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ORIGINAL ARTICLE

Magnetorheological damper voltage control using artificial neural network for optimum vehicle ride comfort

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ABSTRACT – Suspension system design is an important challenging duty that facing car manufacturers, so the challenge has become to design the best system in terms of providing ride comfort and handling ability under all driving situations. The goal of this paper is to provide assistance in enhancing the effectiveness of the suspension system. A full car model with eight degrees of freedom (DOF) was developed using MATLAB/Simulink. Validation of the Simulink model was obtained. The model was assumed to travel over a speed hump that has a half sine wave shape and amplitude that changing from 0.01 to 0.2 m. The vehicle was moving with variable speeds from 20 to 120 km/h. Magneto Rheological (MR) damper was implanted to the model to study its effect on ride comfort. Artificial Neural Network (ANN) was used to find the optimum voltage value applied to the MR damper, to skip the hump at least displacement. This network uses road profile and the vehicle speed as inputs. A comparison of the results for passive suspension system and model with MR damper, are illustrated. Results show that the MR damper give significant improvements of the vehicle ride performance over the passive suspension system.

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Ride comfort; full vehicle model; eight DOF model; MR damper; ANN

INTRODUCTION

The function of the suspension is to protect the vehicle from the vibrations that receive when traveling on a rough road surface. In general, based on the damper utilized and the actuator added to the suspension framework, this system can be sorted or classified in light on the external power input into three types, each one of them has its advantages and disadvantages, which are: passive suspension, semi-active and active suspension system [1, 2]. The more effective suspension system is who provide greater protection and lower level of concussion moving to the car body depending on the interaction with uneven road surface [3, 4]. There are various model utilized in these types of studies: quarter car model $[3-11]$ half car model $[12-20]$and full car model $[21-30]$.

Many types of research have been made to increase and enhance ride comfort by using different active controllers. Linear Quadratic Regulator (LQR) and Proportional Integral Derivative (PID) controller were used by [5] to investigate the performance of an active suspension system. Results show that the performance of body displacement and wheel displacement can be improved by using these types of controllers. A linear mathematical model was presented by [7] to design a slide mode controller that helps to avoid the variation of the road profile over the sprung mass of the car body. Their results demonstrate that the fundamental control target can be achieved the travelers' comfort. A novel Neural Network (NN) has been presented by [6] to improve the performance of the model concerning the body acceleration under different types of road input. The response using the NN was compared to the cell using a conventional PID controller and a PID that was tuned using a genetic algorithm and a passive suspension system. Simulations show the effectiveness of the NN compared to all these systems. A quarter car model with passenger body and seat was developed by [9] to capture the dynamic behavior of a car to improve ride comfort and safety. Two controllers, which are Adaptive Neuro-Fuzzy Inference System (ANFIS) and Hybrid ANFIS PID (HANFISPID) was developed by [9]. Results demonstrate that the proposed HANFISPID control plan achieves better ride comfort and safety of travel compared to the passive system and ANFIS controller. A Genetic Algorithm (GA) was applied by [12] to search for the ideal parameters of the seat and vehicle suspension system. Responses obtained show a reduction in human vertical peak acceleration compared with a passive system. Conventional PID controller, self-tunable fuzzy inference system (STFIS) controller, and the passive suspension system were investigated by [13] to show that the STFIS is more effective to achieve ride comfort and road handling qualities when compared to the two other systems [14] proposed a new adaptive control algorithm that combines a PID controller for suspension deflection together with a sliding mode reference conditioning outer loop that uses the vertical acceleration of the car body as a complementary source of control. Results show an improvement of the ride comfort over the same PID controller without the outer conditioning loop and passive system. PID, H∞ and fuzzy logic controllers were used by [15] and developed a self-tuning PID controller based on fuzzy logic to improve the performance of the suspension system. Through the proposed controller, suspension working space (SWS) is minimized and the best comfort of the driver is achieved. A nonlinear adaptive Neuro-Fuzzy Wavelet Network (NFWN)

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control methodology was proposed by [28] to control eight Degree of Freedom (DOF) full car suspension systems. Results obtained from simulations were compared with passive and semi-active suspension systems and show better performance in ride comfort and vehicle stability when using the proposed controller. Reference [31] designed a fuzzy controller for a semi-active suspension system of seven DOF full car model. Simulations show that the performance of the designed controller was better than the passive suspension system based on Magneto-Rheological (MR) damper. Two control ways for the suspension system were presented by [32]. These two methods are optimization using GA to find the optimum values of spring stiffness and damping coefficient at different speeds and the other method is the control of active suspension system using the Proportional Integral (PI) controller. Results show an important improvement in terms of sprung mass acceleration when using the presented controllers over the passive system. A non-chattering sliding mode control strategy was proposed by [33]. Numerical simulation results verify that this control method is effective for the vibrations that have nonlinear characteristics of the car suspension model and achieve an improvement in ride comfort by reducing the vibration amplitude when compared to the passive system.

