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Utilizing Hybrid Machine Learning Framework for Half-Vehicle Suspension Control to Minimize Road-Induced Vibrations

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Abstract

In this paper, hybrid feed-forward deep neural network and ANFIS framework is developed to control an active suspension system of half vehicle. The dataset were generated from previous literature that studies driver comfort on different road profiles. The deep neural network aims to learn intricate relationships within dataset between features and output. The deep neural network was trained using back propagation algorithm and automated search method was implemented to obtain optimum network structure. The paper starts generating various road roughness profiles according to ISO 8608. Then, through comprehensive examination of rear and front body displacements and pitch angle accelerations, the study highlights system's significant contributions to ride comfort and vehicle dynamics. The proposed framework outperforms other controllers like proportional-integral-derivative (PID), demonstrating its robustness across different road profiles. The results demonstrated effectiveness of proposed control to minimize peak overshooting and settling times which improves ride comfort and stability significantly. Also, the proposed model has small root mean square error (RMSE) values which indicate smoother and less energetic responses, which are typically preferred for passenger comfort. Furthermore, the adaptive neural fuzzy inference system-deep neural network (ANFIS-DNN)has minimum crest factor (CF) which indicates that the signal has fewer peaks relative to its average.

Keywords: ANFIS, DNN, machine learning, Control systems, Suspension systems.

1. Introduction

The comfortable vehicle ride is relying on the suspension system's effectiveness to minimize vertical vibrations transmitted from road to vehicle body. The ride comfort and the road holding ability are measured by observing acceleration and displacement in vehicle body. The overall vehicle performance in terms of ride comfort and the road handling is regulated by the type of assembled suspension system such as passive, semi-active or active type. The active suspension system is the most accepted one because it effectively achieves the performance improvement [1]. The key to the design of active suspension system is the control strategy because the active suspension system has numerous advantages such as good performance in wide range of frequencies well as generating and supplying force instantly by actuators with high range at low velocities[2,3].Therefore, many studies have been done on these suspension systems. Various control approaches, either classical or intelligent, have been proposed such as optimal control, proportional-integral-derivative (PID) control, Linear Quadratic Controller (LQR), Fuzzy Logic control (FLC), Adaptive Neural-Fuzzy Inference System (ANFIS), and Artificial Neural Network [4-15].

The optimal control theory, which is the synthesis method to optimize the performance index of control system, was implemented on the active suspension system [16]. In addition, the robust control scheme for active suspension systems was presented in [17]. In this approach, the proportional integral sliding mode control scheme has been used. The PID and LQR controllers have been implemented and analyzed for 2 DOF quarter car active suspension systems [18, 19]. In addition, an experimental micro-computerized suspension system was designed by using an actuator force as a control input [20]. However, this proposed model which was considered in this research was a very simple model with one degree-of-freedom (DOF). The ANFIS controller using the data from Fractional Order Proportional Integral Derivative control system for Full car active suspension model has been proposed in [21]. In [22], the ANFIS has been analyzed for half car 6 DOF suspension systems using the data driven approach and the authors compared the obtained performance with the passive suspension. The ANFIS and PID controllers have been developed and tested on an experimental Active suspension setup using LabVIEW software [23]. In [24], the comparison between three linear controllers like Robust, LQR and fuzzy logic was presented. The results illustrated that the proposed controllers have better performance. Design three types of active controller for active suspension

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system were presented in [25]. The three controllers designed were LQR, LQR-fuzzy, and fuzzy-PID. The result of comparison shows that Fuzzy-LQR based active suspension system had better result and stability as compared to other models.

Therefore, the implemented FLC and machine learning schemes have been successfully employed for some practical systems such as electrical traction elevator [26], metal casting processes [27], prediction of surface roughness[28], design of agile supply chains[29], predict the mechanical performance [30], estimated the effect of notch depth on elastic NSCF under combined loading [31], thermal system [32], green fibers and composites applications [33, 34], and non-driven robot [35].However, the design of any system using FLC needs an intelligent behavior with some degree of uncertainty (DOU) which is occurred because of missing, imprecise, or unavailable of data. Although FLC can deal with imprecise concepts and numerous vague, but the fuzzy membership functions (MSF) design is nontrivial task [36-40].Therefore, the selected method to design MSF relies on the nature complexity of DOU as well as the data availability. In our case study, the vehicle active suspension system, DOU could come into the control scheme from numerous resources like the random road surfaces or the variations in the environmental conditions. Some studies were presented two layers FLC that is similar in shape to artificial neural network (ANN), but it does not form the any nodes [41, 42]. However, the processing time has a large computational cost. The type-2 FLC (T2FLC) system was proposed to deal with DOU and to improve the capability of FLC [43-45]. The T2FLC was presented in [45] to deal with DOU and to minimize the vibrations. However, the time of defuzzification stage has large computational cost and T2FLC is not the best selection to deal with stochastic uncertainties [46, 47]. Some researchers have implemented probabilistic fuzzy logic system (PFLS) to deal with the stochastic uncertainties and handle the computing time [48, 49]. In [49], the proposed approach was able to handle DOU in complicated plant dynamics and was able to improve the performance in unstructured dynamic environments. However, PFLS requires measurement repeating during the process to be able to estimate the value with its standard deviation to quantify uncertainty in the system.

Moreover, the environment conditions for suspension vehicle and the random road profiles in practical implementation have led to non-solve all the DOU issues. Thus, the design of a proper FLC becomes harder. To deal with system nonlinearities, the state-observer-based feedback control is proposed in [50]. The particle swarm optimization algorithm had been implemented to optimize the control parameters. Other approaches were developed neural networks (NNs) models for the active suspension system to carry out other missions. For example, the novel road roughness detection and classification model was implemented where the system response in terms of rattle space was used as inputs and the roughness classes as the outputs [51].Even though the NNs had been used in combination with more classical controls , such as neuro-fuzzy, sliding mode, LQR, and PID, to enhance the controller performance, but the data availability is the main problem of the NN techniques which yields to uncertainties and errors in the approximated results. To overcome these difficulties and improve the suspension system, long short-term memory (LSTM) learning had been applied to control the stability of heavy vehicles under different conditions [52]. However, the LSTM techniques may present additional delays in processing, making them potentially less suitable to regulate the systems that require immediate responses in real time application. Moreover, the deep neural network (DNN) is very rarely used to control the active suspension system. DNN can provide real-time responses for the control tasks and they might be more suitable when the control system needs to react quickly to any changes. In addition, DNN is more effective than LSTM and it requires less training data compared to LSTMs.

