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RESEARCH ARTICLE

Active suspension for all-terrain vehicle with intelligent control using artificial neural networks

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ABSTRACT - The automotive industry focuses on developing advanced protection and stability control systems, particularly for suspension and steering, to enhance vehicle comfort, luxury, and safety. This research presents an intelligent controller for ATV suspension systems based on ANN technology. The controller leverages ANN capabilities to optimize system performance. MATLAB simulations were conducted to evaluate its effectiveness under various disturbances. A comparative analysis compared the ANN regulator, classic ANFIS regulator, and passive performance in different disturbance scenarios. The simulation results demonstrate exceptional performance of the ANN-based controller in displacement reduction, speed, acceleration, and robustness. The controller effectively mitigates disturbances, enhancing overall suspension system performance. These findings highlight the advantages of employing ANN technology in ATV suspensions. This research contributes to intelligent control systems advancement in the automotive industry, specifically in ATV suspensions. The demonstrated improvements have the potential to enhance passenger comfort, vehicle stability, and safety across terrains. By implementing ANN-based controllers, automotive manufacturers can optimize suspension systems, leading to improved vehicle performance. Several indicators, including RMSE, MRE, and R^2, were utilized to test and validate the models. The R^2 values for the three quality parameters ranged from 0.989 to 0.999, indicating a high level of consistency in the predictions made by the ANN, a "5-12-1" structure is employed. The results of this study add to the expanding body of knowledge endorsing the efficacy of ANNs in simulating and optimizing quarter-vehicle dynamics.

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1. INTRODUCTION

Driving safety is a critical concern for both road and off-road vehicles, encompassing various factors contributing to reliable transportation. Key aspects include road holding, which involves a vehicle's grip, stability control, and suspension tuning, influencing tire grip and handling characteristics. Vehicle handling, determined by factors like suspension configuration and weight distribution, impacts road holding and maneuverability. Suspension systems connect a vehicle's framework to its components and play a crucial role in achieving optimal traction, stability, and balance [1]. Modern vehicles have transitioned from passive to active suspension systems, incorporating electronic control technology for enhanced comfort and safety. Designing an active suspension system for an All-Terrain Vehicle (ATV) using an Artificial Neural Network (ANN) controller is a complex engineering task. The process involves defining suspension requirements, selecting components, designing the ANN controller, implementing the system, and testing and optimizing its performance. The suspension system acts as a link between the vehicle's structure and components, maximizing friction between wheels and the road surface. Electronic control systems, especially those incorporating ANN controllers, contribute significantly to comfort and safety. ATVs, designed for diverse terrains, rely on their suspension systems to absorb shocks, provide stability, and ensure a smooth ride. A well-functioning suspension system is crucial for optimal ATV performance, comfort, and safety.

Major automotive companies have evolved suspension systems from passive to active, integrating sensors, actuators, and control units. The use of ANN controllers in active suspension systems, driven by Machine Learning techniques, optimizes functionality by adapting to dynamic conditions. The controller's learning capabilities enhance ride quality and stability, making it valuable for various vehicles, including ATVs. The ANN-based controller is trained to recognize patterns and make real-time decisions based on input data from sensors. Compared to conventional methods, utilizing an ANN-driven controller offers benefits such as heightened precision, adaptability, and flexibility. This technology proves invaluable for various vehicle types, including ATVs, improving ride comfort and overall safety. Building on previous research in heavy trucks, this article explores applying ANN-driven controllers for ATV suspension systems. Simulations in MATLAB evaluated the controller's performance against other microcontrollers. The ANN controller demonstrated exceptional proficiency in absorbing displacements and mitigating vibrations, showcasing its potential in enhancing ATV suspension systems' performance, stability, and passenger comfort.

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In suspension systems research, mathematical models like the quarter, half, and full vehicle models are commonly utilized. Investigations often categorize based on the mathematical models employed. These models play a significant role in understanding and improving suspension system dynamics. In summary, driving safety relies on various factors, with suspension systems being a critical component for road holding and vehicle handling. The evolution from passive to active suspension systems, especially those incorporating ANN controllers, marks a significant advancement in enhancing comfort, safety, and performance across diverse terrains for vehicles like ATVs. Ongoing research [2] and simulations underscore the potential of ANN technology in improving suspension system performance and overall ride quality. Mathematical models contribute to scholarly works, providing insights into suspension system dynamics based on different vehicle configurations [3].