A decent ride quality means diverse things to various individuals. Somebody who is acquainted with driving a new Lexus or Mercedes will have a unique thought of ride quality from the person who drives a multiyear old pick-up. Great ride quality is characterized as the capacity to limit the impacts of street irregularities on the vehicle travellers. At the point when the vehicle experiences a pothole or bump, it should transverse the impediment with little body movement as possible. The world today and mainly in Europe use the ISO 2631 as a strategy to objectively assess the ride comfort (likewise referred to as a human reaction to vibration) also there are more methods to evaluate ride quality like the British standard BS 6841. Austria and Germany utilize VDI 2057, while average absorbed power (AAP) is used by the United States of America. The “ride comfort” quality is affected by several factors which are vertical acceleration and jerks of sprung mass and passenger seat also pitch and roll acceleration of the car body and suspension travel or rattle space, while handling capability is affected by the road holding or dynamic tire load [34].

In the present study, a full passenger car model considering eight DOF is used. MR damper, which uses ANN to find the optimum voltage value to skip the road disturbance at least displacement, is implanted to the model to study its effect on ride comfort, especially sprung mass and seat vertical displacements, of the vehicle.

MODEL AND MATHEMATICAL MODEL

Full Car Model

A full car model with the driver’s seat is considered to study in this research. Figure 1 shows an eight DOF full vehicle model, it consists of the driver seat, sprung mass which refers to the part supported by springs, unsprung masses which refers to the front and rear wheels assembly.

The suspension between the passenger seat and the sprung mass, also the suspension system between the sprung and unsprung masses are modeled as springs and dampers with linear characteristics. The four tires are modeled as linear spring and its damping coefficient is neglected because the damping characteristics of a tire are negligible compared to tire stiffness as indicated by [31, 35, 36]. The sprung mass is considered to have three DOF which refer to pitch, roll, and bounce motion. The driver seat and the four unsprung masses are modeled to have one DOF each in the vertical direction [34, 35]. The mathematical equations of the full car model with eight DOF and the MATLAB SIMULINK model [34] are used in this study. The labels and parameters adopted in this model and that have been used by [34] are shown in Table 1.

Table 1. Nomenclature and parameters used in the full car model [34]

Parameter	Description	Value	Unit
M_p	Passenger seat mass	100	kg
M	Sprung mass	2160	
M_1	Front left side un-sprung mass	85	
M_2	Rear left side un-sprung mass	60	
M_3	Front right side un-sprung mass	85	
M_4	Rear right side un-sprung mass	60	
K_p	Passenger seat stiffness	98935	N/m
K_1	Front left side suspension spring stiffness	96861	
K_2	Rear left side suspension spring stiffness	52310	
K_3	Front right side suspension spring stiffness	96861	
K_4	Rear right side suspension spring stiffness	52310	
K_t	Tire stiffness	200000	

Table 2. Nomenclature and parameters used in the full car model [34] (cont.)

Parameter	Description	Value	Unit
C_p	Passenger seat damping coefficient	615	Ns/m
C_1	Front left side suspension damping coefficient	2460	
C_2	Rear left side suspension damping coefficient	2281	
C_3	Front right side suspension damping coefficient	2460	
C_4	Rear right side suspension damping coefficient	2281	
a	Center of gravity (CG) location from front axle	1.524	m
b	Center of gravity (CG) location from rear axle	1.156	
$2W$	Wheel track	1.45	
X_p	Distance of seat position from CG of sprung mass	0.234	
Y_p	Distance of seat position from CG of sprung mass	0.375	
I_x	Mass moment of inertia for pitch	946	kg- m^2
I_y	Mass moment of inertia for roll	4140	
Q_1	Road input at front left side		
Q_2	Road input at rear left side		
Q_3	Road input at front right side		
Q_4	Road input at rear left side		

Mathematical Modeling

Using Newton's second law of motion and free-body diagram concept, the following equations "Eq. (1) – Eq. (8)" of motion are determined.

For passenger seat displacement:

$$\ddot{Z}_p = -\frac{1}{M_p}(K_pZ_p - K_pZ - K_pX_p\,\theta - K_pY_p\varphi + C_p\dot{Z}_p - C_p\dot{Z} - C_pX_p\dot{\theta} - C_pY_p\dot{\varphi}) \tag{1}$$

For vehicle body bounce motion (Sprung Mass):

$$\begin{aligned}\ddot{Z} = -\frac{1}{M}\big[&K_1(Z - a\theta + W\varphi - Z_1) + C_1(\dot{Z} - a\dot{\theta} + W\dot{\varphi} - \dot{Z}_1) + K_2(Z + b\theta + W\varphi - Z_2)\\ &+ C_2(\dot{Z} + b\dot{\theta} + W\dot{\varphi} - \dot{Z}_2) + K_3(Z - a\theta - W\varphi - Z_3) + C_3(\dot{Z} - a\dot{\theta} - W\dot{\varphi} - \dot{Z}_3)\\ &+ K_4(Z + b\theta - W\varphi - Z_4) + C_4(\dot{Z} + b\dot{\theta} - W\dot{\varphi} - \dot{Z}_4) - K_p(Z_p - Z - X_p\theta - Y_p\varphi)\\ &- C_p(\dot{Z}_p - \dot{Z} - X_p\dot{\theta} - Y_p\dot{\varphi})\big]\end{aligned} \tag{2}$$

