive suspension systems that can adjust multiple parameters, including ride height, stiffness, and damping rates.

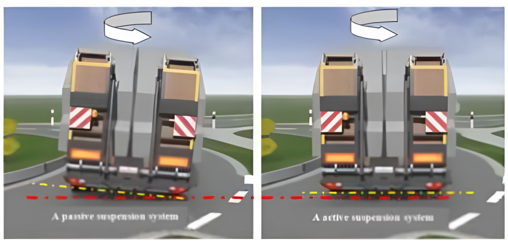
The semi-, figure 2.2 (a), and fully-, figure 2.2 (b), active suspension system are introduced. [12]



(a) (b)

Figure 2.2: Schematics of (a) Semi-active and (b) Fully-active suspension systems [2]

Active suspension system is even beneficial for the HVG (Heavy Goods Vehicle) in case of the vehicle negotiating a turn.



(a) (b)

Figure 2.3: Difference between the behavior of the truck body in a curve: with passive suspension (a) and with active suspension (b). [3]

2.2 Recent Research

2.2.1 PID controller

Many studies have explored various control strategies for active suspension systems over the last few decades. One of the commonly used approaches is the PID (Proportional-Integral-Derivative) algorithm, which was employed by [15] to control the dynamics of active suspension systems. The PID controller operates in three distinct stages, each corresponding to one of the three tuning coefficients: K_p (proportional), K_D (derivative), and K_i (integral). These coefficients can either be self-tuned through adaptive techniques or selected using standard methods like Ziegler-Nichols's method, which is a heuristic approach to tuning PID controllers based on system response characteristics [16]. This method helps achieve a balance between the system's stability and response speed.

However, the effectiveness of PID controllers often suffers from limitations in complex or nonlinear systems, where manual tuning or standard methods may not yield optimal results. To address these challenges, alternative approaches have been explored. For instance, [17] applied the Fuzzy logic algorithm to tune the PID controller's variables dynamically based on real-time excitation signals from the road. Fuzzy logic controllers can handle imprecision and uncertainty, offering a more adaptable solution in environments with unpredictable disturbances. Another advanced approach involves using Genetic Algorithms (GA) to optimize the PID controller's parameters. The GA, based on principles of natural selection and genetics, can search for optimal parameter values by evaluating fitness over successive generations. This technique was demonstrated by [18], who applied it to fine-tune the PID controller. The GA solution allows for more flexibility in choosing optimal values for K_p, K_D, and K_i, adjusting to varying system conditions. The size of the population and the number of generations required for convergence are typically determined by the designer's experience and the complexity of the system.

In contrast to the GA, the Particle Swarm Optimization (PSO) method offers another optimization technique inspired by the social behaviors of animals. PSO mimics the flocking behavior of birds or the schooling behavior of fish, where individual particles (agents) adjust their positions based on their own experience and the collective experience of their neighbors. This swarm-based approach was used by [19] to optimize the PID controller's coefficients. The PSO algorithm is particularly useful for problems with a large number of variables and complex search spaces, as it can efficiently explore the solution space without requiring detailed knowledge of the system's underlying dynamics.

Moreover, numerous other intelligent algorithms, such as Ant Colony Optimization (ACO) and Bee Colony Optimization (BCO), have also been explored for the optimal search of controller parameters. These bio-inspired algorithms exhibit strong performance in dynamic optimization problems, as they can adjust to system changes over time [20]. These algorithms, like PSO and GA, offer robust alternatives to traditional optimization techniques by incorporating flexibility and adaptability.

However, when dealing with complex systems involving multiple controlled objects, a single PID controller might not be sufficient to handle all the required parameters simultaneously. In such cases, one solution is to use multiple PID controllers, each responsible for controlling different aspects or subsystems of the overall system. [21] explored this approach, where multiple PID controllers were used in parallel to handle the multiple degrees of freedom in an active suspension system. This method can improve performance by distributing the control efforts across different subsystems, thus ensuring better overall system behavior.

2.2.2 LQR controller

The Linear-Quadratic Regulator (LQR) controller is increasingly used to replace conventional Proportional-Integral-Derivative (PID) controllers, particularly in Multi-Input Multi-Output (MIMO) systems where multiple variables need to be controlled simultaneously [22]. The key advantage of the LQR controller lies in its ability to optimize the system's performance by minimizing a predefined cost function, thereby improving the stability and efficiency of the system [23]. The optimization process involves minimizing a cost function that balances both state variables and control inputs, ensuring the system's behavior is optimal. To implement the LQR controller, the system's mathematical model must be represented in state-space form, where the system dynamics are captured by a set of linear differential equations expressed as a state matrix [24]. This allows for the precise calculation of the control input that minimizes the cost function at any given time.

A significant extension of the LQR controller is the Linear-Quadratic-Gaussian (LQG) controller, which combines the LQR framework with a Gaussian filter. The LQG controller incorporates the ability to estimate system states in the presence of noise and uncertainty, making it more robust in real-world applications. By combining state estimation techniques, such as Kalman filtering, with LQR control, the LQG controller can address uncertainties in system modeling and measurement, providing better control performance in dynamic environments [25].

Recent advancements in Linear Quadratic Regulator (LQR) control have contributed significantly to the evolution of control theory, leading to improvements in both stability and applicability. One of the notable developments is the revisitation of the LQR problem for singular systems. Researchers have focused on extending the traditional LQR techniques to handle singular systems, where the system dynamics are not fully controllable or observable in the standard sense. These singular LQR techniques help broaden the applicability of LQR controllers to more complex and unconventional systems [26].

Furthermore, the role of predictions in enhancing LQR performance has been explored, especially in online control scenarios under stochastic and adversarial disturbances. By incorporating predictive models, LQR controllers can anticipate future system states and adjust the control actions proactively, improving the system's robustness against uncertainties and disturbances [27]. In addition, data-driven approaches have gained traction, with researchers proposing LQR frameworks that rely on recursive learning algorithms and policy gradient methods. These data-driven LQR frameworks not only ensure stability but also allow the system to adapt to changing conditions by learning from past experiences, making them suitable for modern, adaptive control systems [28].

The above methods are only used for linear objects. If the object is nonlinear, more complex algorithms need to be used such as SMC MPC and RL.

2.2.3 SMC controller

The Sliding Mode Control (SMC) algorithm is widely used for controlling complex nonlinear systems due to its robustness and ability to handle uncertainties and disturbances effectively [29]. Kazemian et al. applied the SMC algorithm to control hydraulic actuators, which are commonly used in active suspension systems for their ability to provide precise force control. However, to simplify the modeling of the hydraulic actuator and make the control design more tractable, a linearization process is often performed. This process, which helps approximate the nonlinearities of the actuator, was outlined by Nguyen [30]. By linearizing the system, it becomes easier to apply traditional control techniques, though it still retains the essential dynamics for practical use. Subsequently, a quarter-dynamic model that considers the influence of the actuator on the vehicle's suspension system is introduced. This model typically involves five state variables, which represent the system's key dynamic parameters, such as displacement, velocity, and force [31].

According to Zhao et al. [32], the sliding surface plays a crucial role in the effectiveness of the SMC algorithm. The sliding surface is a boundary that separates desirable system states from undesirable ones. In the context of active suspension systems, this surface is used to drive the system's state to a steady condition, ensuring that the vehicle's suspension behaves in a stable manner. Once the system reaches the sliding surface, it can travel along this surface to achieve equilibrium, effectively nullifying the impact of disturbances and uncertainties.

A common issue with SMC, however, is the phenomenon known as "chattering." Chattering occurs when the control signal oscillates at high frequencies with small amplitudes, which can lead to undesirable vibrations in the system and potentially cause wear and tear on mechanical components. This issue is particularly problematic in applications like active suspension systems, where smooth control is essential for ride comfort. To mitigate chattering, researchers have proposed combining the SMC algorithm with other control strategies, such as Proportional-Integral-Derivative (PID) controllers or Fuzzy Logic controllers. For instance, Hsiao and Wang [33] introduced an innovative algorithm that integrates SMC with Fuzzy Logic, resulting in a Self-tuning Fuzzy Sliding Mode Controller (STFSMC). The fuzzy logic component allows for adaptive tuning of the control parameters, which helps reduce chattering while maintaining the robustness of the SMC algorithm.

Another approach, suggested by Suhail et al. [34], is the use of the Adaptive Sliding Mode Control (ASMC) algorithm. This method adapts the sliding mode controller in real-time, adjusting its parameters based on the system's changing conditions. By doing so, it enhances the controller's performance and minimizes the chattering phenomenon. The combination of adaptive control and SMC offers an effective solution to the challenges of controlling nonlinear active suspension systems. Studies have shown that using such advanced control methods significantly improves ride comfort by optimizing the suspension's response to road disturbances [35]. Furthermore, numerous other advanced control strategies have been applied to active suspension systems, each bringing high levels of efficiency, adaptability, and precision, making them highly suitable for modern automotive applications.

2.2.4 RL controller

Recent advancements in the application of reinforcement learning (RL) for active suspension systems have yielded promising results, particularly in enhancing ride comfort and vehicle stability. Reinforcement learning, with its ability to adapt and optimize in real-time, offers a dynamic approach to controlling active suspension systems. For instance, a study on deep reinforcement learning for active suspension control demonstrates its potential to meet the stringent ISO 2631-5 comfort requirements, which assess human exposure to vibration during vehicle operation [36]. This study showcases how deep RL algorithms can effectively minimize vibrations and improve comfort by learning to adjust suspension parameters to various road conditions. Another research effort introduced a TD3-based control algorithm, specifically designed to address actuator delays in active suspension systems. The TD3 algorithm, known for its stability and efficiency in continuous action spaces, proves to be particularly useful in reducing the negative impact of actuator delays on system performance, resulting in better responsiveness and smoother ride quality [37].

The optimization of full-vehicle active suspension systems using advanced reinforcement learning controllers has also been extensively explored, leading to significant improvements in both ride comfort and vehicle dynamics. Full-vehicle suspension systems are often subjected to a variety of road irregularities, vehicle loads, and driving conditions, making their control more complex. However, RL controllers, which can learn from these real-world variations, have shown considerable success in optimizing suspension behavior. These controllers can continuously adapt to changing conditions, leading to more efficient suspension responses and improved overall ride comfort [38]. Similarly, RL-based vibration control for half-car active suspension systems has demonstrated the effectiveness of adaptive dynamic programming (ADP) algorithms in reducing road-induced vibrations and improving the damping characteristics of the system. These algorithms learn to dynamically adjust control parameters, which helps to suppress unwanted vibrations that affect vehicle stability and passenger comfort [39].

The sim-to-real transfer of active suspension control has become an essential area of research, with the goal of bridging the gap between simulated environments and real-world applications. RL-based models are often trained in idealized simulations, but transferring these models to real-world systems can present significant challenges due to model discrepancies, noise, and environmental variations. To address this, researchers have developed methods that help RL controllers generalize well from simulation to real-world deployment, ensuring they can adapt to the unpredictable nature of real-world driving conditions. This process is crucial for making RL-based active suspension systems viable in commercial vehicles [40]. Additionally, a novel approach using a closed-chain five-bar active suspension system integrated with deep reinforcement learning has shown promising results in both vehicle stability and obstacle traversal. This closed-chain configuration, which involves complex mechanical linkages, benefits from RL's ability to optimize suspension control in real-time, particularly when navigating rough or uneven terrain [41].