Therefore, the main contribution of this paper consists of the following:

1. Develop a database extracted from our previous work. The database were generated from the road profile-vehicle integrated model according to the ISO 8608 Standard. The database batches were divided into inputs and output datasets.;
2. Introduce a novel control system that combines Deep Neural Networks (DNN) with Adaptive Neuro-Fuzzy Inference Systems (ANFIS) for vehicle suspension. This hybrid approach leverages the strengths of both DNNs and ANFIS, offering a unique and potentially more effective control solution. Utilize the DNN control system that adapts perfectly to sequential dataset in order to control half vehicle active suspension system. Then, Create the control script to generate the optimal DNN structure that is automatically iterating over potential structures. Then, the optimum DNN controller is saved. Finally, integrate the DNN model's output into the ANFIS model to enhanced the system performance,
3. Provide comprehensive comparative analysis of the proposed control system against other controllers. This comparison demonstrates the superiority of the DNN-ANFIS model in terms of energy consumption and riding comfort. Energy consumption and ride comfort are critical factors in the design and control of suspension systems,
4. The proposed scheme demonstrated the notable ability to reduce the disturbance, vehicle body accelerations, and tire dynamic loads. Also, the proposed model effectively curtailed vertical vibrations and pitch motion achieving high balance between handling performance and vehicle ride comforts. By effectively reduction the vertical vibrations and pitch motion, the proposed model achieves a high balance between handling performance and ride comfort, which are paramount in vehicle dynamics.

2. Generated artificial road Roughness profiles

To validate the suspension performance in time-domain, different models of the road profiles are taken into consideration. This will allow investigating suspension dynamics with respect to ride comfort and handling capability of the vehicle. The random road profiles surfaces, which are based on ISO-8608, are being used to examine response and performance of the proposed model.

2.1. Random exciting function

The deterministic shapes that are presented in the previous section are not ideal representation for real practical applications as well as they are not valid to study the actual behavior. Meanwhile, the power spectral density (PSD) theory provides an ability to represent road surface profiles as a random exciting function. The road surface could be simulated based on ISO-8608 to verify the performance of the suspension system on various road surface conditions [53, 54]. Thus, the roughness road surface could be derived from Table I and it can be approximately as follows

$$M_d(n) = M_d(n_o).\left(\frac{n}{n_o}\right)^{-2} \quad (1)$$

$$M_d(\Omega) = M_d(\Omega_o).\left(\frac{\Omega}{\Omega_o}\right)^{-2} \quad (2)$$

Where Ω=2π/L denotes the angular spatial frequency, L is the wavelength, Ωo=1 rad/m which defines as angular spatial frequency. The no=0.1cycle/m and n =Ω /2π is the spatial frequency. Furthermore, to generate the road profile with length L as spatial domain, it can be described as a simple harmonic function h(x) [54]. Within the frequency domain, the spatial frequency values n_i are equally spaced with an interval of Δn=1/L.

$$h(x) = \sum_{i=0}^{N} A_i \cos(2\pi n_i x + \varphi_i) \quad (3)$$

$$h(x) = \sum_{i=0}^{N} A_i \cos(2\pi i\Delta n x + \varphi_i) \quad (4)$$

Where Ai is the amplitude, ni is the generic spatial frequency which can be computed as i·Δn. Where Δn is the frequency band and φ is the phase angle. It is possible to demonstrate that the mean square value of this harmonic signal β=$M_d(i\Delta n)$, therefore,

$$\Delta n A_i^{\,2} = 2.\Delta n.\beta_x^{\,2}(n_i) \quad (5)$$

and thus

$$A_{i=}\sqrt{\Delta n}\,.\sqrt{2M_d(i\Delta n)}. \quad (6)$$

Re arrange the equation to obtain

$$A_{i=}\sqrt{\Delta n}\,.\sqrt{2M_d(n_o).(n/n_o)^{-2}} \quad (7)$$

Or

$$A_i = \sqrt{\Delta n}\,.\sqrt{2M_d(n_o).(\mathrm{i}\Delta n/n_o)^{-2}} \quad (8)$$

Thus,

$$A_i = \sqrt{\Delta n}\,.\frac{n_o}{\mathrm{i}\Delta n}\sqrt{2M_d(n_o)}. \quad (9)$$

From Table I, the value of$M_d(n_o) is 2^k \times 10^{-6}$; thus, $A_{i=}\sqrt{\Delta n}\,.(n_o/\mathrm{i}\Delta n).2^k.10^{-3}$. Therefore, when the PSD function of vertical displacement is known, the road surface can be generated with uniform probabilities distribution within 0-2π [55]. As a result, the road profile is described with the final harmonic function h(x) as follows

$$h(x)\sum_{i=0}^{N}\sqrt{\Delta n}\,.\frac{n_o}{\mathrm{i}\Delta n}.2^k.10^{-3}.\cos(\mathrm{q}_1) \quad (10)$$

Where q1=$2\pi i\Delta n x + \varphi_i$, x is the abscissa variable within range {0, L}, k is a constant value depends on ISO road profile classification from Table I and it is assumed as integers increasing from 3 to 9, n0=0.1 cycles/m; φ_i random phase angle following an uniform probabilistic distribution within the 0–2π. During this research, the road profile has length L =250m. The spatial frequency value was considered during the simulation within 0.004 to 4 m-1. The generated road profile with length L=250m is illustrated in Figure 2 as spatial domain. Moreover, when the vehicle is assumed to travel over road length L with a constant speed v, the temporal road profile, as it is illustrated in Figure 3, can be generated in time domain as:

$$h(t) = \sum_{i=0}^{N} A_i \sin(i\omega_o t - \varphi_i),\ \Delta\Omega = \frac{2\pi}{L} \quad (11)$$

$\omega_o = \Delta\Omega v_0$, thus; the fundamental temporal frequency may be found as the following

$$A_{i=}\sqrt{2\Delta\Omega.M_d(i\Delta\Omega)} \quad (12)$$

$$A_{i=}\sqrt{\Delta\Omega}\,.\sqrt{2M_d(\Omega_o).\left(\frac{i\Delta\Omega}{\Omega_o}\right)^{-2}} \quad (13)$$

Therefore,

$$M_d(\Omega_o) = 2^k.10^{-6} \quad (14)$$

And thus,

$$A_{i=}\sqrt{\Delta\Omega}\,.\frac{\Omega_o}{\mathrm{i}\Delta\Omega}.2^k.10^{-3} \quad (15)$$

Finally, road profile can be generated in time domain as

$$h(t) = \sum_{i=0}^{N}\sqrt{\Delta\Omega}\,.\frac{\Omega_o}{\mathrm{i}\Delta\Omega}.2^k.10^{-3}.\sin\left(\frac{2\pi i v_o}{L}t - \varphi_i\right) \quad (16)$$

Table 1. Road roughness value classified by ISO [56].