For vehicle body rolling motion (Sprung Mass):

$$\begin{aligned}\ddot{\varphi} = -\frac{1}{I_x}\big[&WK_1(Z - a\theta + W\varphi - Z_1) - WC_1(\dot{Z} - a\dot{\theta} + W\dot{\varphi} - \dot{Z}_1) + WK_2(Z + b\theta + W\varphi - Z_2)\\ &+ WC_2(\dot{Z} + b\dot{\theta} + W\dot{\varphi} - \dot{Z}_2) - WK_3(Z - a\theta - W\varphi - Z_3)\\ &- WC_3(\dot{Z} - a\dot{\theta} - W\dot{\varphi} - \dot{Z}_3) - WK_4(Z + b\theta - W\varphi - Z_4)\\ &- WC_4(\dot{Z} + b\dot{\theta} - W\dot{\varphi} - \dot{Z}_4) + Y_pK_p(Z_p - Z - X_p\theta - Y_p\varphi)\\ &+ Y_pC_p(\dot{Z}_p - \dot{Z} - X_p\dot{\theta} - Y_p\dot{\varphi})\big]\end{aligned} \tag{3}$$

For vehicle body pitching motion (Sprung Mass):

$$\begin{aligned}\ddot{\theta} = -\frac{1}{I_y}\big[&-aK_1(Z - a\theta + W\varphi - Z_1) + aC_1(\dot{Z} - a\dot{\theta} + W\dot{\varphi} - \dot{Z}_1) + bK_2(Z + b\theta + W\varphi - Z_2)\\ &+ bC_2(\dot{Z} + b\dot{\theta} + W\dot{\varphi} - \dot{Z}_2) - aK_3(Z - a\theta - W\varphi - Z_3)\\ &- aC_3(\dot{Z} - a\dot{\theta} - W\dot{\varphi} - \dot{Z}_3) + bK_4(Z + b\theta - W\varphi - Z_4) + bC_4(\dot{Z} + b\theta - W\dot{\varphi} - \dot{Z}_4)\\ &+ X_pK_p(Z_p - Z - X_p\theta - Y_p\varphi) + X_pC_p(\dot{Z}_p - \dot{Z} - X_p\dot{\theta} - Y_p\dot{\varphi})\big]\end{aligned} \tag{4}$$

For front left wheel displacement (Un-sprung Mass):

$$\ddot{Z}_1 = -\frac{1}{M_1}\left[-K_1(Z - a\theta + W\varphi - Z_1) - C_1\left(\dot{Z} - a\dot{\theta} + W\dot{\varphi} - \dot{Z}_1\right) + K_t(Z_1 - Q_1)\right] \tag{5}$$

For rear left wheel displacement (Un-sprung Mass):

$$\ddot{Z}_2 = -\frac{1}{M_2}\left[-K_2(Z + b\theta + W\varphi - Z_2) - C_2\left(\dot{Z} + b\dot{\theta} + W\dot{\varphi} - \dot{Z}_2\right) + K_t(Z_2 - Q_2)\right] \tag{6}$$

For front right wheel displacement (Un-sprung Mass):

$$\ddot{Z}_3 = -\frac{1}{M_3}\left[-K_3(Z - a\theta - W\varphi - Z_3) - C_3\left(\dot{Z} - a\dot{\theta} - W\dot{\varphi} - \dot{Z}_3\right) + K_t(Z_3 - Q_3)\right] \tag{7}$$

For rear right wheel displacement (Un-sprung Mass):

$$\ddot{Z}_4 = -\frac{1}{M_4}\left[-K_4(Z + b\theta - W\varphi - Z_4) - C_4\left(\dot{Z} + b\dot{\theta} - W\dot{\varphi} - \dot{Z}_4\right) + K_t(Z_4 - Q_4)\right] \tag{8}$$

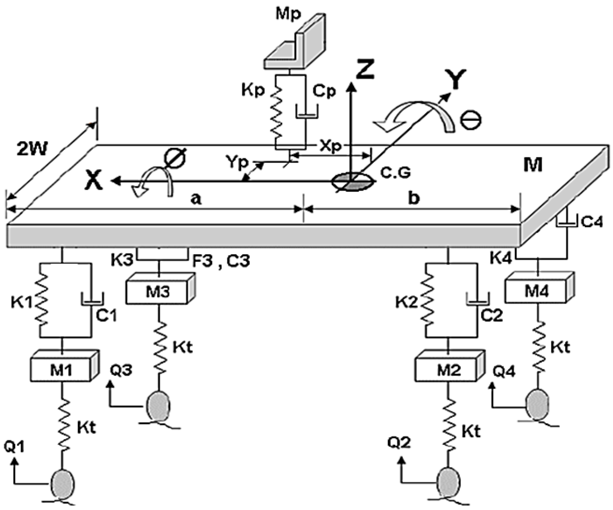

Figure 1. Eight DOF vehicle model [34]

Magneto Rheological (MR) Damper

MR fluid can be used as one of the most important engineering applications which is the construction of damper. This device is called MR linear damper, it is controllable and smart damper. These features can be achieved by applying voltage or current to the damper for creating a magnetic field that changes the yield strength of the MR fluid and therefore the viscosity of the liquid.