Research into magnetorheological (MR)-damped vehicle suspension systems has also been explored using RL techniques. MR dampers, which offer the ability to adjust damping properties in response to changing driving conditions, are well-suited for use in active suspension systems. RL has proven to be highly effective in fine-tuning these dampers for optimal performance. In particular, studies have shown that the TD3 algorithm significantly outperforms traditional control strategies, particularly in terms of system adaptability and robustness. By learning from experience, the RL-based controller can adjust the damping in real time, providing superior ride comfort and handling stability [42]. Finally, iterative learning-based reinforcement methods for road profile estimation and active suspension control in connected vehicles highlight the potential of collaborative frameworks in improving system performance. In connected vehicle environments, data from multiple vehicles can be shared to create more accurate road profile estimations, enabling the suspension system to anticipate road conditions ahead of time. This collaborative approach allows for more precise adjustments to suspension settings, thereby enhancing both ride comfort and vehicle stability across different driving scenarios [43].

Chapter 3

Methodology

This chapter outlines the methodology employed to achieve the project objective. Firstly, a suitable quarter-car model for the active suspension system is selected. Subsequently, a mathematical model is derived, followed by its representation in state-space form. Controllability analysis is then performed on the system. Based on these findings, the following chapter delves into the implementation and evaluation of various control strategies designed to enhance the performance of the active suspension system.

3.1 Two-DOF Quarter Car Model

To analyze the parameters related to the suspension system, a simplified quarter-car model, as shown in 3.1(a), was utilized. The quarter-car model was chosen due to its simplicity and common use in analyzing the vertical vibrations caused by railway disturbances in vehicle dynamic models.

The vehicle's mass is divided into two: the sprung mass (representing the vehicle body) and the unsprung mass (tire). Suspension springs and dampers connect the sprung and unsprung masses and the road.

Both the transverse and longitudinal deflections are considered insignificant compared to the vertical deflections of the suspension system. For the passive suspension system is shown in 3.1(b).

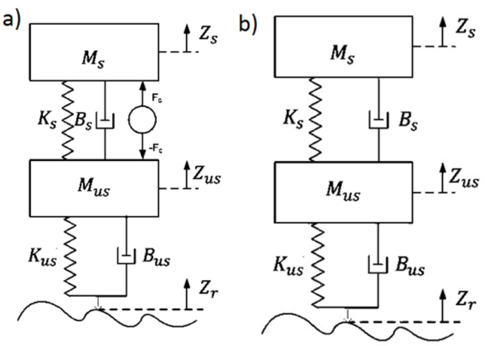


Figure 3.1: Active suspension system (a) and Passive suspension (b).
[44]

Table 3.1: Parameters of Quarter Car Model.

M_s	Vehicle body mass or sprung mass.
M_{us}	Unsprung mass (Tire, wheel, brake caliper, suspension links, etc.)
K_s	Spring constant for the sprung mass.
K_{us}	Spring constant for the unsprung mass.
B_s	Inherent damping coefficient for the suspension system.
B_{us}	Inherent damping coefficient for vehicle wheel assembly.
F_c	The active suspensions actuator control force.
Z_s	Vehicle (sprung mass) body displacement.
Z_{us}	Vehicles wheel displacement and the unsprung masses displacement
Z_r	Excitation due to the railway disturbance.

3.1.1 Passive Suspension Model

The parameters for the PSS are given in the following table:

Table 3.2: Passive Model Parameters

Parameter	Symbol	Value	Unit
Sprung mass	M	30	kg
Unsprung mass	m	13	kg
Spring stiffness	k	6921	N/m
Tire stiffness	k_t	81000	N/m
Damper average damping coefficient	b_s	900	N s/m
Tire damping coefficient	b_{tr}	0	N s/m

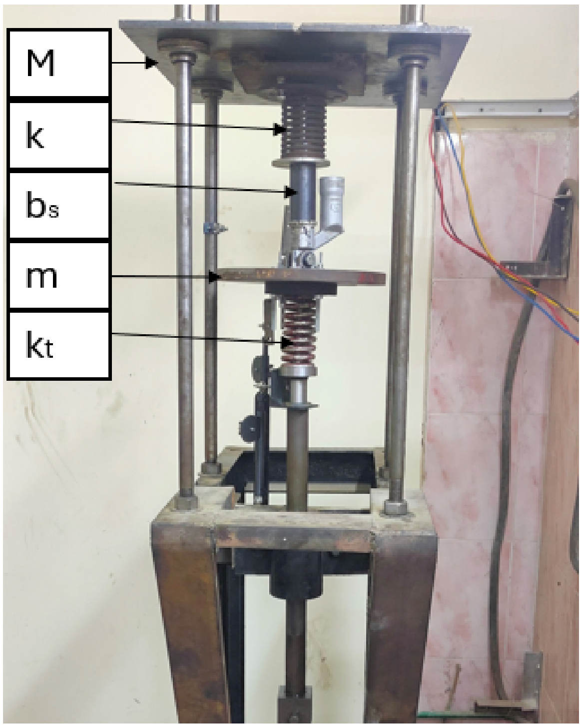


Figure 3.2: PSS Physical Model, by Ain Shams Univresity Students as Graduation Project, Fall 2024, Automotive Department.

3.1.2 Active Suspension Model

The parameters of the modified system is listed in the table below.

Table 3.3: Active Model Parameters

Parameter	Symbol	Value	Unit
Sprung mass	M	34	kg
Unsprung mass	m	11	kg
Spring stiffness	k	6921	N/m
Tire stiffness	k_t	81000	N/m

The setup of the modified Active suspension System is shown in the following figure:

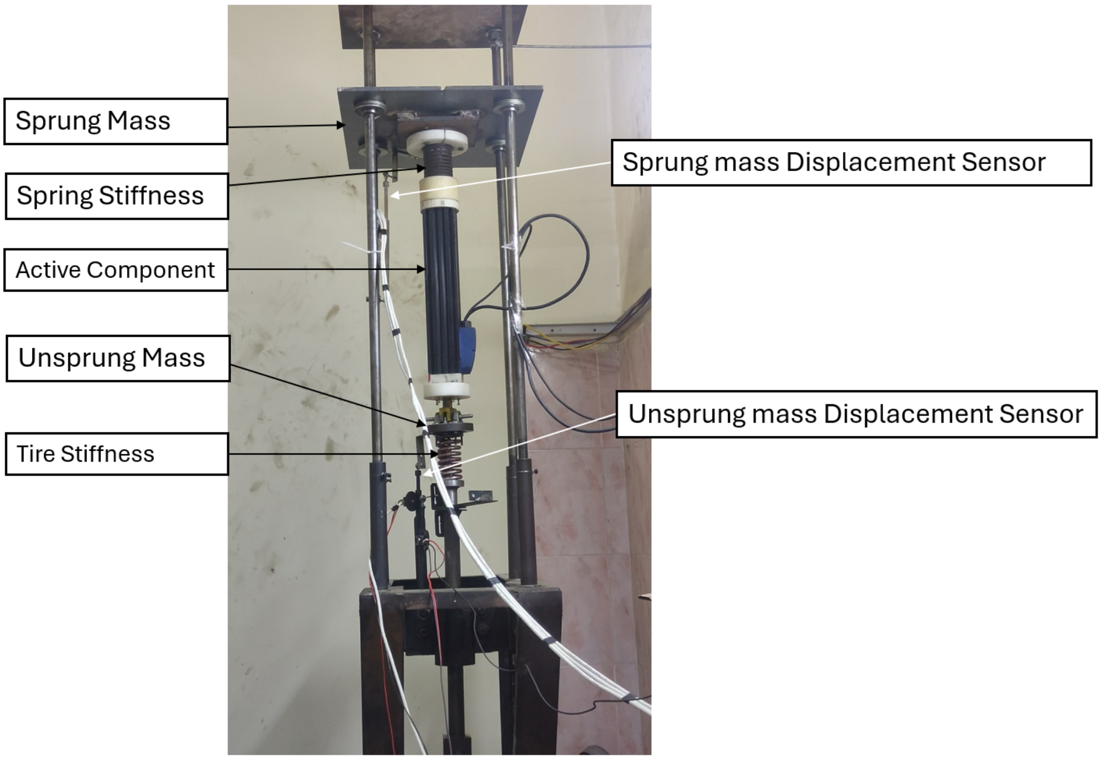


Figure 3.3: ASS Physical Model, by Ain Shams Univresity Students as Graduation Project, Spring 2024, Automotive Department.

3.1.3 Equation Of Motion

Sprung Mass

$$M_s\ddot{Z}_s = B_s\dot{Z}_{us} - B_s\dot{Z}_s - K_s(Z_s - Z_{us}) + F_c \tag{3.1}$$

$$\ddot{Z}_s = \frac{B_s\dot{Z}_{us}}{M_s} - \frac{B_s\dot{Z}_s}{M_s} - \frac{K_s(Z_s - Z_{us})}{M_s} + \frac{1}{M_s}F_c \tag{3.2}$$

Unsprung Mass

$$M_{us}\ddot{Z}_{us} = -B_s\dot{Z}_{us} - B_{us}\dot{Z}_{us} + B_s\dot{Z}_s + B_{us}\dot{Z}_r - K_s(Z_{us} - Z_s) - K_{us}(Z_{us} - Z_r) - F_c \tag{3.3}$$

$$\ddot{Z}_{us} = -\frac{B_s\dot{Z}_{us}}{M_{us}} - \frac{B_{us}\dot{Z}_{us}}{M_{us}} + \frac{B_s\dot{Z}_s}{M_{us}} + \frac{B_{us}\dot{Z}_r}{M_{us}} - \frac{K_s(Z_{us} - Z_s)}{M_{us}} - \frac{K_{us}(Z_{us} - Z_r)}{M_{us}} - \frac{1}{M_{us}}F_c \tag{3.4}$$

3.1.4 State Space Model

A state-space representation is a mathematical model used in modern control theory and system analysis to describe the behavior of a dynamic system. It offers a concise and systematic approach to representing the evolution of a system over time. In contrast to the frequency-domain representation (e.g., transfer functions), which characterizes a system's input-output relationship in terms of frequencies, the state-space representation provides a time-domain description.

The general state-space representation is given by the following:

$$\dot{x}_{(t)} = Ax_{(t)} + Bu_{(t)}$$

$$y_{(t)} = Cx_{(t)} + Du_{(t)}$$

- x: State variables vector.
- $\dot{x}$: Represents the time derivative of the state variables vector.
- y: Output vector.
- u: Input vector.
- A: System matrix.
- B: Input matrix.
- C: Output matrix.
- D: Feedforward matrix.

Table 3.4: State Variables

Variable	Description
$X_1 = Z_s - Z_{us}$	suspension travel
$X_2 = \dot{Z}_s$	sprung mass velocity
$X_3 = Z_{us} - Z_r$	wheel deflection
$X_4 = \dot{Z}_{us}$	wheel vertical velocity

Inputs: We will consider the input $\boldsymbol{u}$ into the system as the road disturbance velocity $\dot{Z}_r$ and the actuator input F_c.

Outputs: We will consider outputs $\boldsymbol{y}$ from the system as the suspension travel $Z_s - Z_{us}$ and the vehicle body (sprung mass) acceleration $\ddot{Z}_s$.