Road	Class	Roughness degree $\phi(n_0)$ [10^{-6}m2/ (cycle/m)]		Roughness degree $\phi(\Omega_0)$(10^{-6}m3), Ω_0 = 1rad/m	
		Lower	*Upper*	*Lower*	*Upper*
Very Good	A	-	32	-	2
Good	B	32	128	2	8
Average	C	128	512	8	32
Poor	D	512	2048	32	128
Very poor	E	2048	8192	128	512

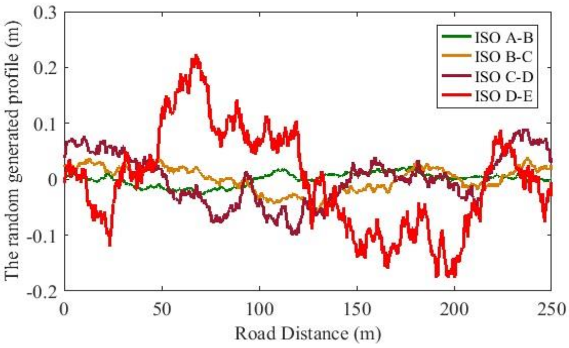

Figure 1. Generated road profile based on ISO-8608 classification

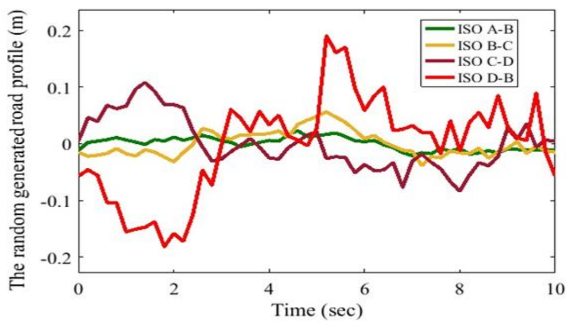

Figure 2. **Generated time domain road profile**

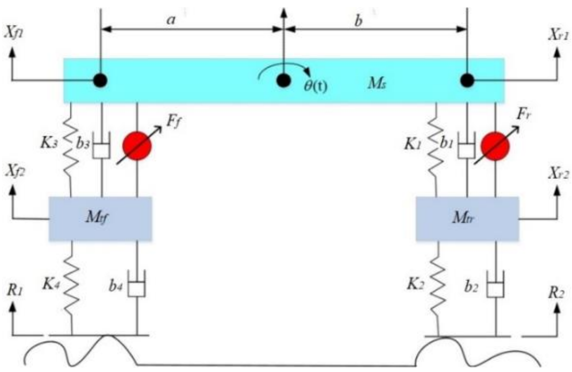

Figure 3. The half-vehicle suspension 4 DOF model

$$Z_1 = F_f + b_3(\dot{X}_{f2} - \dot{X}_{f1}) + k_3(X_{f2} - X_{f1}) \tag{17}$$

$$Z_2 = F_r + b_1(\dot{X}_{r2} - \dot{X}_{r1}) + k_1(X_{r2} - X_{r1}) \tag{18}$$

$$Z_3 = k_4(X_{f2} - R_1) + b_4\left(\dot{X}_{f2} - \dot{R}_1\right) \tag{19}$$

$$Z_4 = k_2(X_{r2} - R_2) + b_2\left(\dot{X}_{r2} - \dot{R}_2\right) \tag{20}$$

$$\ddot{X}_{f1} = Z_1\left(\frac{1}{M_{HCar}} + \frac{a^2}{I}\right) + Z_2\left(\frac{1}{M_{HCar}} - \frac{ab}{I}\right) \tag{21}$$

$$\ddot{X}_{r2} = \frac{-(Z_2 + Z_4)}{M_{tr}} \tag{22}$$

$$\ddot{X}_{r1} = Z_1\left(\frac{1}{M_{HCar}} + \frac{ab}{I}\right) + Z_2\left(\frac{1}{M_{HCar}} - \frac{b^2}{I}\right) \tag{23}$$

$$\ddot{X}_{f2} = \frac{-(Z_1 + Z_3)}{M_{tf}} \tag{24}$$

3. Modeling of half vehicle dynamic

In this paper, the half-vehicle suspension 4 DOF model has been selected for the analysis, as it provides a better insight on the suspension performance, and it provides the balance between efficiency and accuracy as it is shown in Figure 3. Also, to achieve comfortable and high-quality riding, two actuators are implemented in front and rear. The selected parameters of the active suspension and the notations used for the model can be found in [57]. The dynamical equations of the half car model were derived using Newton's second law of motion and they are expressed in (17) to (24). Details of the derivation can be found in [57].

4. The ML proposed model

The proposed hybrid ML model to control the active suspension system is divided into two phases as illustrated in Figure 4. During the first phase, the deep neural network Model (DNN) takes the responsibility of processing the body deflection (displacement) and the body acceleration of body in order to generate the actuator force. Then, in the second phase, the force output produced by DNN will be refined and adjusted through the ANFIS system.

4.1. Deep neural network Model (DNN)

In this research, the database was generated from the road profile-vehicle integrated model. The database contains 50,000 samples for inputs/output features. In addition, the data were generated from simulations with various road profiles and a sampling time of 0.5 millisecond. The batches for DNN were divided into inputs and output datasets. The inputs of the system are body deflection and body acceleration whilst the output is the actuator force. The training and testing data were generated randomly from the same data with 80% for training and 20% for testing. However, the validation data had never seen by the proposed DNN model. The batches aim to train the DNN to cope the behavior of BIFC [57] controller, and to predict the correct force signal to ensure minimizing any oscillations in the unknown road profiles. The input and output data are mapped based on the activation functions (Sigmoid, Tanh, and Rectified linear unit) and the combination of all three functions will ensure more effective for the suspension system. Moreover, the initial weights are randomly generated to create the initial starting point. Then, ***AxB*** weight matrix of the layer has been created, where A is the number of inputs into the layer, and B is the number of hidden nodes from the layer. The back propagation with stochastic gradient descent is the main deep machine learning algorithm used for design the DNN.