So the important asset of this damper is the controllability which can be adjusted to achieve the desired amount of dissipating energy or damping level. Obtaining the desired level of damping is achieved by applying a voltage or current to vary the magnetic induction in an orifice that separates the two chambers of the MR fluid. So this orifice acts as a valve but instead to control it mechanically this valve is controlled electrically by applying a current and thus abuses the MR liquid in flow mode.

Magneto rheological fluids

There are a group of fluids which differ from other typical fluids, they have special characteristics and called MR fluids. They are non-Newtonian rheological stable with shear yield strength and are controlled by applying a magnetic field. This type of fluids is consisting of small particles that have magnetic characteristics and dispersed in a liquid, so the properties of this fluid can be changed or controlled by applying an external magnetic field.

The concentration of the magnetic particles, their shape and size are parameters that determine the properties of the MR liquid in addition to the temperature, the intensity of the magnetic field and the properties of fluid carriers. Some materials that act as fluid bearers are water, mineral oil, silicon, and glycerol. The diameter of the magnetic particles is between 0.5µm and 8µm [37].

Spencer model

Spencer proposed a model with an extension of the Bouc-Wen model, which concerns the presentation of an extra spring (K_1) and damper (C_1) as shown in Figure 2 [38].

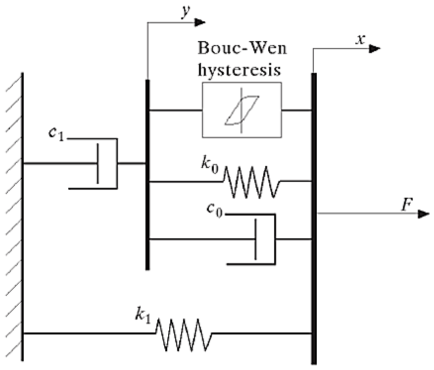

Figure 2. Rheological structure of an MR damper for the Spencer model

The damping force in the Spencer model can be written as:

$$F = C_0(\dot{X} - \dot{y}) + K_0(X - y) + K_1(X - X_0) \tag{9}$$

Or can be also expressed as:

$$F = C_1\dot{y} + K_1(X - X_0) \tag{10}$$

The displacement z and y are respectively described by the following equations:

$$\dot{z} = -\gamma|\dot{X} - \dot{y}|z|z|^{n-1} - \beta(\dot{X} - \dot{y})|z|^n + A(\dot{X} - \dot{y}) \tag{11}$$

$$\dot{y} = \frac{1}{C_0 + C_1}[\alpha z + C_0\dot{X} + K_0(X - y)] \tag{12}$$

where:

$$C_0 = C_{0a} + C_{0b}U \qquad \alpha = \alpha_a + \alpha_b U$$

$$C_1 = C_{1a} + C_{1b}U \qquad \dot{U} = -\mu(U - v)$$

C_1	Parameter that suits viscos damping at high speed.
K_1	Represents the stiffness at high speed.
β, γ, A	Parameters representing the control of the linearity during unloading and the smoothness of transition from the pre-yield to post-yield area.
α	Parameter representing the stiffness of the spring for the damping force component associated with the evolution variable z.
K_0	Parameter representing the stiffness of the spring associated with the nominal damper due to the accumulator.
C_0	Parameter representing viscous damping.
X_0	Parameter representing the initial displacement of the spring with the stiffness K_0.

The values of the above parameters of MR damper are taken as [39].

SIMULATIONS AND CONTROL METHODS

Matlab Simulink Model

The full vehicle model is created using Matlab/Simulink (R2014b Simulink 8.4). Figure 3 shows a flow chart from the input (road profile and speed) to the car body and finally the outputs (seat and sprung mass vertical displacements).

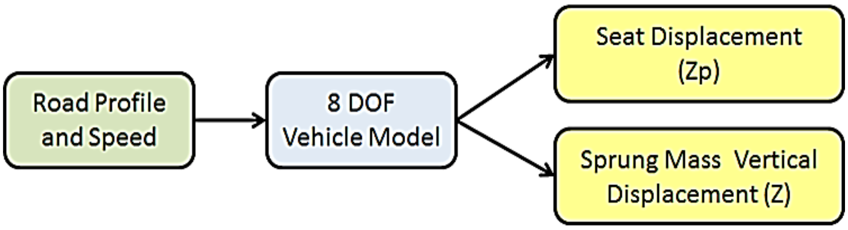

Figure 3. Simulink model flow chart

Model Validation

To check the correctness of this eight DOF full car model comparison has done between the response of this model and that of [34] in term of seat displacement (Z_p) and sprung mass displacement (Z) concerning the time when the same inputs (road profile) are applied to these two models. The road profile is shown in Figure 4 and that used as input is the same as reference the [34].