Rao et al. [4] conducted a study on passive and semi-active suspension systems using a quarter model with three degrees of freedom. The objective of the study was to evaluate algorithms for semi-active suspension systems in relation to their capacity to promptly react and dampen vibrations. The researchers developed a theoretical model simulating passenger movement over multiple bumps at varying speeds and demonstrated the potential for replacing negative dampers in traditional suspension systems. This study adds to the advancement of more effective suspension systems aimed at enhancing ride comfort and minimizing vehicle degradation. Nitish and Sanjay [5] aimed to optimize the traditional Proportional Integral Derivative (PID) controller for a quarter car suspension model using the genetic algorithm. The study centered on augmenting the reactivity of the suspension system and demonstrated notable advancements in performance when compared to the conventional PID controller. The investigation underscores the efficacy of employing genetic algorithms to enhance conventional suspension systems, resulting in more seamless and enjoyable rides. Abdolvahab et al. [6] formulated a mathematical representation for passive and active suspension systems employing a quarter-car model. The study utilized the Linear Quadratic technique Control (LQR) to design the controller and compared it for both passive and active systems. The simulation outcomes showcased the efficacy of the LQR controller in managing actuators and guaranteeing vibration isolation across different road conditions. These findings aid in the advancement of sophisticated vehicle suspension systems. Amit et al. [7] conducted a comparative analysis of three controller variants (fuzzy logic, PID, and GA-PID genetic algorithm) for active suspension systems. The fuzzy and GA-PID controllers demonstrated superior performance compared to the PID controller, exhibiting enhanced capabilities in attenuating and dissipating vibrations. Abroon et al. [8] devised a fuzzy logic controller for Semi-Active suspension systems by employing the Particle Swarm Optimization (PSO) algorithm. Although the controller exhibited commendable performance, its feasibility was compromised by constraints associated with the mathematical model and the assumed linearity of the vehicle's motion. Swati and Sheilza [9] endeavored to diminish vibrations in a bus suspension system by implementing PI and PID controllers on a Quarter Model suspension system with the objective of vibration reduction. The PID controller demonstrated a faster and more accurate response time compared to the PI controller, with both controllers performing better than conventional micro-controllers. However, further improvements are needed for practical applications. Homael and Heidari and Homaei [10] devised a PID controller for a quarter model suspension system by utilizing back-propagation neural networks to ascertain the gain parameters. The controller aimed to improve response speed and accuracy but fell short of the required level. Additional improvements are necessary for better control. Ahmed et al. [11] performed a simulation of the mathematical model of a quar-ter-vehicle suspension system and devised a controller of PID nature for it. The controller performed well for passive suspension systems under different input conditions, demon-strating its effectiveness and versatility. Dixit and Borse [12] developed a controller for a semi-active suspension system employing a quarter vehicle model. They compared skyhook, ground hook, and hybrid controllers and found that the hybrid controller outperformed the others in reducing vehicle body displacement and tire deflection, improving ride comfort. Ramasastry et al. [13] investigated the ride comfort of a semi-active suspension system equipped with Magneto-rheological dampers by analyz-ing a human body mass model with seven degrees of freedom. The system significantly improved ride comfort compared to a passive damper system. Vivekanandan and Fulambarkar [14] performed an investigation into the efficacy of an active suspension system in minimizing chassis displacement by employing a quarter-vehicle model. They introduced a mist control approach and employed a hydraulic actuator for active suspension control. The study evaluated the active suspension system's performance in comparison to a passive suspension system and revealed that the active system achieved a 30% reduction in chassis displacement and a 69% decrease in settling time compared to the passive system. Aela et al. [15] presented a novel adaptive control system (NAC) for a limited quarter-vehicle electrohydraulic active suspension system. The NAC aimed to achieve a trade-off between passenger comfort and road holding, as well as passenger comfort and suspension travel, while minimizing suspension travel oscillations. The control approach incorporated an adaptive neural network backstepping control and a non-linear control filtering system. The NAC effectively handled car-road stability, ride comfort, and safe suspension travel compared to previous studies. Perrelli et al. [16] emphasized the importance of assessing the dynamic performance of passenger cars in the automotive industry for safety evaluation and handling/comfort metrics. They discussed the use of simulation software to predict a vehicle's behavior using virtual scenarios, which can reduce development time compared to costly and time-consuming experimental activities. The paper presented a simulation environment that concurrently simulates vehicles with different characteristics, using a 14 degree-of-freedom full-vehicle model and scalable-detail models for subsystems. Autonomous virtual drivers employed to evaluate vehicle dynamic performance objectively, and the scalability of the simulation environment was discussed for different driving scenarios. Haemers et al. [17] tackled the difficulties associated with achieving optimal designs for hardware architecture and control configurations in intricate systems. They proposed a co-design optimization approach that concurrently optimizes the positioning and choice of actuators and sensors, along with the control architecture and tuning parameters of the controller. The approach was implemented on a downscaled active car suspension laboratory setup, and the outcomes were represented by a Pareto front that strikes a balance between performance and implementation cost. The co-design outcomes were verified through physical measurements, confirming the efficacy of determining optimal parameters. Rodriguez-Guevara et al. [18] examined the challenges associated with managing the active suspension system of a vehicle utilizing electro-hydraulic actuators. They put forth a novel linear parameter varying state-space model that captures the nonlinearity of the half-car active suspension system. The model incorporates four scheduling parameters to accommodate the nonlinearity of the suspension and actuators. The study employed a model predictive control-linear quadratic regulator approach with quadratic stability conditions to guarantee stability. The proposed controller demonstrated improved comfort and road-holding over typical road disturbances. Chen et al. [19] proposed an improved firefly algorithm to determine the parameters of a Magneto rheological damper model and combined it with a quarter-car model to create a semi-active three degrees of freedom seat control system. They discovered that the semi-active seat suspension controlled by PID and Fuzzy-PID exhibited efficacy in enhancing ride comfort and operational safety in contrast to a passive seat suspension. Luan et al. [20] introduced a novel seat suspension equipped with a variable equivalent inertance-variable damping (VEI-VD) device and a semi-active vibration control strategy for heavy-duty vehicles, military vehicles, and high-speed crafts. The VEI-VD equipment enabled controllable capability in all four quadrants of the force-velocity diagram. The researchers created a prototype and suggested a semi-active vibration control approach for the VEI-VD seat suspension, showcasing significant promise in mitigating vibration and enhancing ride comfort. Zhang et al. [21] introduced an innovative form of semi-active cab suspension that combines an air spring and a variable damping electromagnetic damper (A-EMD) to diminish vibrations and enhance ride comfort. The study utilized the Takagi-Sugeno fuzzy method to linearize the air spring's non-linear stiffness characteristics and designed an H_∞ state feedback semi-active controller for the EMD. Numerical simulations revealed substantial enhancements in ride comfort in contrast to a passive suspension system. Basargan et al. [22] proposed an integration method for an intelligent, road-adaptive, semi-active suspension control, and cruise control system to enhance driving comfort and vehicle stability. The road-responsive, semi-active suspension controller was formulated utilizing the novel linear parameter varying approach and integrated a road adaptability algorithm. The cruise control utilized look-ahead road information and a velocity-tracking controller based on the ISO 2631-1 standard. The combined approach was verified in a simulated setting, showcasing enhancements in ride comfort and vehicle stability. In the research conducted by Fu et al. [23], they presented a pragmatic approach using a finite state LQR control technique for vehicle suspension systems. This approach streamlined the control system design by leveraging the output state of the finite sensor and an optimization model to determine the LQR weight coefficients. The finite state LQR control method demonstrated exceptional overall control performance, taking into account various aspects of the suspension system. Moreover, the method solely relied on the current sensor output and control input, obviating the necessity to estimate unknown intermediate states.

It is important to highlight that prior investigations have primarily concentrated on the vertical displacement of the vehicle body in quarter-car sports models. Nonetheless, to develop a dependable control system for suspension systems, it is essential to assess the controller across additional degrees of freedom to replicate various motions of the vehicle body, encompassing lateral, longitudinal, and rotational movements. This holistic approach will foster an enhanced comprehension of the system's dynamics and guarantee superior performance and safety in suspension design.

2. MATERIALS AND METHODS

This section provides a description of the materials and methods employed for data acquisition, development, validation, and testing of the virtual controller. The virtualized controller relies on a smart model integrating Artificial Neural Networks (ANNs) to alleviate the acceleration of the suspended mass. The subsequent paragraphs provide a comprehensive overview of the specifics: Firstly, it presents the parameters of the examined all-terrain vehicle and the associated mathematical model. This section encompasses details about the software employed as well as descriptions of the study's scenarios. Subsequently, the system model centered on ANNs used for the virtualized controller is elucidated. This entails an explanation of the model's structure and the methodology implemented for optimizing hyper-parameters.

Creating an intelligent control system for an ATV that incorporates ANN entails a complex endeavor requiring a profound grasp of mechanical engineering principles, applied mathematics, programming, and machine learning. The key steps involve defining suspension specifications by establishing desired parameters like performance, weight, size, cost, durability, and safety, serving as the foundation for the suspension design process. The suspension geometry is then designed to ensure utmost stability and efficiency across various driving circumstances, determining the configuration of crucial components such as springs, shock absorbers, suspension arms, and wheels. Appropriate suspension elements are selected based on specified criteria. A control system is devised to enable precise real-time management of the suspension, utilizing ANN to develop an intelligent system adaptable to different driving conditions and capable of enhancing suspension performance. Coding and training the ANN involve implementing machine learning techniques to recognize variations in driving conditions and make appropriate adaptations to the suspension. Extensive field trials are conducted to evaluate the efficacy and dependability of the engineered suspension and control system, with fine-tuning performed if necessary. Adhering to these systematic instructions makes it feasible to develop an ATV active suspension system with intelligent control using ANN, offering significant potential to enhance the ATV's performance across various driving conditions.