During the back propagation method [58,59], the error between the target response and the actual output is computed using cross entropy loss functions. The stochastic gradient descent calculates the error multiplied by the derivative of the activation functions to compute β, and then updates the weights to minimize the loss function values. The developed DNN algorithm aimed to automate the process of adjusting the parameters that have an impact on the training performance of the DNN. These parameters include activation functions, number of hidden layers, epochs, momentum, learning-rate, and nodes per layer. The model specifies the number of layers, nodes, and epochs, including their corresponding range and step size. Then, the script algorithm will evaluate these parameters across all activation functions. In order to determine the optimum DNN structure, the automated search method was applied to ensure that the optimum structure has been achieved. Although this process requires high computing power, but it is applied only once and during the offline process. As it is known that increasing the number of layers will increase the performance of the DNNs model; however, more than seven layers will rise the computation time to beyond ten days slight improved in the accuracy. Therefore, seven layers had been chosen to ensure a practical computational time frame of 24-36 hours. The best results would be obtained using twenty nodes per layer; using nodes above or below 20 nodes led to either overfitting or underfitting of the output. The total number of combinations of activation functions for a DNN with seven layers and three types of activation functions is 2187 and this becomes the number of configurations to be considered for the DNN. Moreover, the best performance with seven layers and 20 nodes per layer is illustrated in Table II. This table provides a comparison of how various combinations of activation functions along with varying numbers of hidden layers would affect the mean squared error (MSE). These results were carried out for the feed-forward DNN model structure to help selecting the best DNN architecture. It is found that the best performance with lowest mean square error happened after 171 iteration. This combination has ReLU (R), Sigmoid (S), and Tanh (T) for hidden layers and ReLU (R) for output layer as illustrated in Figure 5. Nevertheless, the accuracy achieved during both training and testing phases was not sufficient. To address the accuracy issue, a practical approach was implemented. This involved training the DNN using a learning rate of 0.01 for 150 epochs to achieve a quick convergence at the initial stage. Then, the DNN was further trained using a learning rate of 0.001 in increments of five epochs. This process continued until the accuracy reached a satisfactory level. The momentum value of 0.7 was chosen after using various values, and this value was determined to provide good stability and effective convergence. The Comparison result to check the performance of the DNN model is illustrated in Figure 6. It is clearly seen that the DNN model output response has no deviation and it coincides with the target. The deep learning algorithm (DL) which is illustrated in Table III represents the DNN controller. This control algorithm is a code that aims to reproduce the DNN structure of iteration 171. The matrix weights (W1 to W7) are loaded into the DNN control to map the body deflection and body accelerations propagate through DNN to generate the force signal. In addition, the activation function ReLU is applied to optimize the output layer values. After learning process becomes more convergent, the DNN control is saved to be used directly with the second ANFIS stage.

Table 2. The best performing structures with seven layers and 20 nodes per layer.

iteration	Hidden layer (HL) number						Output	
	1	*2*	*3*	*4*	*5*	*6*	*Layer*	*MSE (10^{-4})*
150	**R**	**S**	**S**	**T**	**T**	**S**	**R**	**15.2**
171	**R**	**S**	**R**	**S**	**T**	**S**	**R**	**3.4**
210	**T**	**S**	**T**	**R**	**S**	**T**	**R**	**12.1**
254	**S**	**R**	**T**	**R**	**S**	**R**	**S**	**21.5**
345	**S**	**R**	**R**	**R**	**R**	**T**	**S**	**22.1**
402	**S**	**S**	**R**	**S**	**R**	**R**	**S**	**7.8**

Table3. Deep learning controller function algorithm

```
function force = DL_CONTROLLER(deflection,
acceleration, W1, W2, W3, W4, W5, W6, W7)
   v1 = W1 * [deflection; acceleration];
   y1 = Sigmoid(v1);
   v2 = W2 * y1;  y2 = ReLU(v2);
   v3 = W3 * y2;   y3 = Tanh(v3);
   v4 = W4 * y3;   y4 = ReLU(v4);
   v5 = W5 * y4;   y5 = Sigmoid(v5);
   v6 = W6 * y5;  y6 = ReLU(v6);
   v7 = W7 * y6;  force = ReLU(v7);
end
```