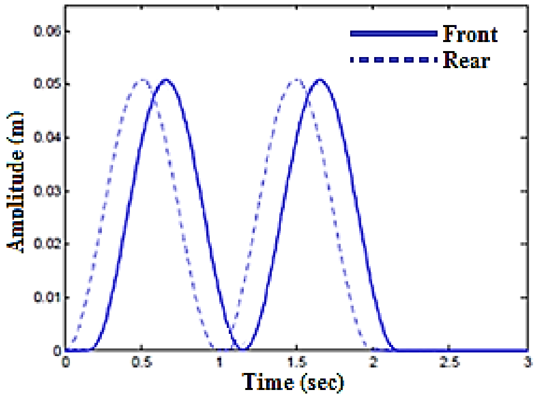

Figure 4. Road profile used for validation of the model

Figure 5 shows the response of the model of reference [34] and that of which used in this study.

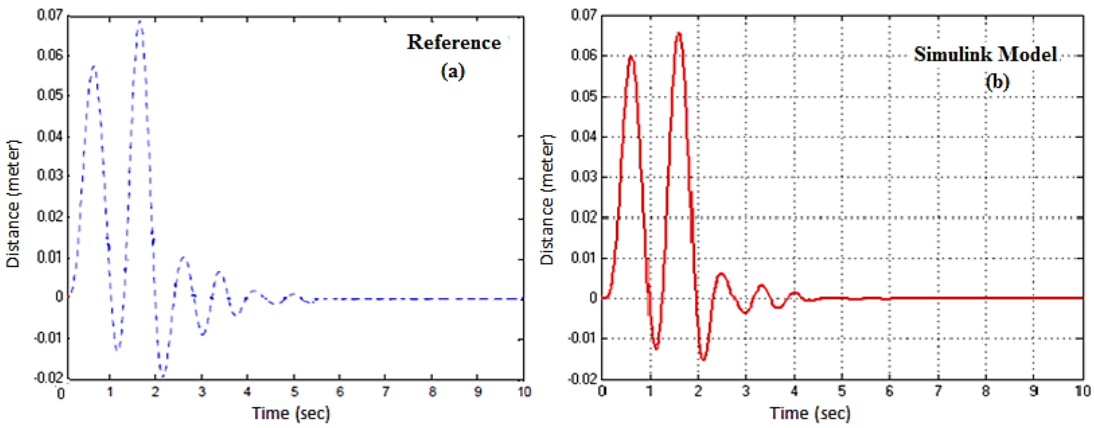

Figure 5. Sprung mass vertical displacement vs. time for (a) Reference [34] and (b) the Simulink model

By comparing the responses of these two models, results show that the Simulink model agrees with the model as given by [34]. So, the eight DOF model created in this study matches the reference, this means that it is valid and can be used to do all needed simulations.

Road Profile

A speed hump is a raised area in the roadway pavement surface extending transversely across the travel way. Speed humps are sometimes referred to as "pavement undulations" or "sleeping policemen". Common speed hump shapes are sinusoidal, parabolic, and circular. Most agencies implement speed humps with a travel length of 12 to 14 feet (3.7 to 4.3 m). Speed humps are generally used on residential local streets.

In this study a speed hump that has a half-sine wave shape with 4 m wavelength. The amplitude of this hump is changed from 0.01 m to 0.2 m to study the effect of these different amplitudes on the vehicle. This hump is used as input to the car model and the vehicle is moving with variable speeds from 20 to 120 km/h, in each change to the hump amplitude, these speeds are adopted. The shape of the road hump is shown in Figure 6 for 0.1 m amplitude and different speeds. The model is assumed to be constant and the hump is moving under it with variable speeds, so the speeds hump time changes from one speed to another. In the simulation stage, the time response is obtained. There is a time delay between the front and rear wheel inputs. The time delay is as shown in Eq. (13):

$$t = \frac{a+b}{v} \tag{13}$$

where, $(a + b)$ is the distance between the front and rear axles and v if the vehicle velocity.