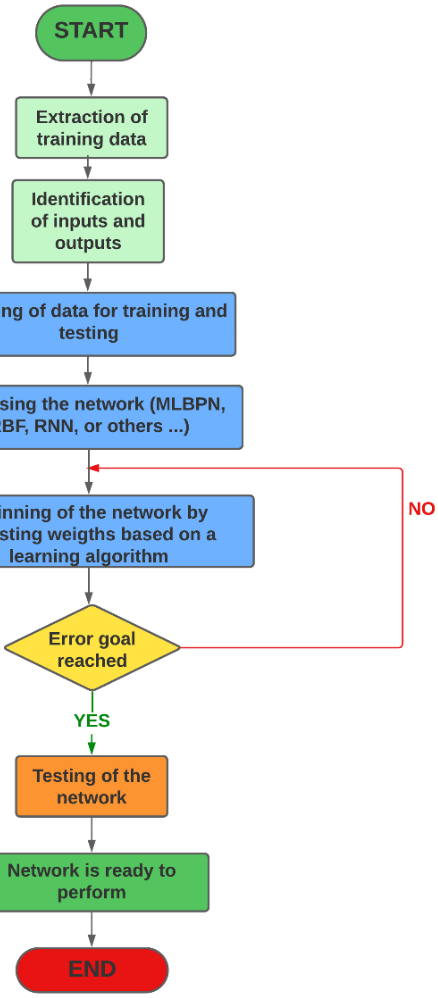


Figure 1. Schematic diagram of the methodology for a general implementation of ANN for a hydraulically controlled of ATV active suspension system

This section presents an extensive account of the materials and methodologies employed in this investigation. The following procedures were executed: Initially, the parameters and mathematical representation of the ATV were addressed. The ATV utilized in this study was a commercially available model with well established specifications concerning mass, suspension characteristics, and tire properties. The mathematical model of the ATV was constructed utilizing Simulink software, a specialized tool for dynamic system modeling and simulation. The ATV model comprised a quartercar configuration incorporating an integrated suspension system with a spring and a damper. In the subsequent phase, the elucidation of the ANN system model was performed. The ANN system model was based on a three-layer feedforward neural network. The input layer consisted of three neurons responsible for receiving information regarding the vehicle's acceleration, velocity, and displacement. The hidden layer comprised ten neurons, while the output layer consisted of a single neuron generating the control signal for the damper. To optimize the ANN's hyperparameters, such as the number of hidden neurons, learning rate, and regularization parameter, a grid search method was employed. The third step entailed the development of the virtual controller utilizing the ANN system model and Simulink software. This controller received inputs from the ATV model and computed the appropriate control signal for the damper using the trained ANN. The performance of the virtual controller was evaluated through testing in diverse scenarios encompassing rough terrain, sudden obstacles, and harmonic disturbances, in order to assess its efficacy in mitigating the acceleration of the suspended mass. The fourth phase involved the validation of the virtual controller by comparing its performance with a conventional controller based on a PID algorithm. The PID controller was also designed using Simulink software and subjected to testing under the same scenarios as the virtual controller. Finally, both the virtual controller and the PID controller underwent testing in various scenarios to evaluate their respective abilities in attenuating the acceleration of the suspended mass. The performance of the controllers was quantified using the Root Mean Square (RMS) value of the acceleration of the suspended mass. Overall, this study employed a combination of mathematical modeling, ANN system modeling, and controller design to develop and assess a virtual controller for an all-terrain vehicle suspension system. The virtual controller demonstrated promising results in mitigating the acceleration of the suspended mass across diverse scenarios. Its performance was validated through a comparison with a conventional PID controller [24].

2.1 ATV Active Suspension Specifications, Geometry and their Components

Passive suspensions typically exhibit a linear velocity-force characteristic, meaning that the force required to compress the suspension is directly proportional to the velocity of compression [25]. In contrast, semi-active suspensions display a non-linear velocity-force characteristic, where the force needed to compress the suspension increases with velocity but eventually levels off beyond a certain point [26]. In contrast, active suspensions exhibit a variable velocity-force profile since they can adjust their damping in response to fluctuations in road conditions and driver inputs [27]. This implies that the force required to compress the suspension varies with velocity but is actively controlled by the system (see Figure 2).

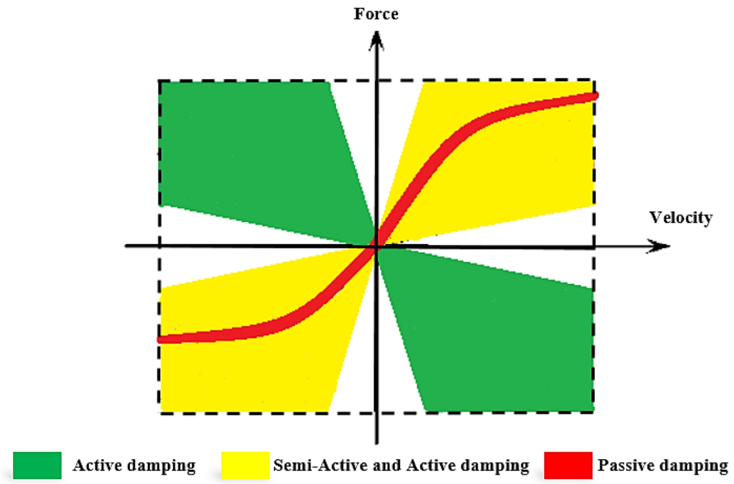


Figure 2. Velocity-force characteristics of different suspension systems

Passive suspensions maintain a uniform force within a designated velocity range, relying exclusively on the velocity of suspension movement. Consequently, these suspensions frequently fall short of delivering optimal ride quality across the full spectrum of vehicle operating conditions. Semi-active suspensions, on the other hand, offer modifiable force within a specific velocity range by employing a blend of passive and active elements. By adjusting the force in response to the vehicle's operating conditions, these suspensions can substantially improve ride quality and handling performance. In contrast, active suspensions provide variable force throughout the entire velocity range by employing active components to regulate the applied force at all times. Although active suspensions provide the utmost level of ride quality and handling performance, they tend to be costlier and more intricate in comparison to alternative suspension variants. Ultimately, the choice of suspension type depends on the desired level of performance, cost considerations, and operating conditions. Therefore, for our off-road car, active suspension systems have chosen to ensure stability and driving comfort. Figure 3 illustrates the simulation model of an actual ATV equipped with the implemented ANNs controller for the active suspension system. Table 1 presents the parameters and specifications of the physical ATV.

Table 1. Nominal ATV parameters values used in simulation

Parameter Definition	Symbol	Value	Unit
Mass of ATV without driver	M	343.2	kg
Quarter body ATV weight (Sprung mass)	M_s	73.3	kg
Mass of the front wheel (Unsprung mass)	M_{uf}	10	kg
Mass of the rear wheel (Unsprung mass)	M_{ur}	15	kg
Track length	LT	0.754	m
Wheelbase length	LW	0.884	m
Height of ATV	H	0.713	m
Centre of Gravity (from rear wheel)	CG_r	0.3446	m
Centre of Gravity (from front wheel)	CG_f	0.5394	m
Moment of inertia along the x axis	I_x	8.09	$kg.m^4$
Moment of inertia along the y axis	I_y	9.685	$kg.m^4$
Moment of inertia along the z axis	I_z	10.15	$kg.m^4$
moment of inertia of the body	I_s	74.3	$kg.m^2$
Elastic stiffness of the front wheel	K_{sf}	22,208	$N.m^{-1}$
Elastic stiffness of the rear wheel	K_{sr}	34,857	$N.m^{-1}$
Elastic stiffness of the tire	K_t	99,760	$N.m^{-1}$
Damping coefficient of the sprung mass	C_s	300	$N.s.m^{-1}$