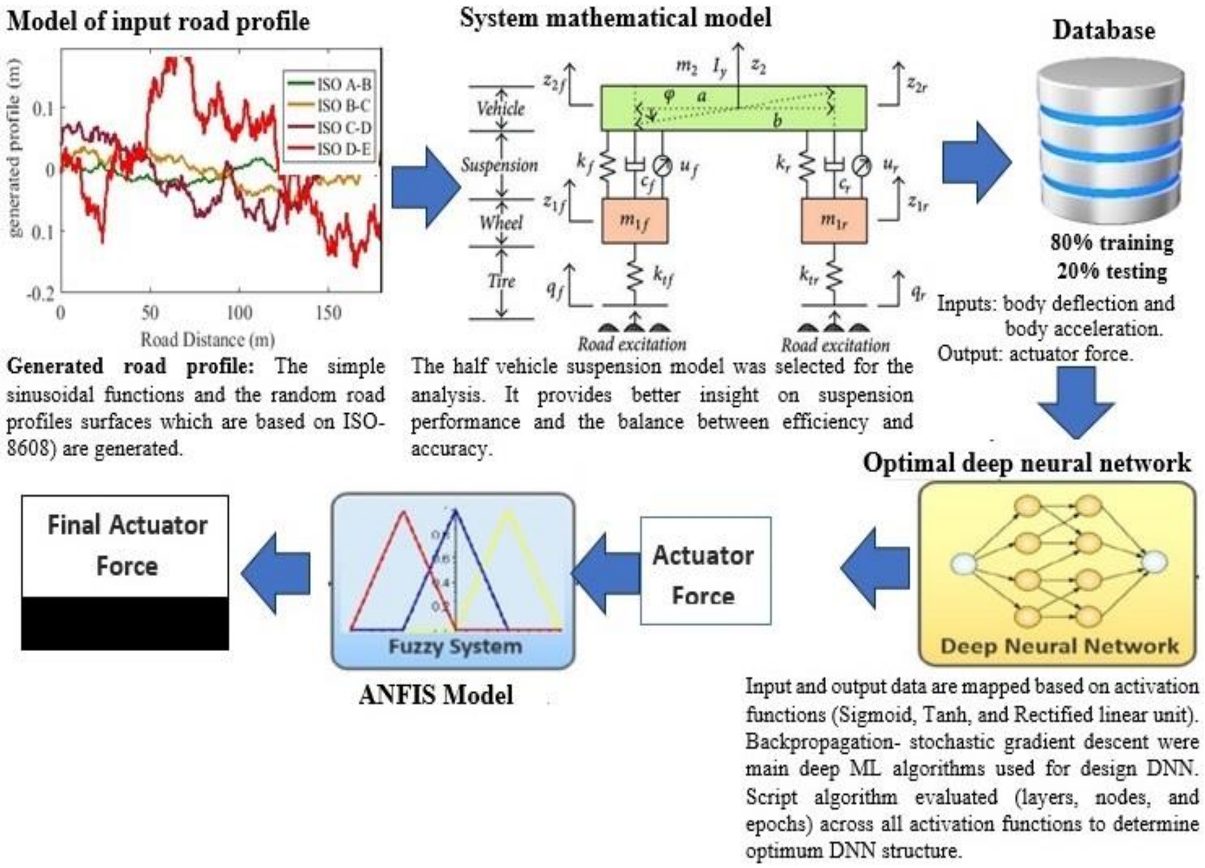

Figure 4. The overall structure of the whole proposed model

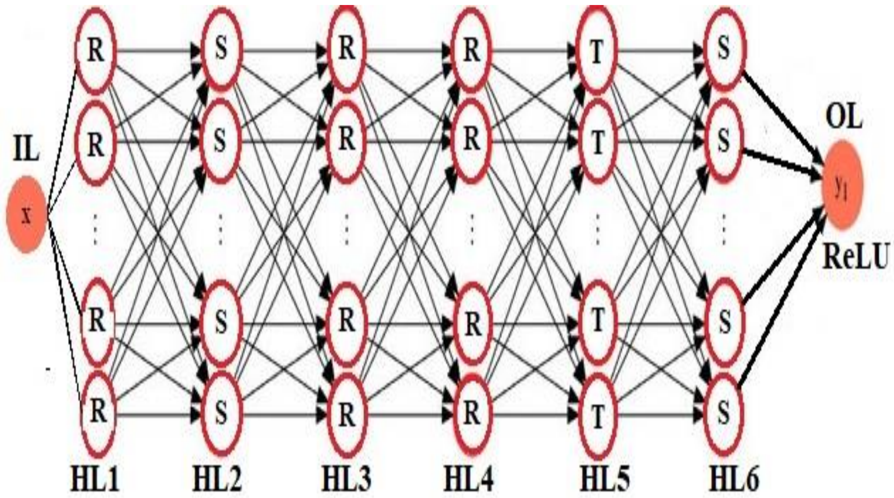

Figure 5. Optimal deep neural network structure: R: ReLU; S:Sig; T:Tanh.

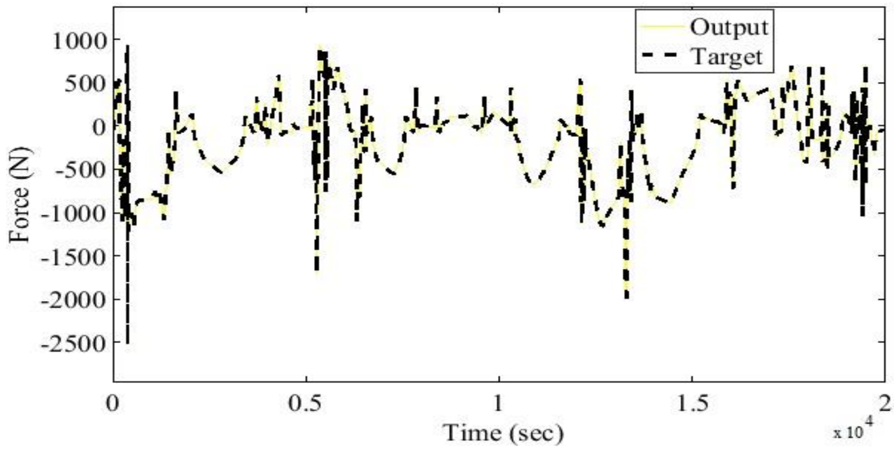

Figure 6. Iteration 171: DNN output and target versus time

4.2. ANFIS model

ANFIS is one of the best methods in modeling non-linear system, and it can give better and more accurate data representation and future prediction [60-63]. Whilst the fuzzy logic system can code and recode numerical inputs into semantic points [64], the intuitionistic fuzzy numbers provide the possibility of presenting uncertainty and doubt from the analysts' point of view [65]. In this paper, the ANFIS model is the second stage where the output from the DNN model will be utilized by the ANFIS structure. The strength of the ANFIS approach comes from the combined advantages of the fuzzy inference system (FIS) and neural networks (NN). Therefore, given sets of input/output training data, ANFIS approach can be used to easily obtain a properly tuned fuzzy control [66-68]. In this work, the ANFIS model is single input- single output model which they are the force signal from DNN model and the final force signal.

5. Results and Discussion

5.1. Unit step Bump

To assess control performance, step input bumps road profiles are employed to acquire system responses and evaluate performance. Hence, the step input is utilized to depict the scenario where the vehicle abruptly encounters a road surface with either a 10cm pothole or a 10cm-high bump. Figure 7 and Figure 8 are illustrated the rear and front body displacement, respectively. It is obviously noticed that the proposed ANFIS control enhances ride comfort through decreasing the displacement “the peak overshoot” and obtaining a smaller settling time in comparison to BIFC and PID models. The reduced “peak overshoot” magnitude will lead to obtain less sprung-mass travel, subsequently leading to decreased vibrations felt by the passenger. The less “settling time” will quickly attenuate the oscillations initiated in the vehicle's body, ensuring best comfort to the passenger. The pitch angle accelerations is illustrated in Figure 9. In regarding to pitch dynamics output response, the proposed method has less peak overshoot, less settling time and more stability in compared to other models. This result demonstrates the effectiveness of ANFIS approach in improving the vehicle's pitch dynamics response, which has implications for both the comfort and the safety during the motion.

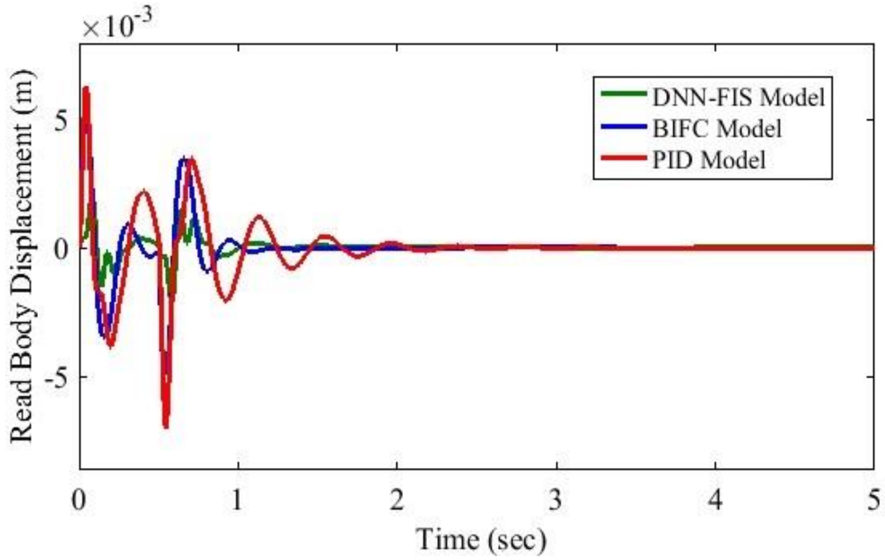

Figure 7. The rear body displacement with 10cm step input.