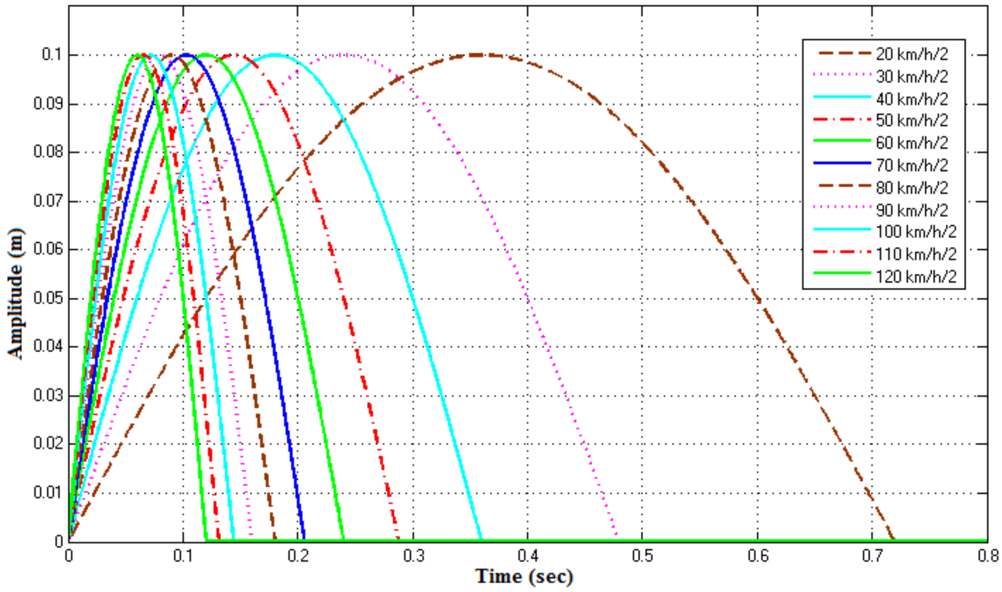

Figure 6. Road hump shapes for different speeds

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a favourable option in contrast to other strategies; it is one of the intelligent controllers. An ANN is a data handling model that is propelled from the biological nervous system, for example, the brain forms data. ANNs are characterized by being similar to humans through learning ability. This tool is arranged for particular applications like data classification or function estimation, through a learning procedure.

In a biological system, learning includes adjustments to the general associations that exist-among neurons. This is valid for ANNs too. They are comprised of straight forward handling units which are connected by weighted association to create structures that can learn or memorize relationships between sets of factors. This heuristic strategy can be valuable for a nonlinear procedure that has unknown functional forms.

The feed-forward networks or multilayer perceptron (MLP) among various neural systems are most generally utilized in engineering. MLP systems are typically arranged in three layers of neurons. The input or information layer and the output layer speak to the input and output factors of the model and lead between them at least one hidden layer that holds the system capacity to learn nonlinear relationships.

Architecture determinations which are one of the serious issues that have a suggestion on the empirical outcomes consist of: the number of input and output variables, the number of hidden layers, output and hidden activation functions and learning algorithm.

Using a trial-error process the number of the hidden unit can be determined where few neurons in hidden layers (hidden units) can prompt under fitting, while an excessive number of neurons can lead to over fitting. The real number of hidden units required in the system must be found by experimentation. In addition, the input utilized by the system must be effective on the esteems of output(s), in actuality the input and output factors ought to be recognized carefully, on the ground that they empower the system to learn connection quicker and to utilize fewer neurons.

The difference between the real output and the ANN output is another critical error. This error can be minimized by adjusting the interconnecting weight and threshold value in every neuron [40, 41].

The network's learning ability can be achieved by applying a Back Propagation (BP) algorithm which is based on the comparison between the neural network simulated output values to the actual values and calculates a prediction error. BP is ordinarily used to update weights of NNs as in [42].

Control Strategy

This section discusses the control method that has been adopted to achieve ride comfort. As mentioned above, the desired goal is achieved by minimizing, as possible, the impact of the vibrations that are transferred to the body of the vehicle and thus to the driver and passengers, resulting from the uneven road surface.

The controller that has adopted in this research to perform this purpose is the MR damper, whose characteristics and method of operation are mentioned above, and since the properties of this damper is changed, in terms of its ability to absorb vibrations or chocks to which it is exposed and dissipate energy, and that is through varying the voltage value applied to the coils. So for each vibration received by this damper a certain voltage value that achieves the best response. Since this damper is used in the car suspension system, the driver is not able to determine the appropriate value of the voltage. First, he is driving on a random road, second, it is unable to get off his car and check the surface of the road he will pass. Also, using one value for the voltage in dealing with different types of road surface will cause many problems. For example, instead of being a cause to reduce vibrations transferred to the car body, it may increase them. So, each surface has to be treated with a suitable voltage value. Therefore, in this study, a solution has been found, and if it is not ideal for different road types, it performs a good function by reducing the vibrations transmitted to the passengers.

MATLAB Simulink software is used to create eight DOF full car model with driver seat, and then use the same model and implanted to it an MR damper, to finally have two models, model without MR damper (only passive damper) and model with MR damper, it should be noted that this model has four MR damper located in the four corners of the vehicle body and implanted between the sprung and unsprung masses. Thus, the response of each model can be obtained and compare between them, when applying the input. After applying the road profile, the comparison has been done between these two models with respect to the sprung mass displacement, so the goal was to find the value of the voltage that achieved the least amount of sprung mass displacement, in terms of response peak. Thus, after changing the amplitude of the speed hump and the velocity of the vehicle and after doing the comparisons, a set of voltage values have been obtained that suit each input and achieved the best possible function. As discussed above, it is very difficult or rather impossible for the driver, each time he passes on an uneven road surface, to get off his car and measure the height of the surface and determine the speed that passes over it exactly, also, one voltage value cannot be adopted in dealing with the different road surface, was form it is necessary to find a solution for this problem. Neural Networks was adopted as a solution in this study. When the comparison was made, a large number of data was obtained, includes the appropriate voltage for each amplitude and velocity. These data have been used to train the ANN. The ANN topology and correlation coefficients are shown in Figures 7 and 8 respectively. This network uses the amplitude of the speed hump and the vehicle speed as inputs and then finds the optimum voltage value to skip the hump at least sprung mass and seat displacement. So that the speed of the car is determined by a special sensor for this function, as well as, through a sensor placed in the front of the car, the network gets a reading of the hump amplitude. When these two conditions are met, the network is able to determine the optimum voltage value.