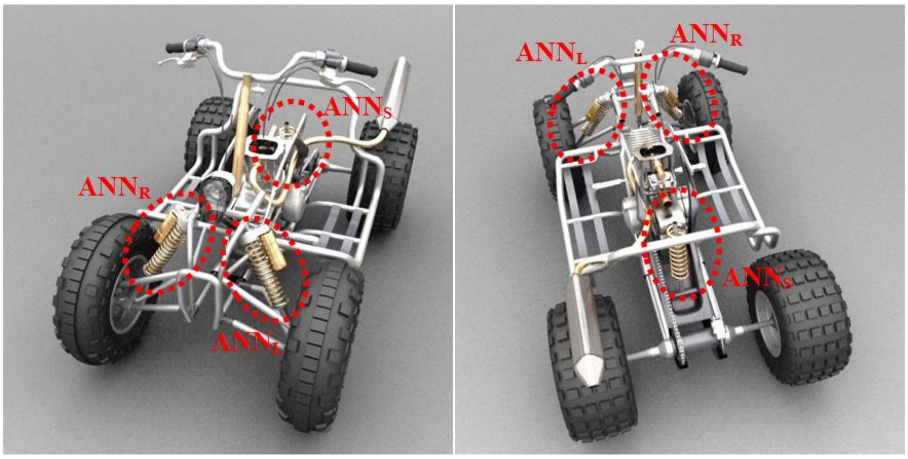


Figure 3. The deployment of artificial neural networks controllers for the ATV

2.2 ATV Design the ANN Control System

To tackle this problem, improvements were implemented in the ANN architecture (see Figure 4) by integrating two supplementary layers [28]. The initial layer consists of two artificial neural networks (ANN$_R$ and ANN$_L$), which facilitate the control of vertical displacements in the front wheels (right and left) and gather data to ensure accurate responses from the second layer. This is crucial for maintaining driver comfort by utilizing the ANN$_S$ controller. The ANN$_S$ controller, depicted in Figure 6, employs ANNs to generate control signals that dynamically adjust the suspension system's characteristics. These modifications are implemented in real time to optimize both the vehicle's comfort during travel and its maneuverability.

Figures 4 and 6 illustrate the impact of longitudinal acceleration on ATVs and their system behavior. When a sudden surge in longitudinal acceleration occurs, marked by notable high frequency elements in the wheel position, the primary intended outcome is the counter directional displacement of the seat relative to the ATV. Longitudinal acceleration refers to the acceleration or deceleration along the ATV's longitudinal axis (i.e., forward or backward), and it can have various consequences on the system's behavior (refer to Figure 5).

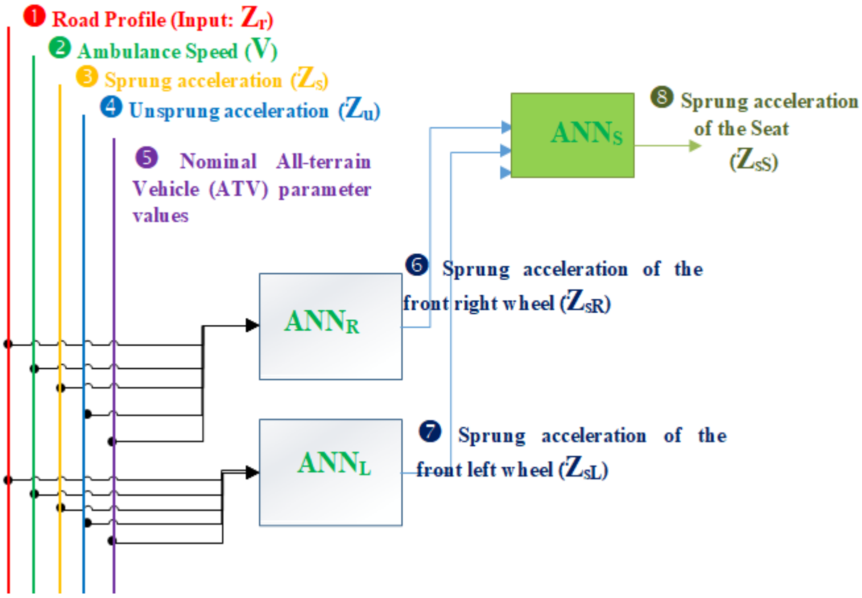


Figure 4. Structure of ANNs controllers

One primary effect of a sudden increase in longitudinal acceleration is the forward shift of the ATV's center of gravity. This causes the front end of the ATV to rise while the rear end squats. As a result, the rider's seat experiences motion in the contrary direction to that of the acceleration. For instance, if the ATV is accelerating forward, the rider's seat may move backward. This phenomenon is commonly known as "squatting" and is a natural response to abrupt acceleration. Additionally, abrupt changes in longitudinal acceleration can result in the loss of traction in the ATV's wheels, leading to slipping or sliding. The frequency of the wheel position also influences the ATV's behavior, as higher frequency components can induce vibrations or instability. In conclusion, an abrupt rise in longitudinal acceleration can result in diverse impacts on the behavior of an ATV, such as a displacement in the vehicle's center of gravity, compression of the rider's seat, and diminished traction. It is crucial for ATV riders to be mindful of these effects and exercise caution when accelerating or decelerating.

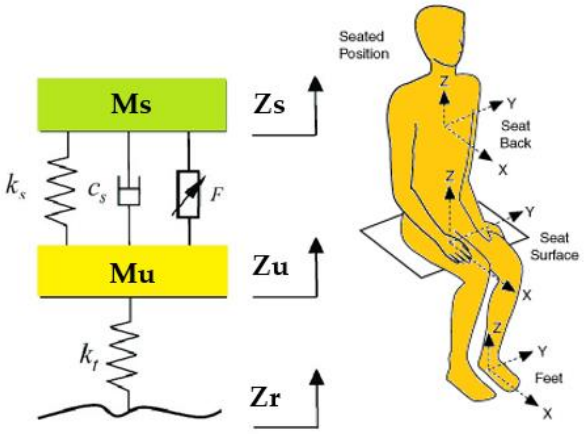


Figure 5. Two degrees of freedom model (2 DoF) of quarter ATV vehicle

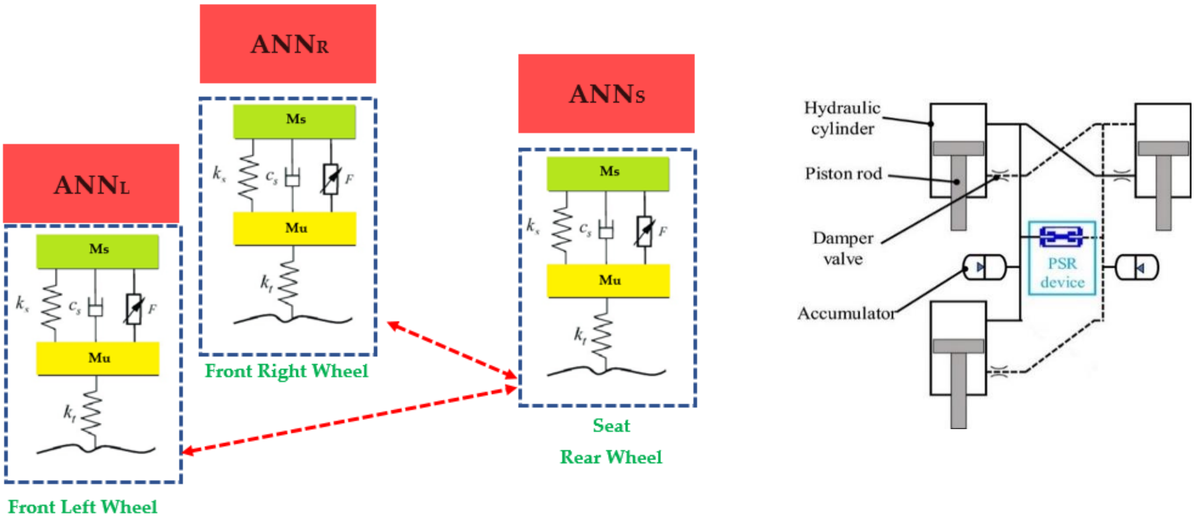


Figure 6. Six degrees of freedom model of full ATV vehicle

2.3 Ride Comfort Simulation

The simulation of ride comfort in active suspension systems generally follows several stages (refer to Figure 7). Initially, a mathematical model is formulated to represent the vehicle and its suspension system, encompassing equations that depict the dynamics of the vehicle body, suspension components, and other relevant elements. Subsequently, an appropriate control strategy is devised based on the mathematical model to attain the desired level of ride comfort. This may entail developing a feedback controller like a PID controller or an intelligent controller such as an ANN controller. The mathematical model and controller are then integrated into a simulation environment that incorporates the road profile as the input to the suspension system and the vehicle model equipped with the active suspension system. The simulation is executed to assess the performance of the active suspension system, taking into consideration factors like ride comfort, suspension travel, and vehicle stability. The obtained results are analyzed to ascertain the effectiveness of the active suspension system in enhancing ride comfort. If necessary, the controller design is optimized through parameter adjustments or modifications to the controller's structure. The simulation is rerun to evaluate the performance of the optimized controller. This iterative process facilitates the evaluation and enhancement of ride comfort in active suspension systems. The aim of ride comfort simulation is to design an active suspension system that proficiently alleviates the impact of irregular road surfaces on vehicle occupants, thus ensuring a pleasurable and smooth ride.