Using the above equations of motion, the state-space model of the active suspension system can easily be obtained and be written in the matrix form shown below:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & -1 \\ -\frac{K_s}{M_s} & -\frac{B_s}{M_s} & 0 & \frac{B_s}{M_s} \\ 0 & 0 & 0 & 1 \\ \frac{K_s}{M_{us}} & \frac{B_s}{M_{us}} & -\frac{K_{us}}{M_{us}} & -\frac{B_s+B_{us}}{M_{us}} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \frac{1}{M_s} \\ -1 & 0 \\ \frac{B_{us}}{M_{us}} & -\frac{1}{M_{us}} \end{bmatrix} \begin{bmatrix} \dot{Z}_r \\ F_c \end{bmatrix} \tag{3.5}$$

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -\frac{K_s}{M_s} & -\frac{B_s}{M_s} & 0 & \frac{B_s}{M_s} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \frac{1}{M_s} \end{bmatrix} \begin{bmatrix} \dot{Z}_r \\ F_c \end{bmatrix} \tag{3.6}$$

3.2 State Space Controllability

State-space controllability refers to the ability to drive a system from any initial state to any desired state within a finite time using an appropriate control input. A linear time-invariant (LTI) system represented in state-space form, is controllable if the controllability matrix has full rank. When this condition is met, it ensures that the system's states can be influenced by the control input, enabling effective feedback control design.

$$\mathcal{C} = \begin{bmatrix} B & AB & A^2B & \cdots & A^{n-1}B \end{bmatrix}$$

$$rank(\mathcal{C}) = n$$

```
% MATLAB script
ms  = 34;           % Sprung Mass (kg)
mus = 11;           % Unsprung Mass (kg)
ks  = 6921;         % Suspension Stiffness (N/m)
kus = 81000;        % Wheel stiffness (N/m)
bs  = 0;            % Suspension Inherent Damping coefficient (sec/m)
bus = 0;            % Wheel Inhenrent Damping coefficient (sec/m)

%% System Dynamics for the Active Suspension system.
A = [ 0 1 0 -1 ;
-ks/ms -bs/ms 0 bs/ms;
0 0 0 1;
ks/mus bs/mus -kus/mus -(bs+bus)/mus];

B = [0  0 ;
0 1/ms ;
-1  0 ;
bus/mus -1/mus ];

C = [ 1 0 0 0 ;
-ks/ms -bs/ms 0 bs/ms ];

D = [0 0;
0 0;
0 0;
0 0;
0 0;
0 1/ms];

%% Controllability
```

```
rank(ctrb(A,B))
```

The following figure shows that the system is controllable, because its controllability matrix is full rank which is equal to the number of states.

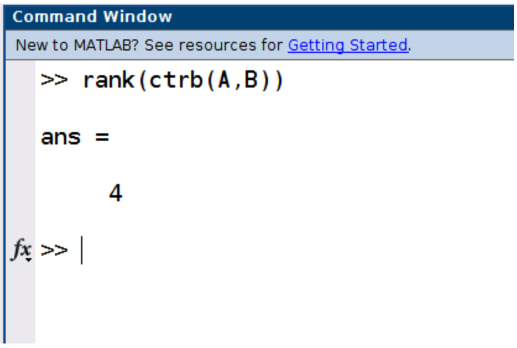


Figure 3.4: Conrollability matrix is full rank

3.3 Road Disturbance Profile

The slider-crank mechanism as shown in3.5 is used to simulate road. This mechanism converts the rotational motion of a crank into the linear motion of a slider, effectively replicating the vertical displacement experienced by a vehicle's suspension system when driving over uneven road surfaces which can change road amplitude by changing eccentricity from crank disk.

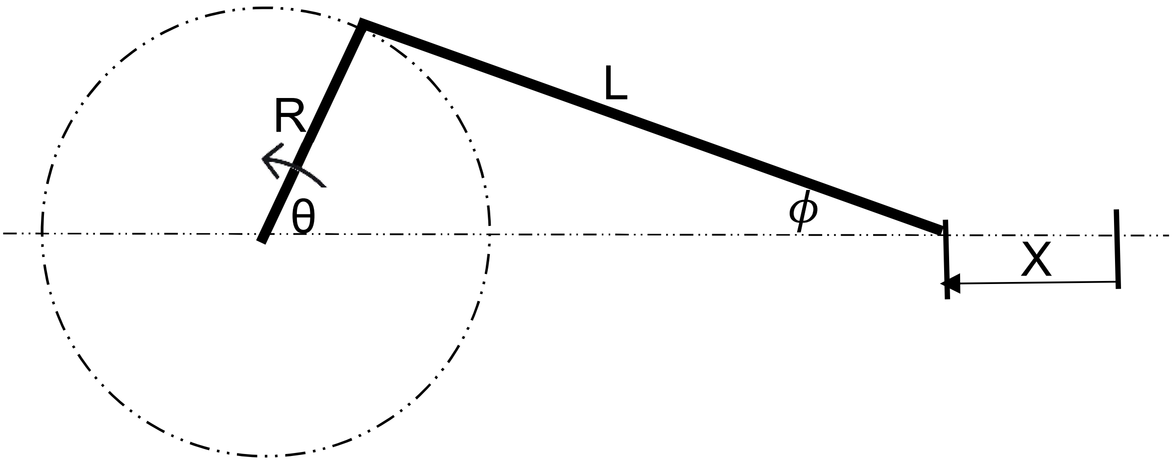


Figure 3.5: the slider crank mechanism

- R: Length of the crank
- L: Length of the connecting rod
- θ: Angle of the crank
- x: Position of the slider

Kinematic Equations

The position x of the slider can be determined using the crank angle θ and ϕ be the angle of the connecting rod with the horizontal. The position x of the slider can be expressed as:

$$x = R\left[1 - \cos\theta + n - \sqrt{n^2 - \sin^2\theta}\right] \tag{3.7}$$

since $n = \frac{L}{R}$.

Chapter 4

Modern Control Techniques

In this chapter, the control algorithms designed for the system are presented, along with their implementation and simulation in MATLAB. The primary objective is to evaluate the performance of different control strategies and analyze their effectiveness in achieving the desired system response. Simulations are then conducted to assess system stability, transient behavior, and robustness under varying conditions.

4.1 Full State Feedback

A full state feedback controller, also referred to as a pole placement controller which is shown in figure 4.1, provides an optimal solution for achieving desired pole locations of a closed-loop system. This approach leverages the fact that all state variables are assumed to be known to the controller at all times and are available for feedback.

The state-space representation of the plant is utilized, where each state variable is fed back to the control input, u, through a gain matrix, K. This feedback gain matrix can be adjusted to achieve the desired closed-loop pole values.

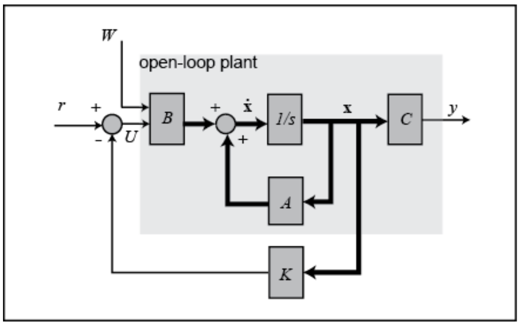


Figure 4.1: Full state feedback block diagram. [4]

Assuming no tracking ($r = 0$) and no external disturbance ($w = 0$), the system input is given by:

$$
\begin{aligned}
u &= -Kx \\
\dot{x} &= Ax - BKx \\
\dot{x} &= x(A - BK)
\end{aligned}
$$

4.2 Linear Quadratic regulator

4.2.1 Overview

LQR controller is a widely used type of state feedback control that offers a systematic method for determining the control gain, K. The LQR approach will be employed in the controller design for the active suspension system, as it is a classic and straightforward option for linear, time-invariant, multiple-input multiple-output (MIMO) systems. One of the key advantages of using an LQR controller is its ability to weight the factors affecting the performance index based on the desired outcome. For this project, the focus of the LQR approach will be on enhancing ride comfort and improving road-handling performance in the quarter-car model.

The function of an LQR controller is to minimize the cost function, J, which is shown in the following equation:

$$J = \frac{1}{2} \int_0^t (x^T Q x + u^T R u) \, dt \tag{4.1}$$

x^T = State vector.

u^T = Input vector.

4.2.2 LQR Implementation

The weighting matrices, Q and R, within the quadratic performance index significantly influence the LQR controller's behavior. These matrices allow for tuning the control system's priorities, such as emphasizing ride comfort or minimizing control effort. The optimal values for Q and R were determined through iterative simulations and tuning within the MATLAB environment. This process involved systematically adjusting the elements of Q and R and observing the resulting system response to determine the combination that best met the desired performance objectives.

The following figure4.2 shows the model used to simulate the dynamics of the quarter car suspension system, based on the state space model represented in the previous chapter.

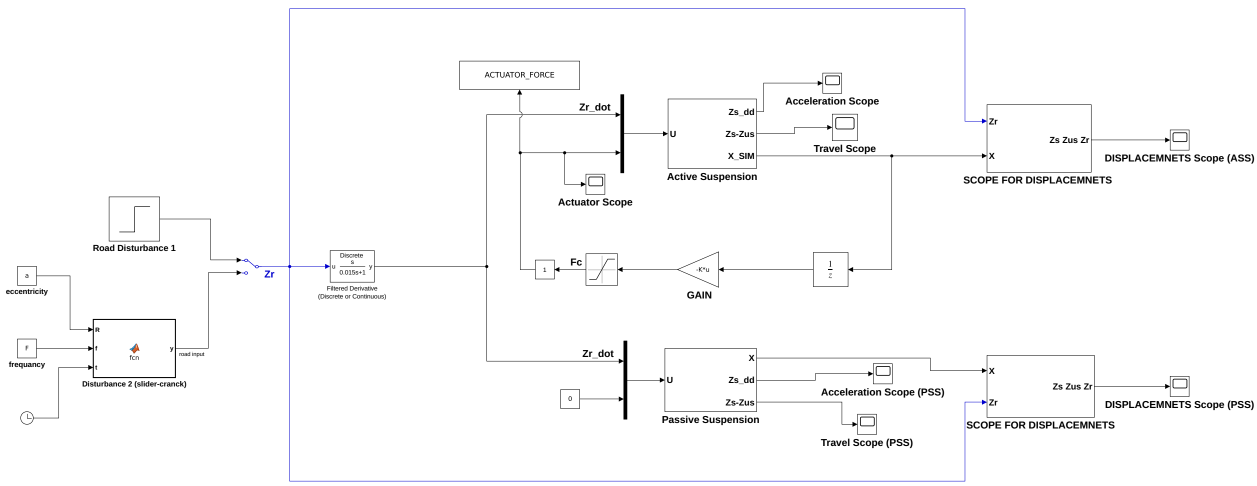


Figure 4.2: provides the block diagram model for the active suspension system

4.3 LQR Simulation Results

To evaluate the performance of the LQR controller we will compare between the passive suspension system and the active suspension sytem in case of two road excitation profiles, the first one will be a simple step input, the second one will be the profile of the slider crank mechanism, that we discussed in the previous chapter (section 3.3)

4.3.1 Step Response

The following figure4.3 shows the effect of LQR on the system, it is a comparison between the passive and active response when excited by a step input of 60 mm amplitude.