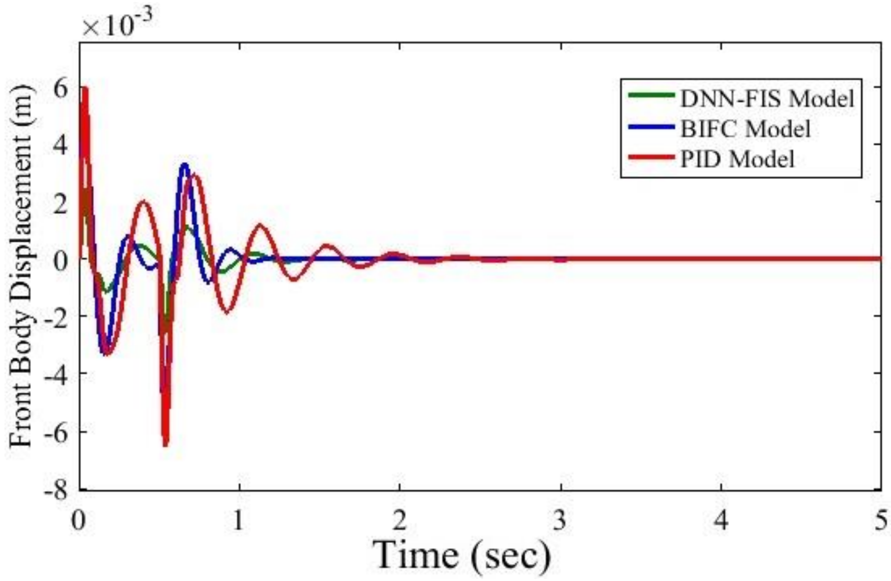

Figure 8. The front body displacement with 10cm step input.

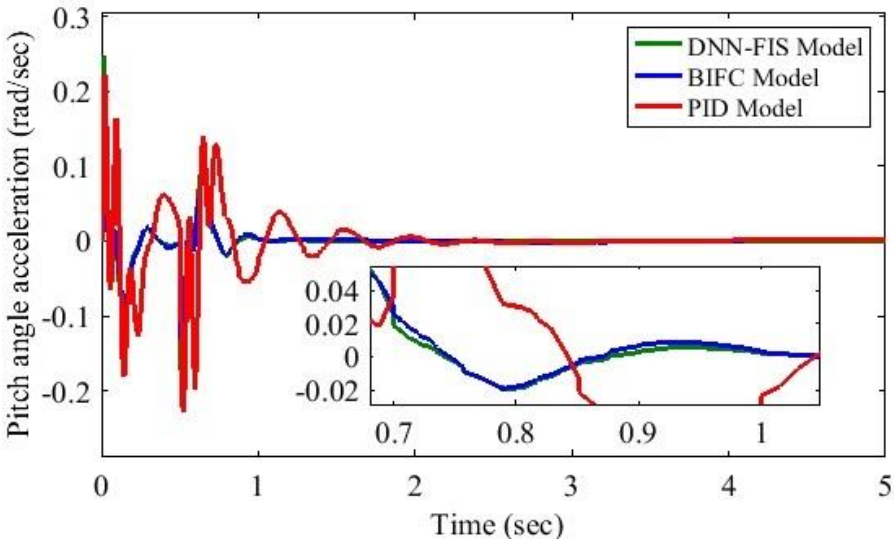

Figure 9. The pitch angle acceleration.

The performance of the proposed control algorithm has been analyzed and compared with BIFC and PID performance. Table IV illustrated the performance regarding to the settling time and the overshoot at front body of vehicle for a step input bumps road profile. The DNN-ANFIS controller outperforms other controllers. Actually, the proposed control is able to reduce the value of overshooting which yields to reduce the sprung-mass travel and hence, minimizing the vibrations felt by the passenger. Moreover, decreasing the settling time will promptly suspend the oscillations that occur in the vehicle body, thus, guaranteeing a more comfortable ride for passenger.

5.2. Random Road

In this scenario, the proposed DNN-ANFIS based suspension system has been compared with other controllers using random road profile to verify that the DNN-ANFIS control has better robust performance than BIFC and PID. Figure 10 shows the suspension systems rear body displacement for different controllers. It is shown that the proposed control has better result compared to other systems. The front body displacement is shown in Figure 11. The results clearly show that the proposed DNN-ANFIS model has better performance compared to BIFC, and PID.

Table 4. The performance at front body velocity of vehicle for speed bump

Control System	Overshoot (meters)				Settling time
	1st peak		*2nd peak*		
	Value	*Time*	*Value*	*Time*	
DNN-ANFIS	0.01	0.104	-0.0177	0.2132	0.88
BIFC [34]	0.0337	0.089	-0.0667	0.2017	1.005
PID	0.034	0.08	-0.0626	0.206	>2

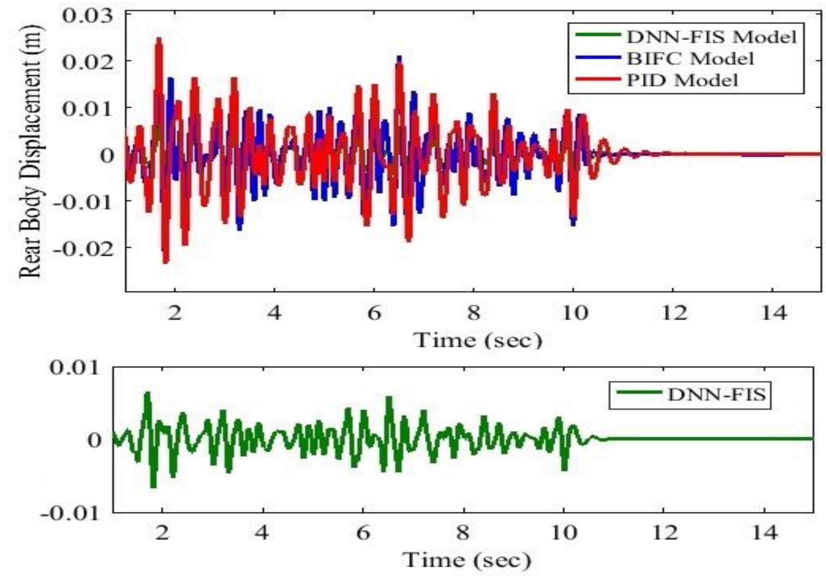

Figure 10. Rear body displacement using random road profile.