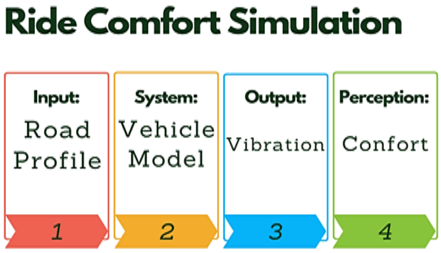


Figure 7. Stages of ride comfort simulation

3. RESULTS AND DISCUSSION

The controller was built using the MATLAB platform, employing the motion acceleration of the mathematical model as the input signal. This motion encompasses vibration acceleration, vibration speed, and velocity, which ultimately contribute to the resulting displacement value. The objective of the controller is to minimize the training error by reducing this value, thereby training the controller (refer to Figure 8).

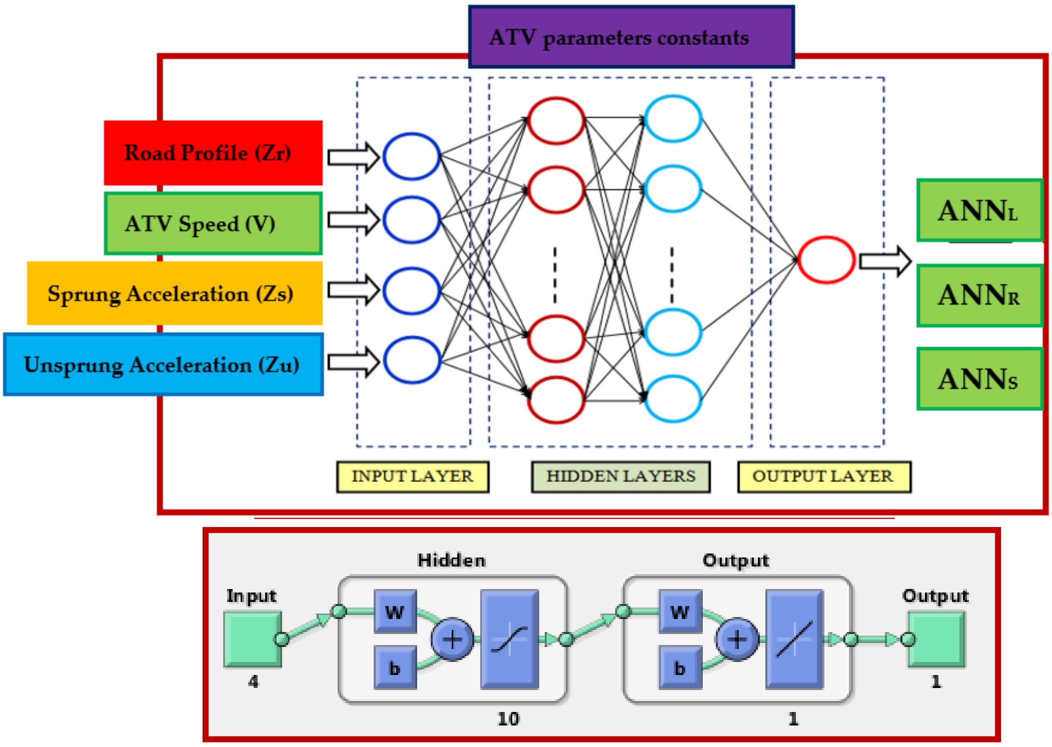


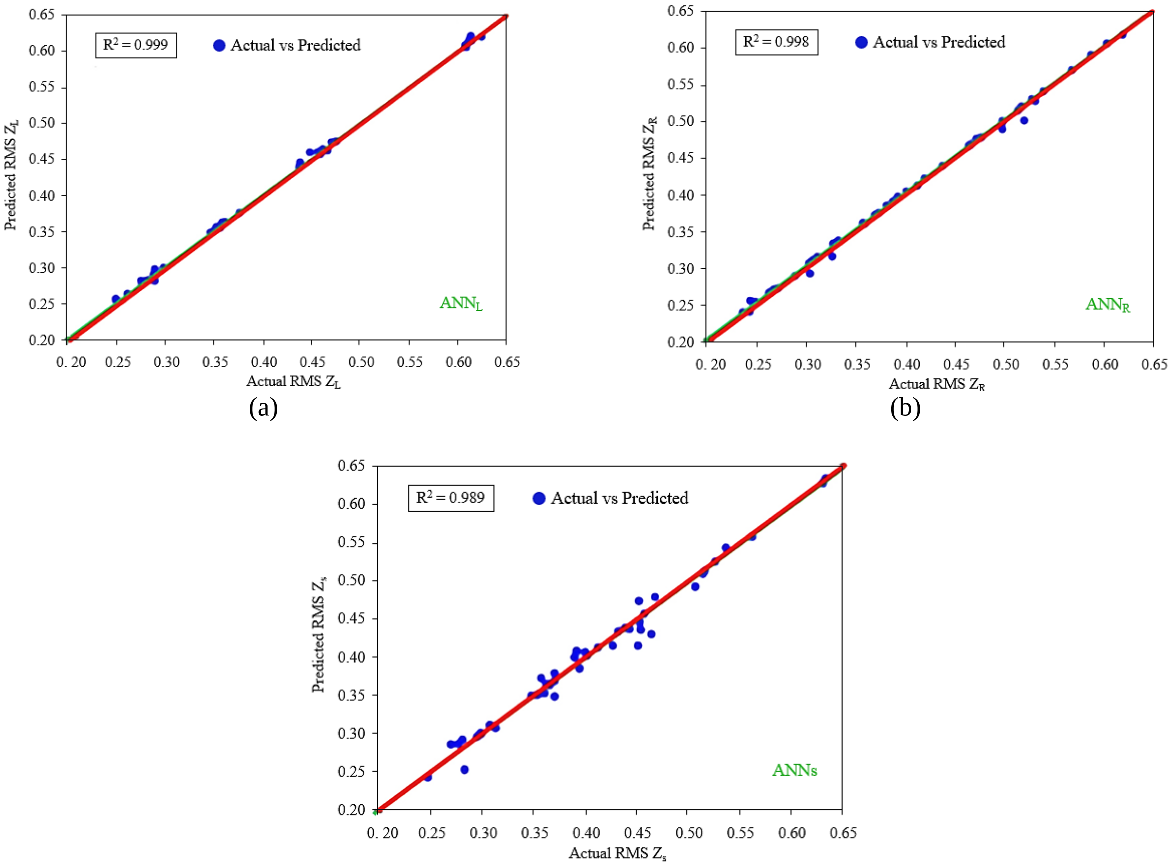
Figure 8. ANN architecture

The ANN controller consists of a multilayer feedforward neural network that considers the present condition of the suspension system, including parameters like suspension deflection, velocity, and acceleration, along with the input from the road. Its main function is to generate the desired damping force as an output. The ANN undergoes training using a collection of input-output data pairs obtained from simulations or experiments. During operation, the trained ANN processes the input signals through multiple layers of neurons, each with adjustable weights and biases. The aim is to generate the target output control signals by continually updating the weights and biases of the ANN through real time adjustments. These adjustments are made by the controller, taking into account the difference between the desired and actual output, with the goal of minimizing this disparity and optimizing the suspension system's performance. The ANN controller provides a versatile and adaptable control strategy that can dynamically modify the suspension system's characteristics based on real time road conditions and vehicle dynamics. In contrast to traditional control methods like PID controllers, the ANN controller excels in managing non-linearity and uncertainties, leading to enhanced ride comfort and handling performance.