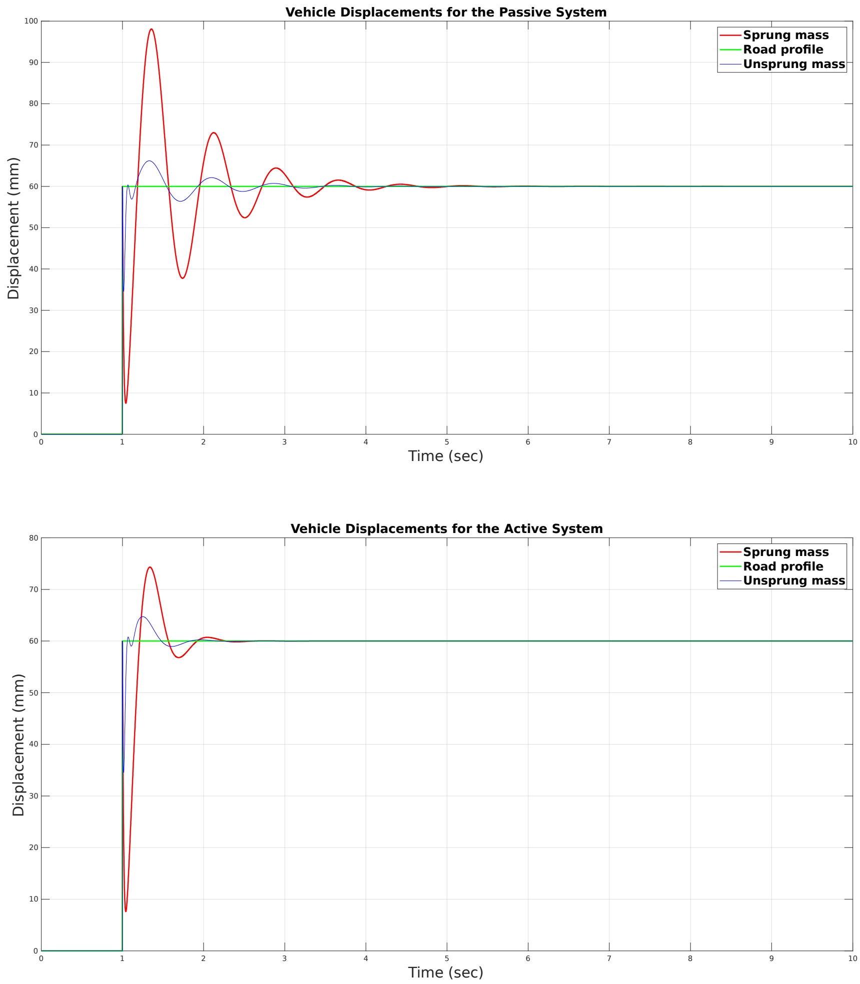


Figure 4.3: Effect of the controller on Sprung and unsprung mass of the system

The following figures4.4 compare between the performance of the system with LQR and without it to a step input:

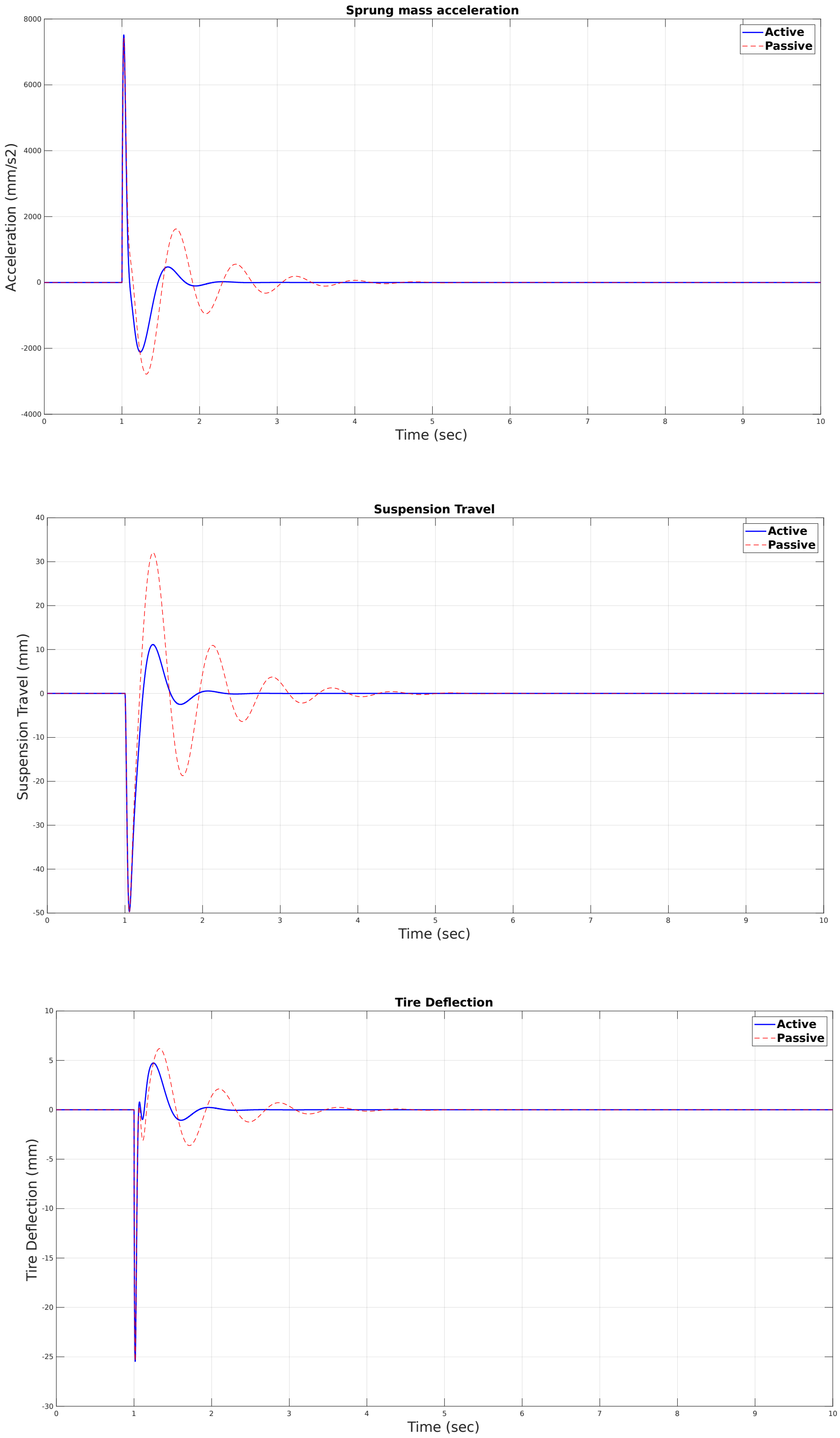


Figure 4.4: Effect of the controller

4.3.2 Road Profile Excitation

This section shows the effect of the controller on the system against a more complicated road disturbance, which is the continuous excitation of the slider crank mechanism at a frequency of 0.3 HZ.

The following figures4.5 compare between the sprung and unsprung mass acceleration in both the passive and active systems:

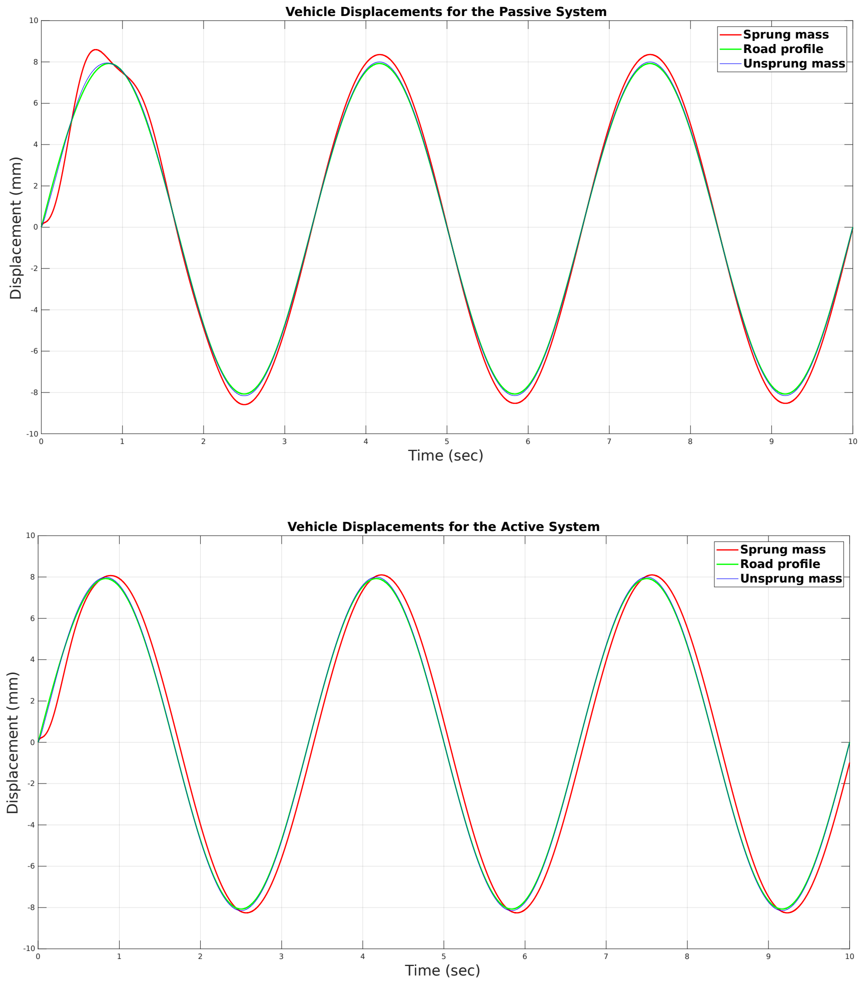


Figure 4.5: Effect of the controller on Sprung and unsprung mass of the system

The following figures4.6 compare between the performance of the system with LQR and without it, against the excitation of the road profile:

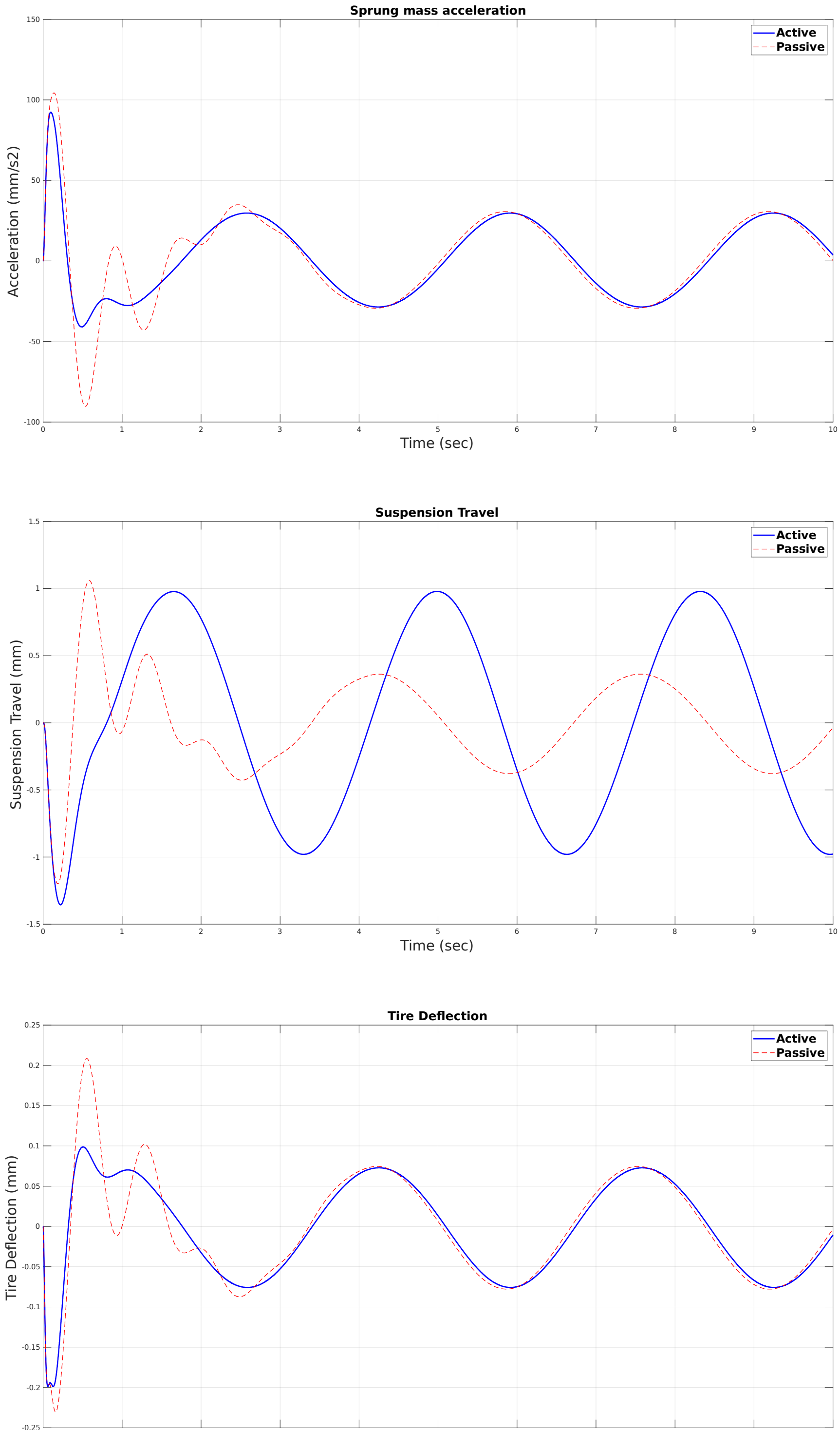


Figure 4.6: Effect of the controller

4.4 Sliding mode control

4.4.1 Overview

Sliding Mode Control (SMC) is a nonlinear control technique featuring remarkable properties of accuracy, robustness, and easy tuning and implementation. There are two main advantages of sliding mode control. First is that the dynamic behavior of the system may be tailored by the particular choice of the sliding function. Secondly, the closed loop response becomes totally insensitive to some particular uncertainties. This principle extends to model parameter uncertainties, disturbance and non-linearity that are bounded. From a practical point of view (SMC) allows for controlling nonlinear processes subject to external disturbances and model uncertainties