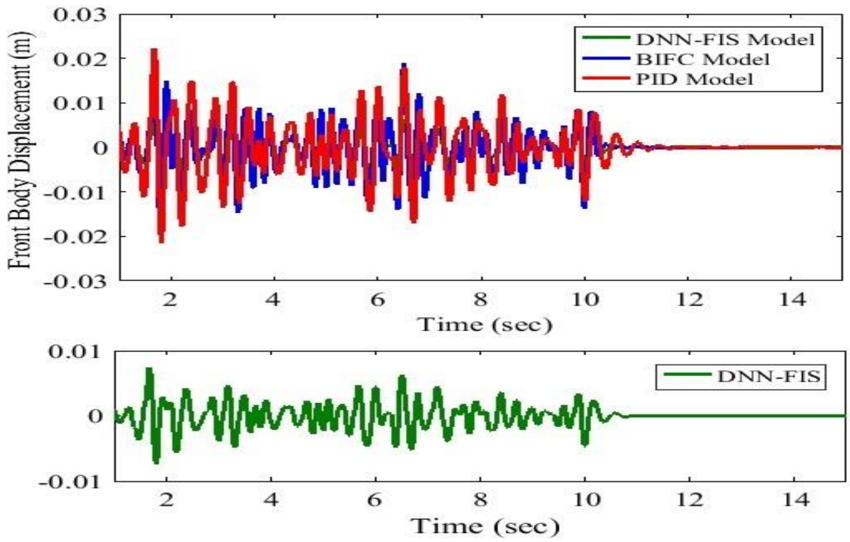

Figure 11. Front body displacement using random road profile

5.3. ISO artificial road profile

In order to provide valuable insights into the behavior of the vehicle's front body displacement under different road profiles, the adopted shaping filter method was used to generate the random road profiles for each class. The proposed control has been applied to understand how it affects the vehicle's response to varying road conditions. In addition, the speed of vehicle has been chosen as 16.6m/s. Figure 12 illustrated front body displacement in response to the ISO A-B input road profile which is characterized by an amplitude ranging from -0.02 to 0.02 m. This type of road profile represents a change from a very smooth to a moderately smooth road. The figure distinctly demonstrates that the implementation of the proposed control significantly reduced the displacement within range from -0.01 to 0.01 m. Therefore, reducing the front body displacement is important for improving overall driving dynamics. Figure 13 illustrated the front body displacement in response to the ISO B-C input road profile which is characterized by shifting from a moderately smooth road (Class B) to a road with some roughness and irregularities. The amplitude range for this type of road was ranging from -0.04 to 0.06 m. The proposed control shows its effectiveness to reduce front body displacement. The maximum body displacement was approximated 0.02 m.

To extend the evaluation of the proposed control model, more challenging road profiles were introduced. Therefore, the front body displacements in response to the ISO C-D and ISO D-E input road profiles are illustrated in Figure 14 and Figure 15, respectively. The maximum value of the body displacement in Figure 15 was 0.035m and -0.011m. In addition, the maximum value of body displacement was 0.072m and -0.08m. This indicated how well the proposed DNN-ANFIS model manages to limit the magnitude of the front body displacements and keep them within acceptable bounds despite the varying road profiles. These results demonstrated the ability of the proposed control to reduce the front body displacement under various road conditions.

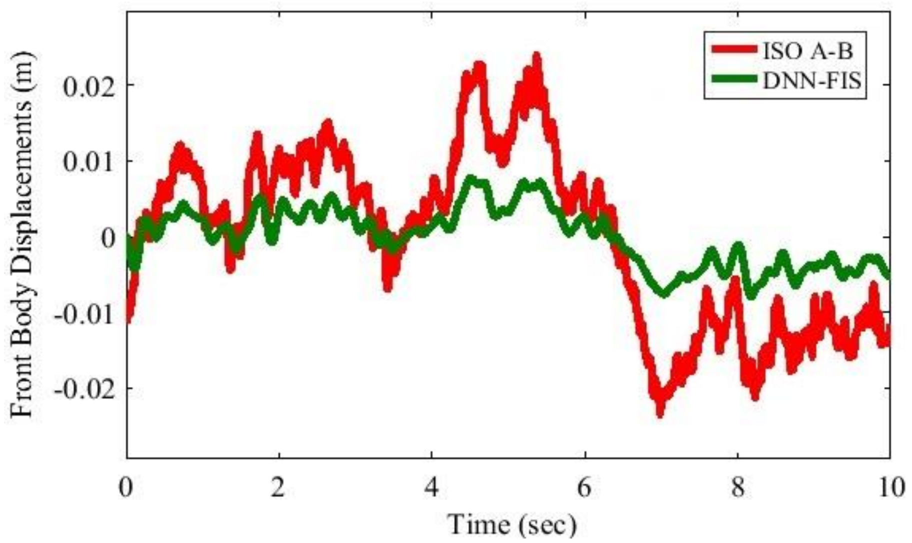

Figure 12. The front body displacement in ISO A-B.

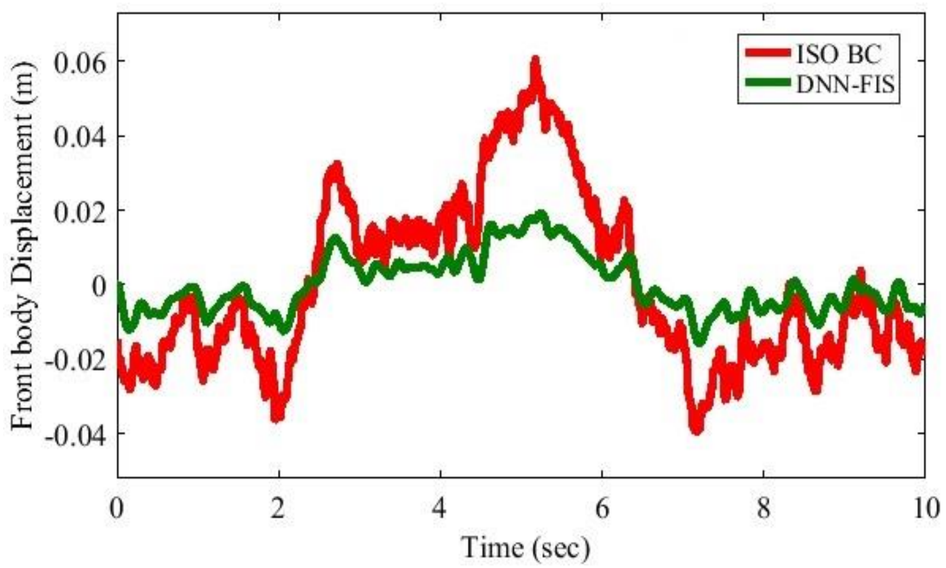

Figure 13. The front body displacement in ISO B-C.