During the learning phase, three distinct neural networks (ANN_L, ANN_R, and ANN_S) are established. Each network is assigned the task of producing one of the five quality parameters: road profile, Z_r, ATV speed, V, sprung acceleration Z_s, unsprung acceleration, Z_u, and nominal ATV parameter values (refer to Table 1). These networks are utilized in Figures 4 and 6. The training dataset is randomly divided into 80 % for training, 15 % for testing, and 5 % for verification of the neural networks. To optimize the performance of each network, a "5-N-1" structure is employed, where the number of hidden neurons, N is determined through multiple simulations (refer to Table 2). The network's performance is evaluated by considering the root mean square error and its generalization capability. The feed-forward neural networks comprise an input layer, an output layer, and a hidden layer with an adjustable number of neurons, as illustrated in Figure 8. The activation value of the output neurons governs the network's response and the resultant output vector it produces. The network should yield accurate solutions for unseen examples during the generalization phase. The choice of the most suitable learning algorithm depends on various factors, such as problem complexity, the number of input nodes, weights and biases in the network, error value, and network usage. In this study, the Levenberg-Marquardt algorithm is employed due to its fast convergence rate and low mean squared learning error.

Table 2. The MSE by predicting the three RMS responses by a 5-N-1

N of neurons in hidden layer	Proposed network : 5-N-1 ANN Model											
	RMS Z_L				RMS Z_R				RMS Z_S			
	Train	Test	MRE	R^2	Train	Test	MRE	R^2	Train	Test	MRE	R^2
5	0.0041	0.001	0.056	0.97	1.2e-04	3.1e-04	0.016	0.996	3.8e-05	2.1e-05	0.048	0.976
7	0.0031	0.0014	0.046	0.98	4.1e-05	1.2e-04	0.011	0.997	2.6e-05	2.7e-05	0.030	0.9
10	0.0039	0.0061	0.031	0.96	4.7e-05	9.5e-05	0.012	0.997	1.5e-05	2.6e-05	0.025	0.991
12	2.7e-04	4.5e-04	0.014	0.999	2.8e-05	1.4e-05	0.005	0.998	5.1e-06	8.8e-06	0.017	0.989
15	9.6e-04	2.8e-04	0.019	0.992	2.1e-04	1.2e-04	0.008	0.997	4.1e-05	4.2e-05	0.039	0.98
18	8.1e-04	4.5e-04	0.015	0.993	1.2e-04	1.5e-04	0.013	0.996	1.5e-05	1.6e-05	0.026	0.993
20	5.8e-04	7.3e-04	0.02	0.995	1.3e-04	2.6e-04	0.019	0.993	3.6e-05	8.9e-06	0.028	0.985



(a) (b) (c)

Figure 9. Regression curve between actual and predicted values of RMS sprung acceleration of: (a) The front left wheel Z_L model, (b) The front right wheel Z_R model, and (c) The seat Z_s model

A simulation was performed to compare the performance of the ATV's active suspension system with that of the passive suspension system. For each quality parameter, three separate output networks were trained using the Modified Backward Propagation (MBP) algorithm, with various tested structures. The tested structures included (5-5-1), (5-7-1), (5-10-1), (5-12-1), (5-15-1), (5-18-1), and (5-20-1) for each quality parameter. Here, represents the input values, represents the correct output (target) values for a specific training data item, and the number of hidden nodes (5, 7, 10, 12, 15, 18, 20) is arbitrary (refer to Table 2). Pearson's linear coefficient of determination, R^2 was used to assess the linear relationship between the predicted and actual values. The R^2 values for the three quality parameters ranged from 0.989 to 0.999, indicating a high level of consistency in the predictions made by the ANN. Several indicators, including RMSE, MRE, and R^2, were utilized to test and validate the models. These indicators were used to compare the measured and estimated values of suspended mass acceleration for different parts of the ATV, such as RMS Z_L, RMS Z_R, and RMS Z_S. Figure 9 displays the scatter plot of predicted values versus experimental values, while Table 2 presents the scatter plot of predicted values with linear regression R^2 trends. Figure 9 shows the regression curve between actual and predicted values of RMS sprung acceleration for the front left wheel Z_L model, front right wheel Z_R model, and seat Z_S model.

ISO 2631 [29] is a standard that offers guidelines for evaluating the impact of whole-body vibration on human exposure. The standard outlines various parameters to assess the potential discomfort caused by vibration, including frequency, amplitude, and duration of exposure. According to ISO 2631, the expected comfort responses to vibration environments are influenced by the frequency and amplitude of the vibration. The standard establishes three frequency ranges: low frequency (0.5 - 4 Hz), medium frequency (4 - 20 Hz), and high frequency (20 - 100 Hz). At lower frequencies, vertical oscillations exert the greatest influence on the human body, potentially resulting in motion sickness related discomfort. In the medium frequency range, horizontal vibrations become more noticeable, leading to motion sickness and muscle fatigue induced discomfort. At higher frequencies, vertical vibrations once again play a significant role, resulting in discomfort in the lower back in the form of pain and unease. ISO 2631 provides a set of criteria for evaluating the level of discomfort resulting from exposure to whole-body vibration, considering the vibration's frequency and amplitude. These criteria are quantified using a vibration dose value and a root mean square acceleration value (see Table 3). Overall, the expected comfort reactions to vibration environments, as outlined by ISO 2631, will vary depending on the specific frequency and amplitude of the vibration, as well as individual factors such as age, gender, and physical condition.

Table 3. Expected comfort reactions to vibration environments according to the ISO 2631

Range of RMS Values of Frequency-Weighted Acceleration (m/s^2)	Comfort Level
< 0.315	Comfortable
0.315 – 0.63	A little uncomfortable
0.5 – 1	Fairly uncomfortable
0.8 – 1.6	Uncomfortable
1.25 – 2.5	Very uncomfortable
> 2	Extremely uncomfortable

ISO 8608 provides a standard framework for evaluating road roughness by measuring the vertical accelerations encountered by a vehicle on a specific road surface. This standard defines various classes of road roughness based on the roughness index (RI). The RI is calculated by measuring the root-mean-square 6 acceleration of the vehicle over a distance of 20 meters (see Table 4). The roughness index serves as a quantification of the road surface's roughness, considering the frequency and amplitude of the road irregularities, such as bumps and dips. In general, Class A roads are characterized as very smooth, offering a comfortable ride for passengers. On the contrary, Class E roads are classified as highly rough, potentially causing discomfort to passengers and posing a risk of damage to vehicles traveling on them. ISO 8608 [30] provides a standardized approach to evaluate road roughness, allowing for consistent assessments of road conditions and their impact on ride quality.

Table 4. The road roughness classes defined in ISO 8608.