4.4.2 Theory

This is a type of non-linear control that provides a sporadic control signal in the process of altering dynamic characteristics of a system. The sliding mode control (SMC) is based on the principle of switching logic between different independent structural systems. The control strategy forces the system to slide along the normal behavioural lines. The control system is structured in such a way that paths always move towards a neighbouring region of the behavioural line with a different degree of control so that the ultimate path would not occur exclusively within one control. It will instead slide along the limits of the controlled structures while minimizing error, as indicated in 4.7. The SMC is, therefore, able to control both linear and non-linear systems. (1) The controller and (2) the sliding surface are the primary parameters of SMC.

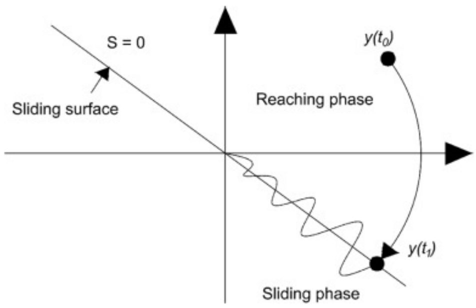


Figure 4.7: Representation of sliding surface and minimization of error. [?]

4.4.3 SMC implementation

Using regulation mode to minimize system vibrations and improve ride comfort the first step is to define the sliding surface

Dfinning the sliding surface

The sliding surface (or switching surface) is a key component of the SMC. It defines the condition under which the system behavior will enter a "sliding" mode. The sliding-mode surface can be described as:

$$s = cZ_s + \dot{Z}_s \tag{4.2}$$

Design reaching law

The reaching law ensures that the state of the system moves towards the sliding surface whatever its initial conditions. The reaching law is given by:

$$h\left(s\left(x\right)\right) = -\eta sign\left(s\right) \tag{4.3}$$

where η is a positive constant that determines the speed of convergence to the sliding surface.

Design the control law

The sliding mode control law is designed to drive the system towards the sliding surface. The derivative of s is given by:

$$\dot{s} = c\dot{Z}_s + \ddot{Z}_s \tag{4.4}$$

From mathematical model equation the sprung mass acceleration is given by:

$$\ddot{Z}_s = \frac{B_s\dot{Z}_{us}}{M_s} - \frac{B_s\dot{Z}_s}{M_s} - \frac{K_s(Z_s - Z_{us})}{M_s} + \frac{1}{M_s}F_c \tag{4.5}$$

substitute in 4.4 :

$$\dot{s} = c\dot{Z}_s - \frac{K_s}{M_s}Z_s + \frac{K_s}{M_s}Z_u s + \frac{1}{M_s}F_c \tag{4.6}$$

Let $\dot{s} = -\eta sign\,(s)$

$$-\eta sign\,(s) = c\dot{Z}_s - \frac{K_s}{M_s}Z_s + \frac{K_s}{M_s}Z_u s + \frac{1}{M_s}F_c \tag{4.7}$$

Therefore, sliding-mode control input is given by :

$$F_c = -cM_s\dot{Z}_s + K_sZ_s - K_sZ_u s - \eta M_s sign\,(s) \tag{4.8}$$

Define boundary layer

Using a saturation boundary layer instead of the sign function can effectively reduce the chattering effect. The idea is to apply the full gain when the system state is outside the boundary layer. However, once the system enters the boundary layer, the gain is made proportional to the distance from the boundary, effectively smoothing the control action. This modification ensures a continuous control signal within the boundary layer, mitigating chattering while maintaining robustness.

$$\mathrm{sat}(s,\phi) = \begin{cases} 1 & \text{if } s > \phi, \\ \frac{s}{\phi} & \text{if } -\phi \le s \le \phi, \\ -1 & \text{if } s < -\phi. \end{cases} \tag{4.9}$$

After designing the control force to enhance the performance of the suspension system, the next step is to implement the Sliding Mode Controller (SMC) using MATLAB/Simulink.

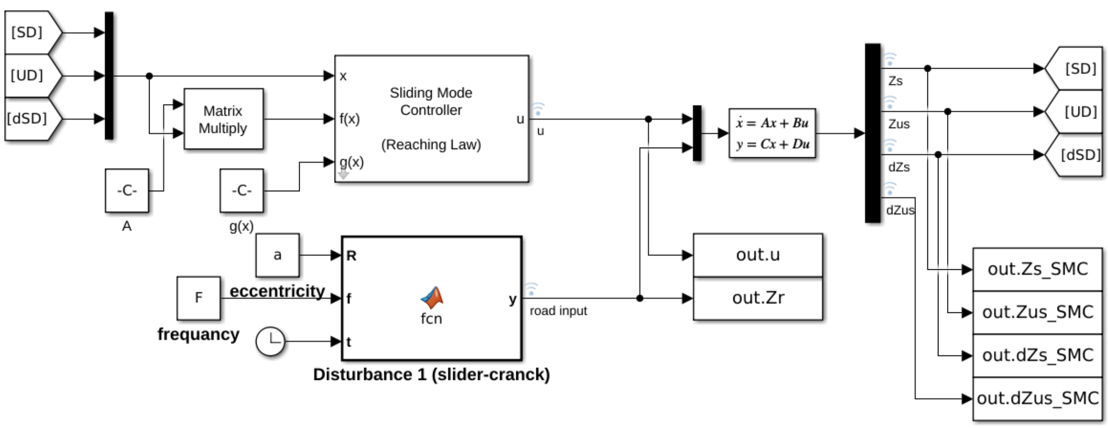


Figure 4.8: SMC simulink model

4.5 SMC Simulation Results

The followinf figures shows the effect of the SMC on the suspension system when excited with the road profile defined by the slider crank mechanism:

Figure4.9 shows the enhancement caused by SMC on the sprung mass, whicle figure 4.10 shows the effect on the unsprung mass. Also the effect on suspension travel is shown in figure 4.11.

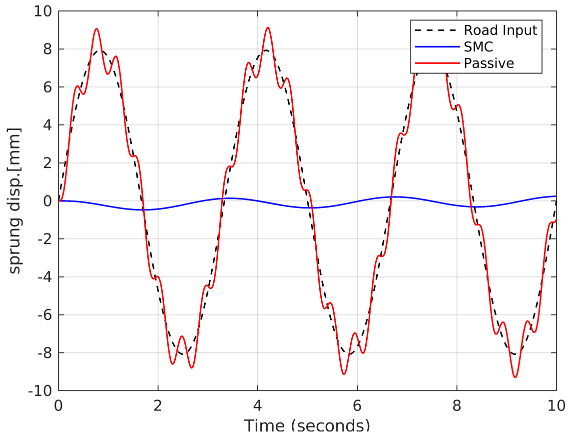


Figure 4.9: Sprung mass displacement.

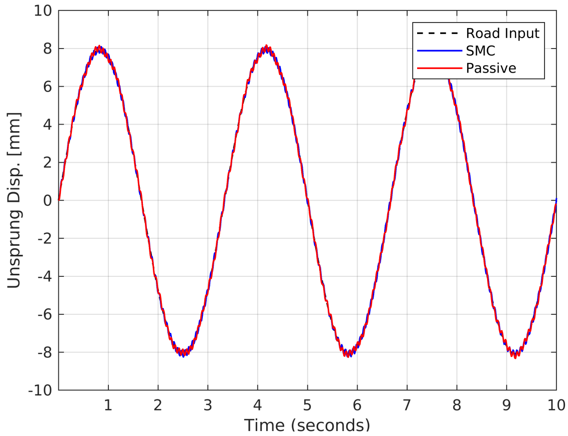


Figure 4.10: Usprung mass displacement.

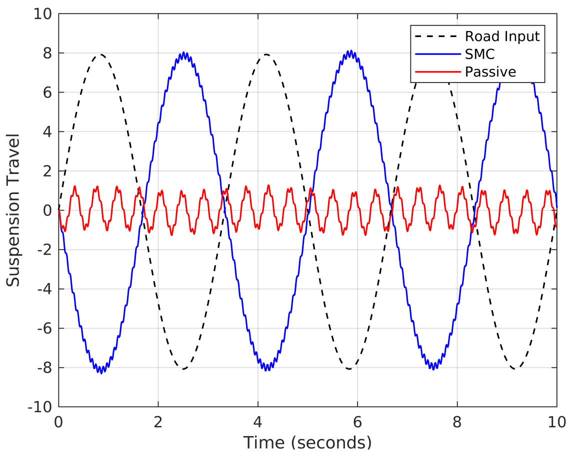


Figure 4.11: Suspension travel.

The following figure 4.12 shows the effect of the SMC on the tire deflection, while figure 4.13 shows the effect on sprung mass acceleration.

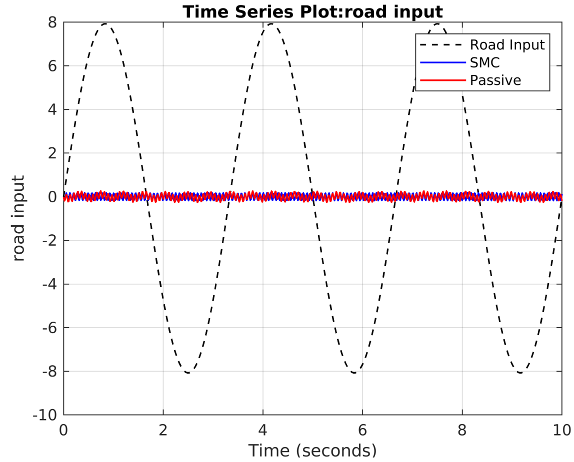


Figure 4.12: Dynamic tire defeliction.

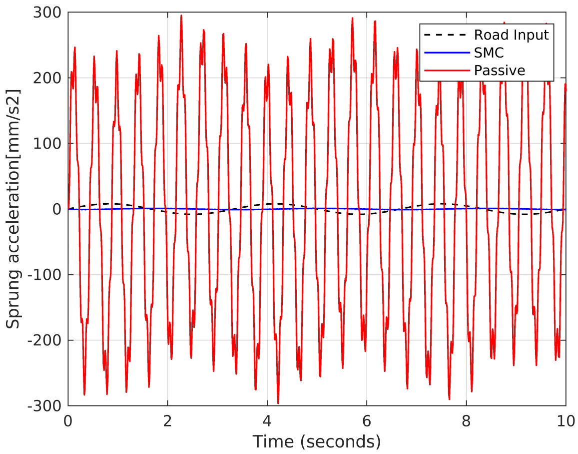


Figure 4.13: Sprung mass acceleration.