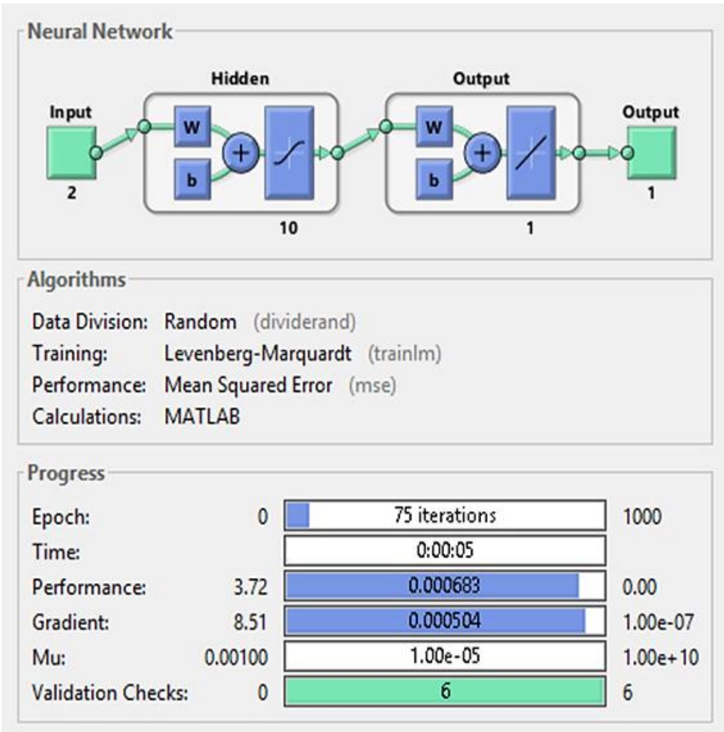

Figure 7. ANN topology

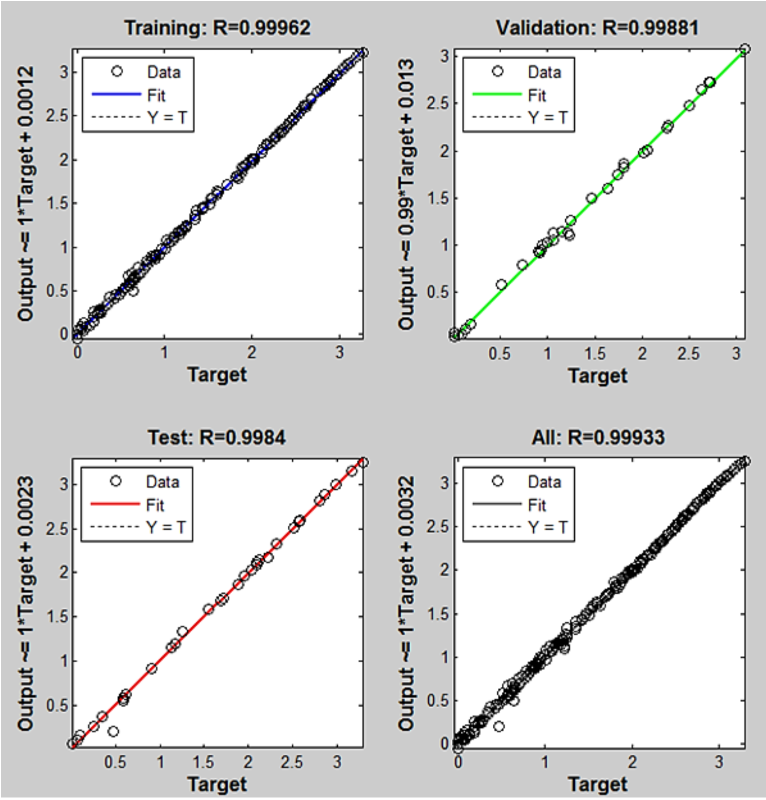

Figure 8. ANN correlation coefficients

The block diagrams used in this study, when using the semi-active system (system with MR damper) and the ANN are shown in Figure 9.