Roughness Index (RI) (m/s$^{1.5}$)	Classes Roads
< 2.5	Class A
2.5 – 5	Class B
5 – 10	Class C
10 – 20	Class D
> 20	Class E

In the field of vehicle dynamics, the Power Spectral Density (PSD) is extensively utilized as a method to describe the vibrations experienced by a vehicle's suspension system. The PSD of the input vibration to the suspension system plays a vital role in the design and assessment of vehicle suspensions since it determines the intensity of vibrations and impacts transmitted to the vehicle's occupants and cargo. Evaluating the PSD of the suspension input vibration usually involves employing sensors mounted on the vehicle's suspension system or conducting simulations using a test rig. The suspension PSD, as illustrated in Figure 10, can be classified into two main constituents: horizontal and vertical. The vertical PSD signifies the vibration input that is transmitted vertically through the vehicle's suspension system, while the horizontal PSD represents the vibration input transmitted along the longitudinal and lateral axes. The vertical PSD of the suspension input vibration assumes particular importance in vehicle dynamics since it directly influences the comfort experienced by passengers during the ride. The vertical PSD is frequently utilized to evaluate the effectiveness of the suspension system and refine its design to reduce the extent of vibration and impact transmitted to the occupants. In conclusion, the PSD of the suspension input vibration plays a crucial role in assessing the efficiency of vehicle suspension systems and optimizing their design to achieve a smooth and comfortable ride for passengers while minimizing the transfer of vibration and impact to them.

The evaluation of the behavior of a suspended mass under different road profiles (see Figure 11) can be achieved through mathematical models and simulation tools. One commonly employed method involves the utilization of a quarter car model, which serves as a simplified representation of a vehicle's suspension system, comprising a mass spring damper arrangement. To simulate the response of the suspended mass to varying road profiles, the corresponding PSD of the road profile is applied as input to the quarter-car model.

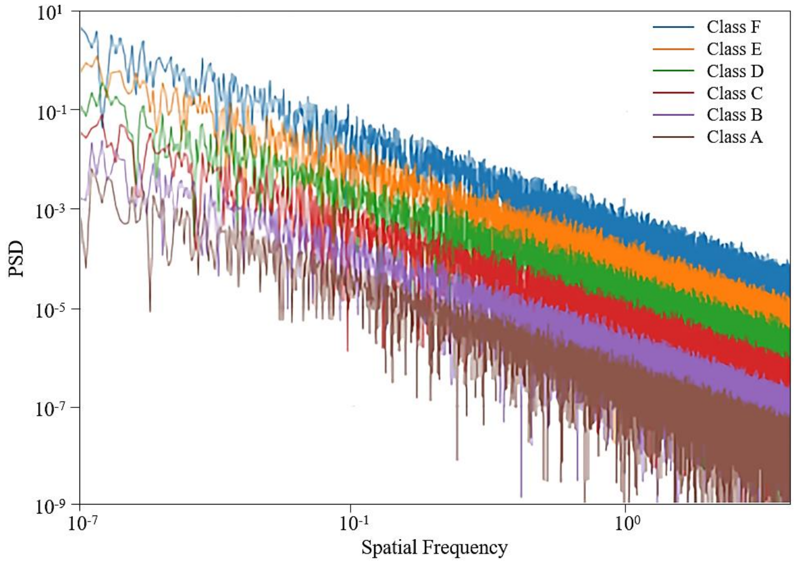


Figure 10. The various PSD of classes used to excite the model controlled by ANN

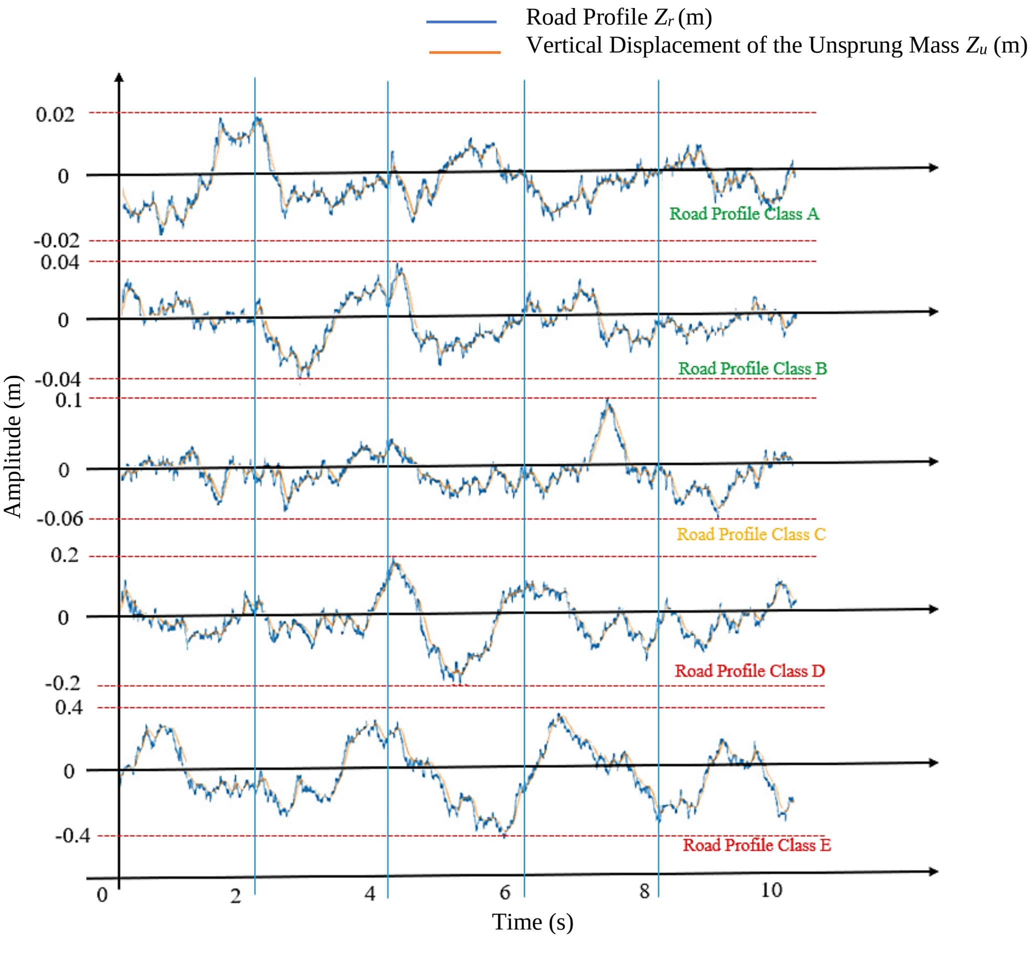


Figure 11. Response of the unsprung mass, Z_u for the excitations of the different road profiles (A, B, C, D, and E)

The assessment of the suspended mass's response to various road profiles involves considering performance metrics like ride comfort, suspension travel, and tire load. Typically, smoother road profiles, such as Class A, result in a more comfortable ride with reduced suspension travel, while rougher profiles, like Class E, lead to less comfort and increased suspension travel. Specific observations regarding the response of the suspended mass under different road profiles include the following: Class A exhibits exceptional smoothness, providing minimal suspension travel and a comfortable ride; Class B, slightly rougher than A, still offers a relatively comfortable ride with moderate suspension travel; Class C, rougher than B, may cause some discomfort for passengers and shows increased suspension travel; Class D, significantly rougher than C, can result in a highly uncomfortable ride with substantial suspension travel; and Class E, representing the roughest road profile as per ISO 8608 [31], leads to an extremely uncomfortable ride with significant suspension travel and potential vehicle damage. The response to various road profiles is influenced by specific suspension system designs and passenger preferences, but ISO 8608 road roughness classes offer a valuable framework for characterizing diverse road profiles and evaluating their potential impact on vehicle suspension systems.