4.5.1 Maximum Actuator force

To ensure the practical feasibility and safety of the proposed control system, actuator limitations were carefully considered throughout the design process. A maximum force constraint of 100 Newtons was imposed on the actuator, which was deemed sufficient for all operating conditions, including the more demanding scenarios encountered with Sliding Mode Control as shown in figure 4.14.

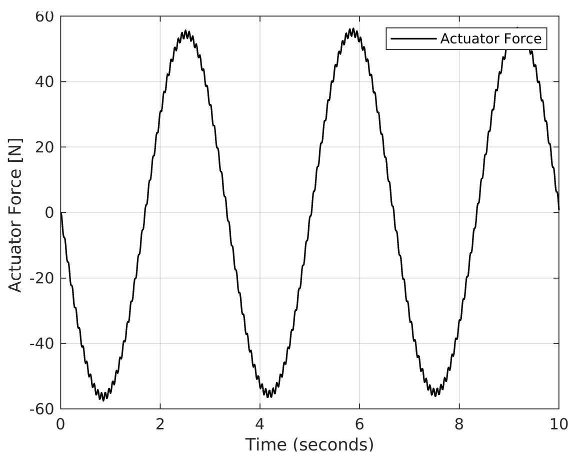


Figure 4.14: Force.

4.6 Reinforcement learning

4.6.1 Overview

Reinforcement learning is a type of machine learning technique where a computer agent learns to perform a task through repeated trial and error interactions with a dynamic environment. This learning approach enables the agent to make a series of decisions that maximize a reward metric for the task without human intervention and without being explicitly programmed to achieve the task. The key components are:

- State (s): Current system observation
- Action (a): Control input applied by the agent
- Reward (r): Feedback signal to guide learning
- Policy : A function mapping states to actions, optimized over time

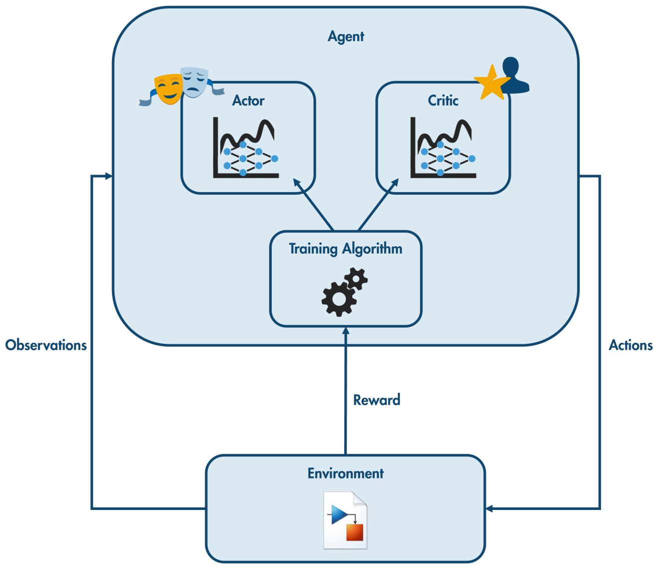


Figure 4.15: Reinforcement learning key components. [5]

4.6.2 Reinforcement learning workflow

The general workflow for training an agent using reinforcement learning includes the following steps:

Figure 4.16: RL worlflow. [6]

Create environment

The environment is modeled using MATLAB/SIMULINK.

- Inputst: Road disturbance, control force from the RL agent.
- Outputs: Sprung mass displacement, suspension travel, road holding.

Figure4.17 show the Model used.

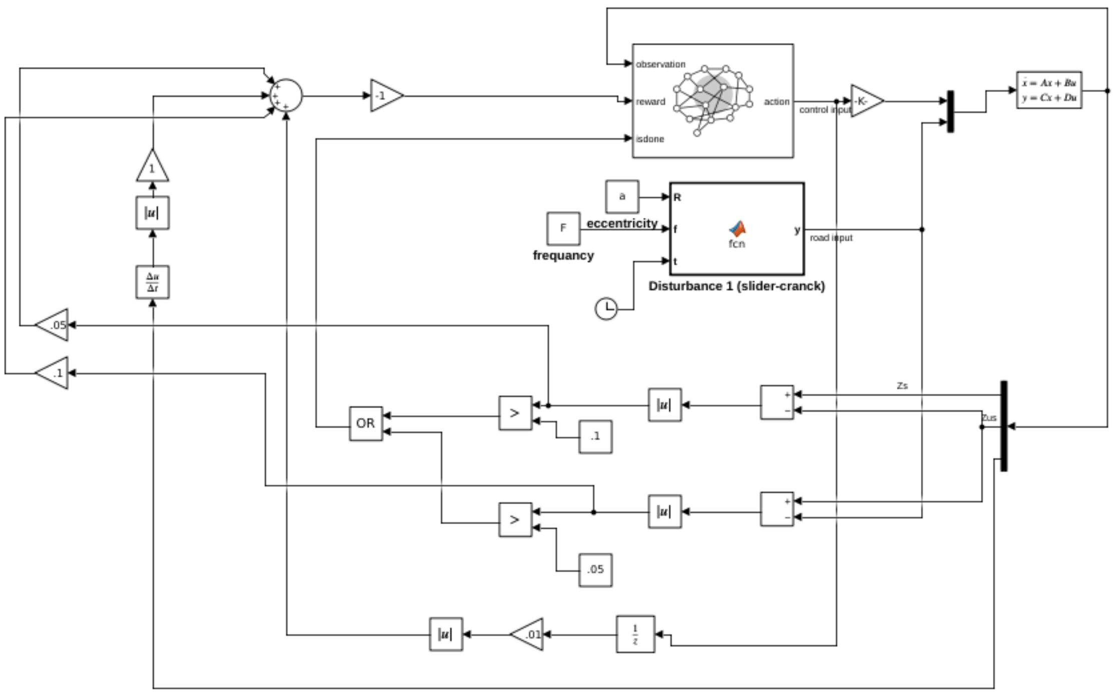


Figure 4.17: Reinforcemet learning simulink Model

Design the Reward Function

Specify the reward signal that the agent uses to measure its performance against the task goals and how to calculate this signal from the environment.

The design objectives are:

- Penalize excessive sprung acceleration (improves ride comfort).
- Penalize large suspension travel (avoids hitting mechanical limits).
- Reward good road holding (minimizing tire deflection).
- Penalize excessive control force (reduces energy consumption).

$$R(t) = -\alpha|\ddot{Z_s}(t)| - \beta|Z_s(t) - Z_u s| - \gamma|Z_u s(t) - Z_r(t)| - \delta|F_c(t)| \tag{4.10}$$

Create agent

There are many Types of agent choosing between them depends on the nature of our system observation and actions.

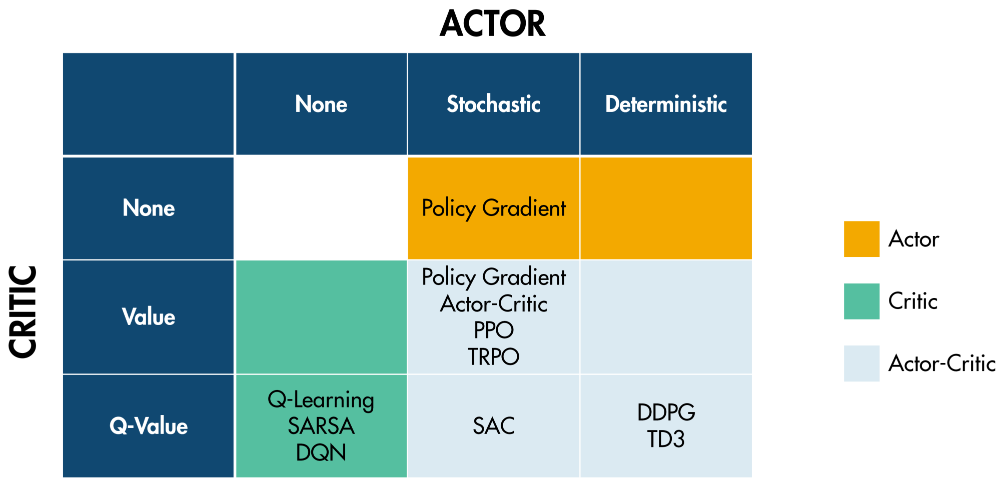


Figure 4.18: Reinforcement learning agents. [7]

For an active suspension system using DDPG deep Deterministic Policy Gradient is suitable for its continuos nature. It's an extension of the Deterministic Policy Gradient (DPG) method and incorporates deep learning techniques to handle complex environments . It uses two network:

- Actor: This network decides which action to take given the current state of the environment.

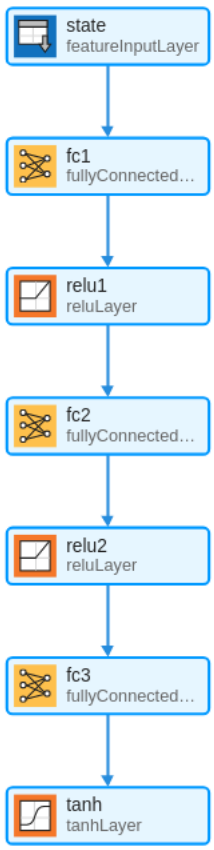


Figure 4.19: actor network

- Critic: This network evaluates the actions taken by the actor by estimating the Q-value (the expected return from taking a particular action in a given state). During training, the Q-values are updated iteratively for each state-action pair based on the agent's experience using Bellman equation. Over time, this update process allows the agent to learn an optimal policy that maximizes cumulative rewards. The Bellman equation is given by:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

where:

- $Q(s,a)$ is the current Q-value for state s and action a.
- α is the learning rate.
- r is the immediate reward after taking action a in state s.
- γ is the discount factor.
- $\max_{a'} Q(s',a')$ is the maximum Q-value for the next state s', over all possible actions a'.
- s' is the next state.

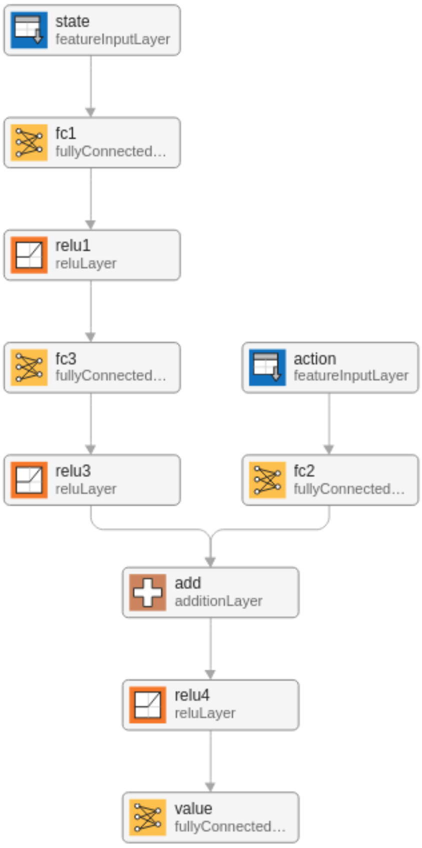


Figure 4.20: critic network

Train agent

The agent is trained by interacting with the environment, and the train function will optimize the agent's policy. The training stats variable will store statistics such as cumulative reward.