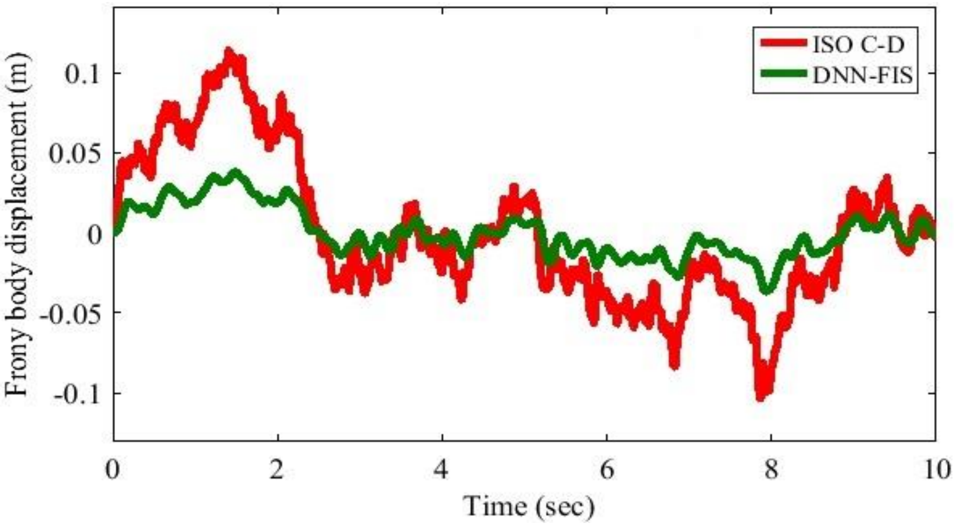

Figure 14. The front body displacement in ISO C-D.

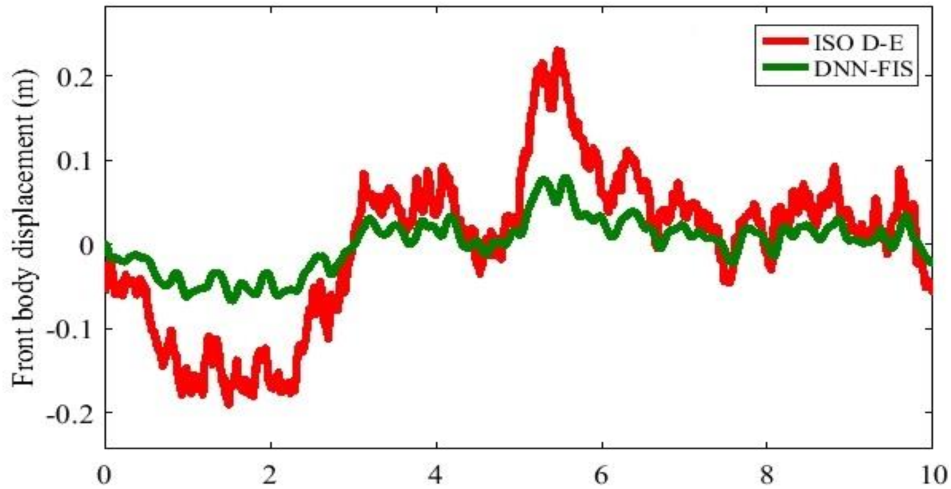

Figure 15. The front body displacement in ISO D-E.

As it is known, reduced body displacement translates into enhanced the driver comfort, and improved vehicle stability. Furthermore, the power spectral density analysis is applied to verify energy present at any given frequency. Thus, the fast Fourier transform (FFT) analysis is used to compute the discrete Fourier transform (DFT). According to ISO 2631, the man body is sensitive to vertical vibrations within frequency range 0.5-80 Hz [69]. However, in the comfort zone, the typical frequency range of interest is usually between 1-10 Hz. Furthermore, the comfort of the ride is associated with the frequency response of body accelerations, while the performance of handling is connected to the dynamic load of the tires. Therefore, the PSD acceleration response of vehicle body and PSD tire dynamic load response under ISO D-E road profiles are computed. It has been found that the proposed control is fully controlled active quarter car model and it achieved a significant reduction of body accelerations in the frequency 7.1 Hz. Also, at smaller tire dynamic loads; the handling performance is being enhanced by the presented control model with frequency equals 8 Hz. According to the ISO criteria [39], the crest factors (CF) is very essential evaluator for vehicle ride comfort. Therefore, the comparison of the RMS, peaks values, and CF are given in Table V. It is clearly seen that the ANFIS-DNN is generally outperform BIFC controller in terms of peak values for all road profiles. This indicates that ANFIS-DNN is better for system stability and safety. Also, the ANFIS-DNN has lower RMS values than BIFC for road profiles AB, BC, and CD. Lower RMS values indicate smoother and less energetic responses, which are typically preferred for passenger comfort. Furthermore, the ANFIS-DNN has minimum CF which indicates that the signal has fewer peaks relative to its average. This would suggest better control of transient events and smoother responses.

Table 5. The comparison of RMS and peak values for front body displacement :

Methods		Road profile classifications			
		AB	*BC*	*CD*	*DE*
ANFIS-DNN	*Peak*	**0.009**	**0.021**	**0.035**	**0.081**
	RMS	**1.023**	**1.284**	**1.512**	**2.145**
	CF	**0.0088**	**0.0163**	**0.0231**	**0.0380**
BIFC	*Peak*	**0.018**	**0.042**	**0.061**	**0.1432**
	RMS	**2.012**	**2.457**	**2.478**	**2.875**
	CF	**0.0089**	**0.0171**	**0.0246**	**0.0498**

Conclusion

In this paper, a hybrid feed-forward deep neural network and ANFIS framework is developed to control an active suspension system of half vehicle. The presented results and discussions provide valuable insights into the performance of the proposed DNN-ANFIS-based suspension control system in various road conditions. Across a range of road profiles, including ISO-8608 road profiles, the proposed control system consistently demonstrates its ability to enhance ride comfort and improve vehicle dynamics. The key findings can be summarized as follows:

- The proposed control system has ability to minimize the overshooting values and settling times. This reduction in overshoot is vital since it translates into a decrease in sprung-mass travel, ultimately leading to a significant reduction in vibrations experienced by passengers. Thus, ensuring a smoother and more pleasant driving experience. Furthermore, minimizing the settling time contributes to optimal passenger comfort by rapidly attenuating oscillations in the vehicle's body, resulting in a more stable and comfortable ride.
- The performance of the proposed control is robust when compared to other traditional controllers, such as BIFC and PID, under random and ISO-8608 road profiles. This robust performance suggests that the DNN-ANFIS-based suspension system can maintain its effectiveness across various road conditions, enhancing passenger comfort and vehicle stability in real-world driving scenarios.

Declaration of interests:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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