In the context of vehicle suspension systems, the term "vehicle displacement output" (see Figure 12) can be understood as the vertical movement or displacement of the vehicle body, resulting from the forces and motions exerted on the vehicle during its operation. When a random perturbation is applied to the suspension system, the vehicle body experiences vibrations and oscillations, which can be quantified in terms of the displacement output. This displacement output can be captured through sensor measurements and recorded as a temporal sequence, which can subsequently be analyzed to evaluate the suspension system's effectiveness in mitigating vibrations and delivering a smooth and pleasant ride experience to the occupants. The displacement output can be influenced by several variables, including the nature and magnitude of the disturbance, the suspension system's design and parameters, and the characteristics of both the vehicle body and occupants. Hence, conducting simulation studies allows for the assessment of various suspension system designs and control approaches across different operational scenarios and disturbances. These simulations offer valuable insights into the underlying mechanisms of the suspension system and facilitate the optimization of its performance to enhance both ride comfort and safety.

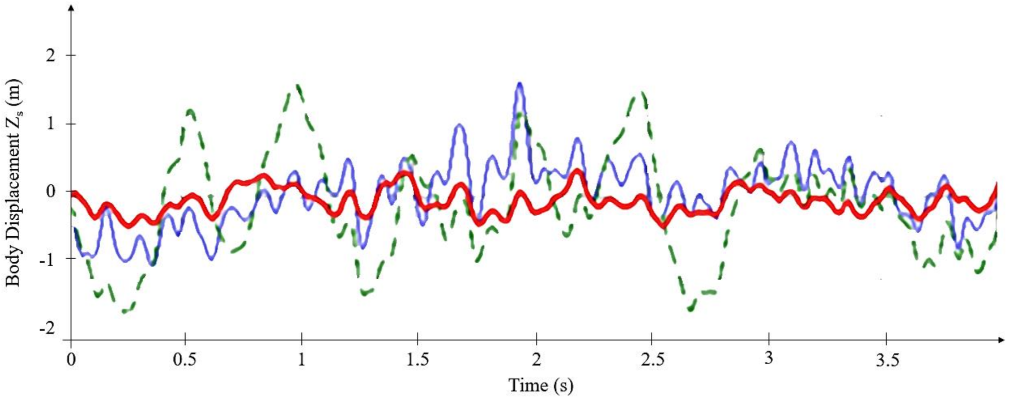


Figure 12. Vehicle displacement output generated by random perturbation

4. CONCLUSIONS

The automotive manufacturing industry is significantly focusing on enhancing stability control systems and safety features, with a particular emphasis on the electronic management of suspension and steering systems. This is aimed at improving the comfort, luxury, and safety of vehicles. The suspension system, especially in the context of all-terrain vehicles, is of critical importance as it plays a key role in ensuring stability, balance, and passenger comfort over various terrains.This research article presents a groundbreaking approach to improve ATV suspension systems by incorporating an intelligent controller based on Artificial Neural Network technology. The principal aim of this innovative controller is to optimize the overall performance of the suspension system. To thoroughly evaluate its effectiveness, extensive simulations were carried out using MATLAB, encompassing diverse disturbances commonly experienced in ATV operations. A comprehensive evaluation was conducted to compare the effectiveness of various regulators, including the ANN, ANFIS regulator, and passive, across different disturbance scenarios. The simulation results indicated that the proposed ANN based controller showcased exceptional performance in reducing displacement, enhancing speed and acceleration, and displaying robustness.

The results of this study emphasize the capacity of the ANN based controller to significantly enhance the performance of ATV suspension systems. By harnessing the potential of ANN, this intelligent controller presents new opportunities for enhancing ride comfort, stability, and overall safety in ATV applications. In the domain of ATV suspension systems, a novel ANN controller has been proposed. This controller is formulated utilizing the tenets of ANN and integrates a flexible reasoning system. By employing clustering algorithms and modifying the ANN system's structure, the controller leverages the analysis of input data to determine membership functions and automatically determines the number of these functions through clustering algorithms. To evaluate the effectiveness of the ANN Controller, a simulated mathematical model of a quarter vehicle was employed. A thorough analysis was conducted, comparing the performance of the ANN based controller (comprising ANNL, ANNR, and ANNS) with that of the passive system under diverse disturbance scenarios. The simulations were aimed at assessing the efficacy of the ANN controller in enhancing the behavior of the quarter-vehicle model. The results demonstrated the accuracy of ANN in faithfully simulating the quarter-vehicle mathematical model. The implemented ANN based controller demonstrated exceptional performance, outperforming the passive system, especially when confronted with disturbances. This outcome emphasizes the efficacy of ANN in enhancing the control and response of ATV suspension systems. The results demonstrated the efficacy of ANN in accurately simulating the quarter-vehicle mathematical model. The built ANN based controller exhibited notable performance, surpassing the passive system, particularly in the presence of disturbances. This outcome underscores the effectiveness of ANNs in enhancing the control and response of ATV suspension systems. Overall, the introduction of Controller based on ANN technology presents a promising advancement in ATV suspension systems, offering improved control capabilities and enhanced vehicle behavior. The results of this study add to the expanding body of knowledge endorsing the efficacy of ANN in simulating and optimizing quarter-vehicle dynamics. By implementing ANN-based controllers, automotive manufacturers can optimize suspension systems, leading to improved vehicle performance. Several indicators, including RMSE, MRE, and R^2, were utilized to test and validate the models. The R^2 values for the three quality parameters ranged from 0.989 to 0.999, indicating a high level of consistency in the predictions made by the ANN, a {5-12-1} structure is employed. The results of this study add to the expanding body of knowledge endorsing the efficacy of ANNs in simulating and optimizing quarter-vehicle dynamics. In conclusion, we can also affirm that the simulation results of our ANN controller obtained under the Matlab/Toolbox environment are satisfactory. The results obtained during the application confirmed the advantages and contribution of the control approach based on artificial neural networks for an active suspension system for ATVs. They show that the ANN controller is a powerful optimization tool, especially in terms of reaction time and speed, which ensures control and stability, unlike traditional control methods. Several perspectives are proposed following this research work and may be the subject of other future work such as: The development of a controller (ANFIS + ANN) to ensure the control and stability of a complete model of ATV (FC) multi-axis (4-axis, 6-axis, 8-axis, etc.); The generalization of our model takes into account several other factors of the control and stability of ATVs such as: the interaction between the suspension systems and the braking systems, the relationship between the chassis and the driver's seat, etc.; Testing of programs on test benches carried out in collaboration with the higher institute of technological studies of Gabes; and The creation of an application (software) capable of carrying out structural analysis for different types of active suspension systems.

The main conclusion of the study is that the implementation of an ANN based controller significantly improves the performance of ATV suspension systems. This innovative controller optimizes the suspension system by enhancing stability, balance, and comfort across various terrains, thus improving ride comfort, luxury, and safety. The effectiveness of the ANN controller was demonstrated through extensive simulations using MATLAB, which showed that the ANN-based system outperforms traditional passive systems and other types of regulators, particularly in handling diverse disturbances. The ANN controller's superiority was evident in its ability to reduce displacement, increase speed and acceleration, and exhibit robustness under different disturbance scenarios. The study underscores the potential of ANN technology in revolutionizing ATV suspension systems, presenting it as a promising advancement for optimizing vehicle performance. The results, supported by high consistency in predictions and satisfactory simulation outcomes, affirm the ANN controller's role as a powerful optimization tool for active suspension systems, highlighting its advantages in reaction time and speed which ensures superior control and stability compared to traditional control methods. Future research directions are proposed to extend the applicability and efficiency of ANN and ANFIS controllers for comprehensive ATV models and to explore the integration with other vehicle systems.

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