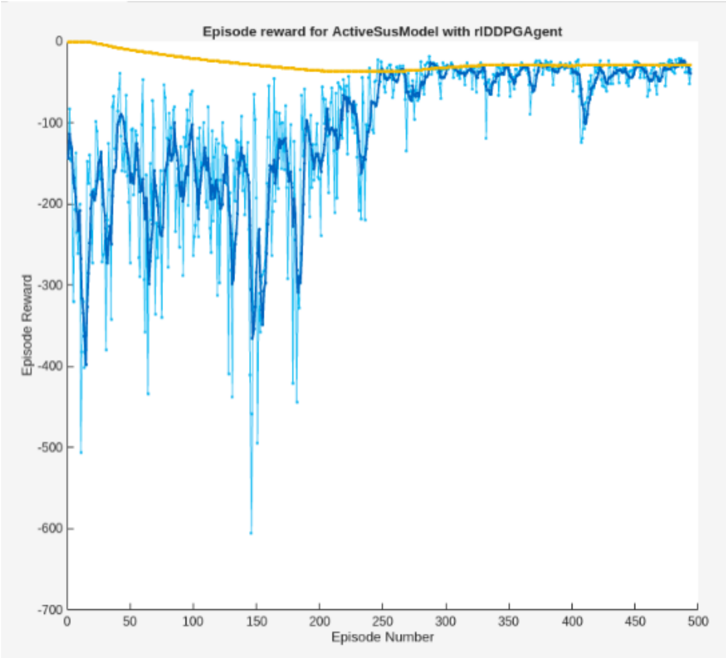


Figure 4.21: training results

Training hyper parameters need more tuning and more iterations untill the average reward converge and gives acceptable behavior. Then the tained agent will be validated to make sure it well behave well after deploying in hardware.

The following sections discusses some problems that will arise upon implementing the hardware sensors and actuators for the active system, and how to solve it.

4.7 Magnetic Field effect on Sensor Signals

When an electric motor operates in an active suspension system, it generates a strong magnetic field due to the current flowing through its coils. This magnetic field can significantly affect the electrical signals transmitted through nearby wires, causing interference or distortion in these signals. Several mathematical principles explain this effect.

4.7.1 Electromagnetic Induction (Faraday's Law of Induction)

When a wire is exposed to a changing magnetic field, it induces an electric current in the wire. This phenomenon is known as electromagnetic induction, and it is described by Faraday's Law of Induction, which states that the induced electromotive force (EMF) (E) is proportional to the rate of change of magnetic flux through the wire. The equation governing this phenomenon is:

$$E = -\frac{d\Phi_B}{dt}$$

Where:

- E is the induced electromotive force (EMF).
- Φ_B is the magnetic flux, calculated as:

$$\Phi_B = B \cdot A$$

- B is the magnetic field strength.
- A is the area through which the magnetic flux passes.

When the wire is exposed to the magnetic field generated by the motor, the changing magnetic field induces a current in the wire. This induced current can interfere with the original signal being transmitted, leading to signal distortion. In sensitive systems like active suspension, this interference can result in loss of data integrity in the transmitted signals.

4.7.2 Effect of the Magnetic Field on Electron Motion in Wires

The magnetic field acting on a current-carrying wire also exerts a Lorentz force on the moving electrons inside the wire. This force affects the electron motion and can result in changes in current or signal distortion. This force is described by Lorentz's Law:

$$F = q(v \times B)$$

Where:

- F is the force acting on the charge q.
- v is the velocity of the charge.
- B is the magnetic field.

This force causes the electrons to deviate from their path, which leads to changes in the current flowing through the wire and, consequently, in the electrical signal itself.

4.7.3 Electromagnetic Interference (EMI)

The magnetic field produced by the motor can also cause electromagnetic interference (EMI), which results in the generation of unwanted signals or noise that interferes with the electrical signal transmitted through the wires. Electromagnetic interference can alter both the frequency and amplitude of the signal, leading to signal distortion and loss of signal clarity.

4.8 Sensor Accuracy Issues in the System

Sensors in the active suspension system are crucial for measuring various parameters such as vibration and position. If these sensors are inaccurate, it can directly affect the system's performance. This leads to an incorrect response from the system in controlling the suspension.

4.8.1 Measurement Error in Sensors

Every sensor can have a measurement error due to various factors, such as electromagnetic interference or environmental influences (e.g., temperature and vibration). The relative error in measurements can be expressed using the following equation:

$$\epsilon = \frac{\Delta S}{S}$$

Where:

- ϵ is the relative error in the measurement.
- ΔS is the change in the actual measurement.
- S is the ideal or reference measurement.

The relative error represents the variance between the actual measurements and the ideal measurements. A large relative error indicates that the sensor is inaccurate, which may lead to incorrect readings that negatively impact the system's performance.

4.8.2 Impact of Electromagnetic Interference on Sensors

If sensors are exposed to electromagnetic interference from the motor or other devices within the system, it can lead to an increase in noise within the signal that the sensor measures. Electromagnetic interference from the motor can cause the sensor to record incorrect values. This noise affects the measurement of angles, vibrations, and other critical parameters, leading to an inaccurate system response.

The level of electromagnetic noise caused by multiple sources can be calculated using the following equation:

$$N = \sum_{i=1}^{n} \frac{1}{r_i^2} \cdot Power_i$$

Where:

- N is the total noise level caused by multiple sources.
- r_i is the distance between the noise source and the sensor.
- $Power_i$ is the power of the interference from source i.
- n is the number of sources causing interference.

If the electromagnetic interference from the motor or other devices is strong, it can cause a significant increase in noise, which adversely affects the accuracy of the sensor measurements.

The magnetic field generated by the motor in an active suspension system induces current in nearby wires, leading to signal distortion due to electromagnetic induction and Lorentz forces. This interference results in noise and loss of data integrity in the transmitted signals. Additionally, sensor inaccuracies due to electromagnetic interference or sensor-related issues can reduce the accuracy of the measurements used for system control. These effects compromise the system's ability to respond accurately.

4.9 Solutions to the Effect of Magnetic Field inference

This section discusses the issue of magnetic field interference caused by motors that can significantly impact signal integrity in sensors used in our system.

Below are some scientifically proven solutions to address this problem:

4.9.1 Ferrite Beads

Ferrite beads are simple yet highly effective electronic components used to suppress electromagnetic interference (EMI) in electrical circuits. They operate by providing high impedance to high-frequency noise while allowing low-frequency signals to pass. Ferrite beads are widely used in applications such as laptop chargers, industrial control systems, and sensitive electronic devices. Studies have shown that ferrite beads can significantly reduce high-frequency noise.

4.9.2 Shielded Wires

Shielded wires are specifically designed to protect internal signals from external electromagnetic interference. These wires are covered with a conductive shield (e.g., metallic braiding or foil), which absorbs or redirects electromagnetic fields. They are essential in applications where signal integrity is critical, such as telecommunications, medical equipment, and industrial machinery.

4.9.3 Electronic Filters

Electronic filters are critical components for managing signal processing and reducing noise. These devices allow specific frequency ranges to pass while attenuating unwanted frequencies. Filters improve signal quality by removing noise caused by EMI or other sources.

4.10 Extended Kalman Filter

4.10.1 Overview of the Extended Kalman Filter

The Extended Kalman Filter (EKF) is an extension of the traditional Kalman Filter (KF) designed to handle nonlinear systems. Unlike the KF, which assumes a linear model, the EKF linearizes the system at each time step using a first-order Taylor expansion around the current state estimate.

4.10.2 Key Features of the Extended Kalman Filter

- **Nonlinear Systems:** The EKF can handle nonlinear system dynamics by linearizing the system around the current estimate.
- **Noise Handling:** The EKF, like the KF, accounts for noise in both the process and measurements.
- **Optimality:** It provides the best possible estimate in a least-squares sense by minimizing the Mean Squared Error (MSE).

4.10.3 Mathematical Formulation

1. **State Equation:**

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{u}_k) + \mathbf{w}_{k-1}$$

where:

- $\mathbf{x}_k$: State vector at time step k.
- $f(\cdot)$: Nonlinear state transition function.
- $\mathbf{w}_{k-1}$: Process noise (assumed to be Gaussian with zero mean and covariance $\mathbf{Q}$).

2. **Measurement Equation:**

$$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k$$

where:

- $\mathbf{z}_k$: Measurement vector.
- $h(\cdot)$: Nonlinear measurement function.
- $\mathbf{v}_k$: Measurement noise (assumed to be Gaussian with zero mean and covariance $\mathbf{R}$).

4.10.4 Steps in the Extended Kalman Filter

1. Initialization

- Initial state estimate: $\hat{\mathbf{x}}_0$.
- Initial error covariance: $\mathbf{P}_0$.

2. Prediction

$$\begin{aligned}
\text{Predict the next state:} \quad & \hat{\mathbf{x}}_{k|k-1} = f(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_k) \\
\text{Compute the Jacobian of the state transition:} \quad & \mathbf{F}_k = \left.\frac{\partial f}{\partial \mathbf{x}}\right|_{\hat{\mathbf{x}}_{k-1|k-1}} \\
\text{Predict the error covariance:} \quad & \mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^T + \mathbf{Q}
\end{aligned}$$

3. Update

$$\begin{aligned}
\text{Compute the Jacobian of the measurement function:} \quad & \mathbf{H}_k = \left.\frac{\partial h}{\partial \mathbf{x}}\right|_{\hat{\mathbf{x}}_{k|k-1}} \\
\text{Compute the Kalman Gain:} \quad & \mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R})^{-1} \\
\text{Update the state estimate:} \quad & \hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k (\mathbf{z}_k - h(\hat{\mathbf{x}}_{k|k-1})) \\
\text{Update the error covariance:} \quad & \mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_{k|k-1}
\end{aligned}$$

4.11 Application of the Extended Kalman Filter to the Active Suspension Model

The active suspension system can also be modeled using the EKF approach. Since the suspension system typically includes nonlinearities, the EKF is more suitable than the standard Kalman filter for state estimation.

4.11.1 State-Space Representation of the Suspension System

The state-space representation of the suspension system will have nonlinear functions for both the state transition and the measurement models. Let's define:

State Vector ($\mathbf{x}(t)$)

$$\mathbf{x}(t) = \begin{bmatrix} z_s(t) \\ \dot{z}_s(t) \\ z_u(t) \\ \dot{z}_u(t) \end{bmatrix}$$

where:

- $z_s(t)$: Sprung mass displacement.
- $\dot{z}_s(t)$: Sprung mass velocity.
- $z_u(t)$: Unsprung mass displacement.
- $\dot{z}_u(t)$: Unsprung mass velocity.

Input Vector ($\mathbf{u}(t)$)

$$\mathbf{u}(t) = \begin{bmatrix} \dot{Z}_r(t) \\ F_c(t) \end{bmatrix}$$

where:

- $\dot{Z}_r(t)$: Road disturbance velocity.
- $F_c(t)$: Control force from the active suspension.

Measurement Vector ($\mathbf{y}(t)$)

$$\mathbf{y}(t) = \begin{bmatrix} z_s(t) \\ \dot{z}_s(t) \end{bmatrix}$$

4.11.2 Nonlinear State Transition and Measurement Functions

Nonlinear State Transition Function $f(\mathbf{x}, \mathbf{u})$:

$$f(\mathbf{x}, \mathbf{u}) = \begin{bmatrix} \dot{z}_s(t) \\ -\frac{K_s}{M_s} z_s(t) - \frac{B_s}{M_s} \dot{z}_s(t) + \frac{K_s}{M_s} z_u(t) + \frac{B_s}{M_s} \dot{z}_u(t) + F_c(t) \\ \dot{z}_u(t) \\ \frac{K_s}{M_u} z_s(t) + \frac{B_s}{M_u} \dot{z}_s(t) - \frac{K_s+K_u}{M_u} z_u(t) - \frac{B_s+B_u}{M_u} \dot{z}_u(t) \end{bmatrix}$$

Nonlinear Measurement Function $h(\mathbf{x})$:

$$h(\mathbf{x}) = \begin{bmatrix} z_s(t) \\ \dot{z}_s(t) \end{bmatrix}$$

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This study demonstrated that the sliding mode controller (SMC) outperforms the linear quadratic regulator (LQR). As expected from the literature, the LQR provides an improvement over passive control but lacks the robustness and adaptability of advanced control strategies. While reinforcement learning (RL) has shown promise in recent studies, a direct comparison was not feasible due to the extensive training and tuning required. Overall, SMC proves to be a more effective solution for achieving superior performance and robustness in this application.

5.2 Future Work

In the next semester we will implement, and experimentally validate a Hardware-in-the-Loop (HIL) results for the active suspension system on a quarter-car model test rig. This will involve:

- Integrating the previously developed simulation models with the real quarter-car model test rig.
- Developing and implementing data acquisition and the simulated control algorithms within the HIL environment.
- Conducting rigorous experimental testing to compare the performance of the simulated and real-time implementations of the active suspension system under various road excitations.
- Analyzing the experimental results to assess the accuracy and effectiveness of the control algorithms, identify any difference between the simulated and real-world behavior of the quarter-car model, and quantify the achieved ride comfort and handling improvements.
- Investigating and mitigating the effects of sensor noise and actuator limitations on the system's performance within the context of the quarter-car model test rig.
- Refining the control algorithms based on the experimental findings to optimize the suspension system's ride comfort, handling, and road holding capabilities on the quarter-car model.

Appendix A

Appendices

A.1 Appendix 1

The following are some characteristics of springs:

Suspension Rate or Stiffness (K) is one of the characteristics that mean that the force needed to compress or extend a suspension spring by a specific amount of distance is known as the spring rate, also known as stiffness. Newtons per millimeter (N/m) are the common units of measurement.

Increased spring rates give the suspension more stiffness, which enhances responsiveness and handling. But too stiff of springs can make for a rough ride. And this will be well discussed in the suspension system conflicts section. [10]

A.2 Appendix 2

- **Vibration Isolation:** This term means the response of the sprung mass (all components directly supported by the suspension system. Vehicle body and passenger passengers) to the various excitation types from the road. In most cases, **the transmissibility ratio** (transfer function) is used for evaluating a linear suspension system's vibration isolation ability.

$$TR = \frac{Z_{\mathrm{s}}}{Z_0} \tag{A.1}$$

  where:

  - TR is the transmissibility ratio of the suspension system.
  - Z_{s} is the sprung mass displacement.
  - Z_0 is the road excitation displacement.

- **Suspension Travel (ST):** This means the deflection of the suspension spring or the relative displacement between the sprung mass (Car Body) and unsprung mass (components that are not supported by the suspension system i.e. The wheels and tires).

$$ST = \frac{Z_{\mathrm{us}} - Z_{\mathrm{s}}}{Z_0} \tag{A.2}$$

  where:

  - ST is the suspension travel relative to road excitation displacement.
  - Z_{us} is the unsprung mass displacement.
  - Z_{s} is the sprung mass displacement.

- **Roadholding:** The usual force acting between the tire and the road varies as the vehicle system vibrates on the road. The roadholding capabilities, handling, and performance of the vehicle are all influenced by tire vibration, since the cornering force, tractive effort, and braking effort generated by the tire are all associated with the tire's normal load. The displacement of the unsprung mass with respect to the road surface can be used to depict the normal force between the tire and the road during vibration. **The dynamic tire deflection** is used as a measurable term for evaluating the suspension performance characteristic as this formula:

$$DTD = \frac{Z_0 - Z_{\mathrm{us}}}{Z_0} \tag{A.3}$$

where:

- DTD is the dynamic tire deflection.
- Z_0 is the road excitation displacement.
- Z_{us} is the unsprung mass displacement.

A.3 Appendix 3

As an illustration figures A.1 and A.2 shows the tradeoffs in suspension design, the response of a passive suspension system at different suspension parameters implemented by suspension mathematical modeling using MATLAB software, it resulted:

A stiffer suspension behavior is required to enhance tire contact with the road-dynamic tire deflection-and the vehicle's dynamic behavior during braking and turning, whereas a softer suspension behavior is required to increase vehicle vibration isolation and enhance passenger comfort. [45]

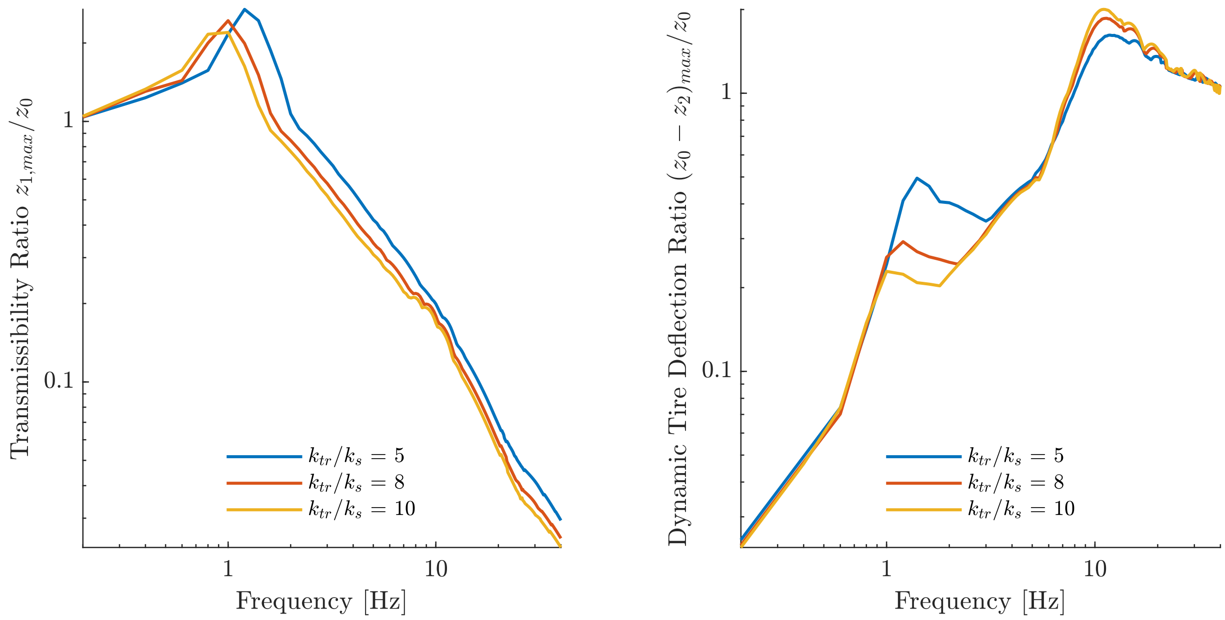


Figure A.1: Transmissibility ratio (left) and Dynamic Tire Deflection (right) as a function of frequency for the sprung mass of a suspension system with different ratios of tire stiffness to suspension spring stiffness

On the other hand, As shown in figures 1.3 and 1.4, talking about the damping ratio (ζ), the smaller damping ratio is required to high vibration isolation and good ride quality (lower transmissibility ratio), the natural frequency of the sprung mass or close to the natural frequency of the unsprung mass, to maintain good roadholding capability, higher damping is required. [2]

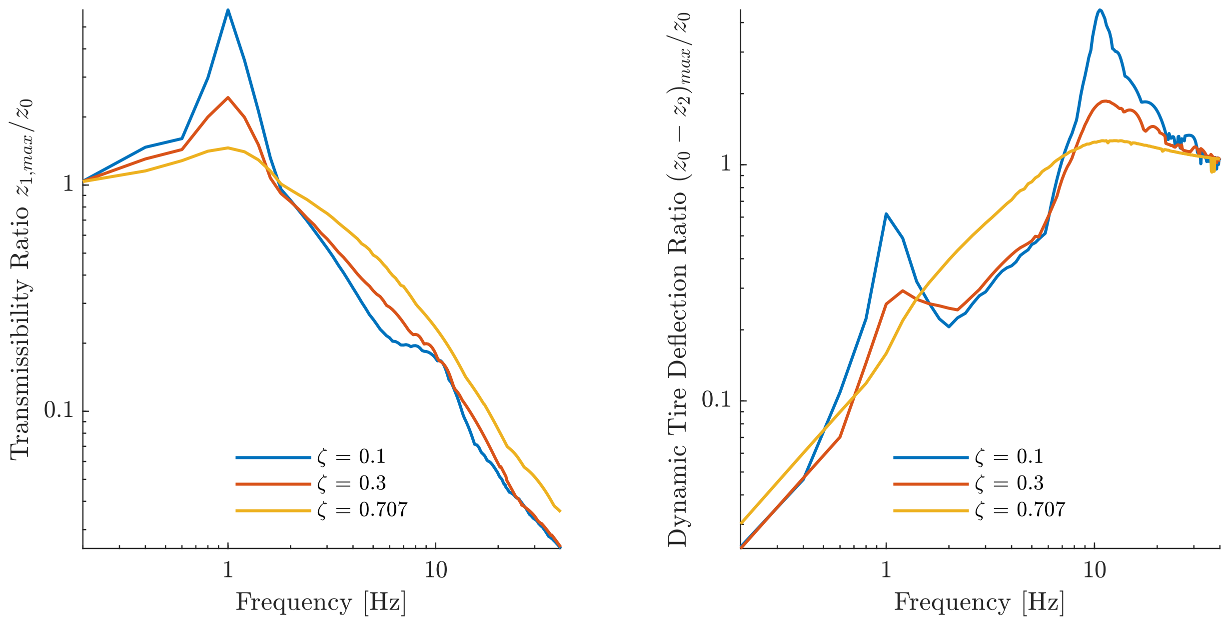


Figure A.2: Transmissibility ratio (left) and Dynamic Tire Deflection (right) as a function of frequency for the sprung mass of a suspension system with different damping ratios.

And this presents a very difficult challenge for the designers, who have to make some compromises to strike a balance barely that is appropriate for maintaining the luxurious and safe driving experience of the vehicle. Furthermore, these compromises affect overall driving experience or vehicle safety and handling. [45]

For talking about **compromises in better overall driving experience** or ride quality, the International Standard IS0 2631 provides an extensive basis for characterizing human tolerance to whole-body vibration. The guide provides three different limits for whole-body vibration: Exposure limit, fatigue, and Reduced comfort. And is suggested for use in industry and in the evaluation of vibratory environments in transport vehicles. And may be considered as guiding for designers in determining the trade-off limits between vehicle road holding and ride comfort reduction. [46]

Exposure limits: which, unless there is a specific reason, should not be exceeded in order to preserve safety (or health).

Fatigue or decreased proficiency boundaries: They pertain to maintaining operational efficiency and are applicable to jobs like operating a tractor or a road vehicle (driving for many hours).

Reduced comfort boundaries: which deal with maintaining comfort in transportation vehicles and are associated with activities like eating, writing, and reading in a car. [45], [46]

-Road Holding

On the other hand, talking about **compromises in road holding**, when a vehicle travels on the road, many factors may affect the vehicle holding cause instability. Among the problems related to car instability, reduced road holding in steering or braking or roll over condition, and this is the most dangerous phenomenon. All passengers and goods on board are threatened when the vehicle get instability in the road. Even the life of the car user may not be guaranteed once the instability accident occurs. Developed countries have better road conditions so that cars can travel at very high speeds. But this is not enough to avoid reduced road holding in all driving conditions. [47]

In general luxury cars typically have suspension systems that prioritize comfort over handling dynamics, which may cause the car to lose stability when braking and turning at specific high speeds. As a result, these vehicles offer a comfortable ride and are adept at swallowing bumps, but handling and control are compromised. However, the suspension of sports cars is usually designed with a focus on handling, meaning that while improving the road holding and stability, ride quality and comfort are compromised. Therefore, there is a trade-off between comfort and vehicle control when using passive suspension systems (PSS). [48]

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