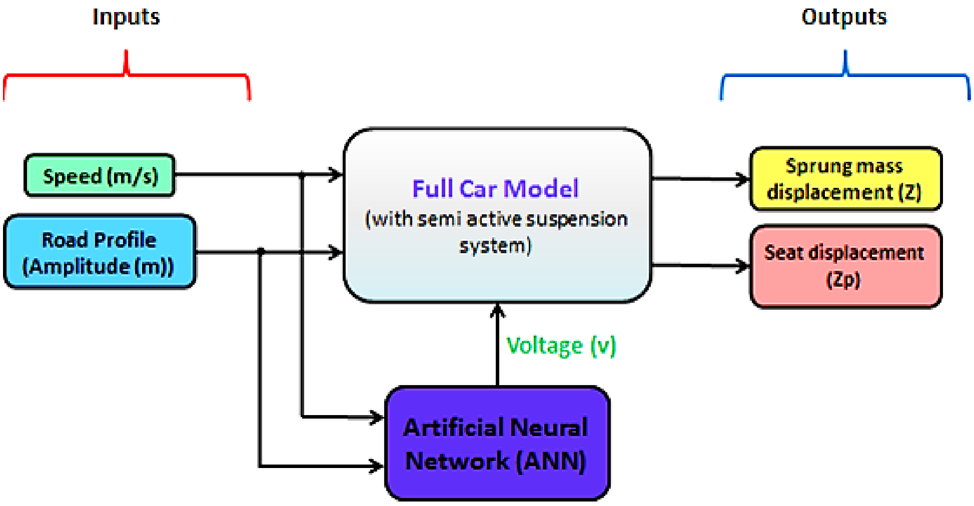

Figure 9. Full car Simulink model with MR damper and ANN

RESULTS AND DISCUSSION

Results

The following figures (Figures 10-13) show the response of the body and seat displacements at 0.12 and 0.1 m amplitude for 120 and 60 km/h speeds.

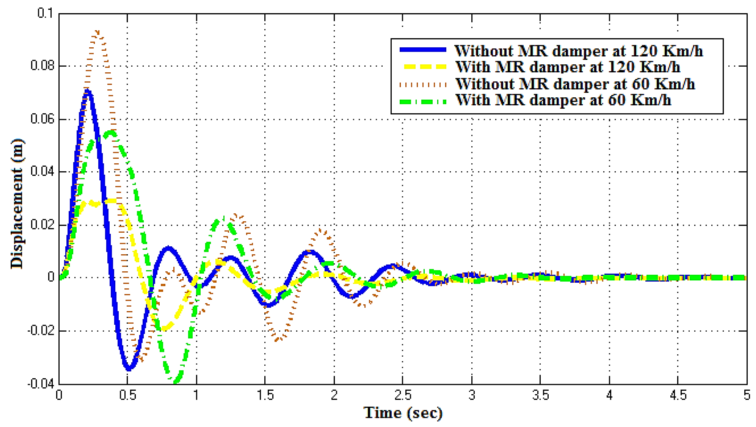

Figure 10. Sprung mass vertical displacements at 0.12 m amplitude for 60 and 120 km/h speeds

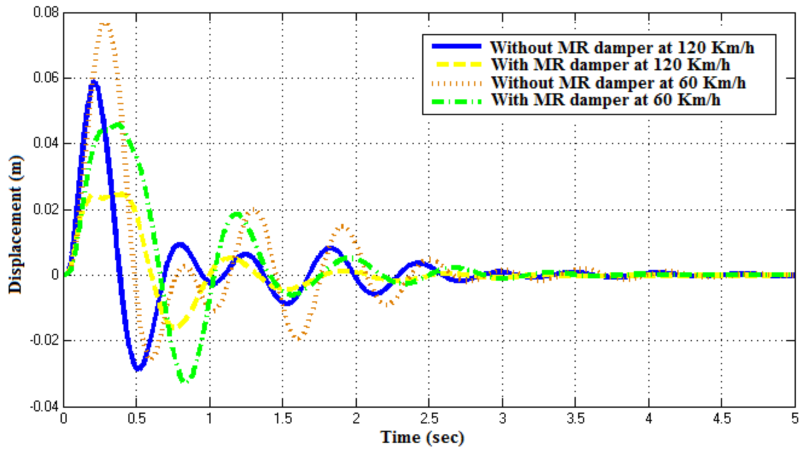

Figure 11. Sprung mass vertical displacements at 0.1m amplitude for 60 and 120 km/h speeds

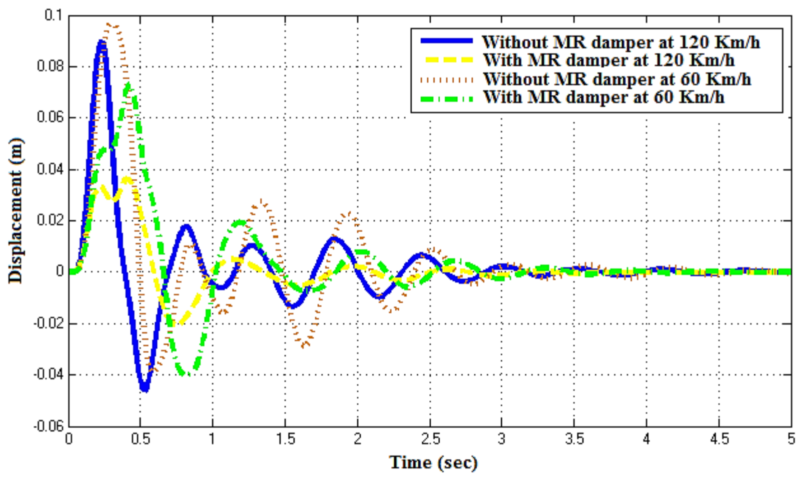

Figure 12. Driver seat vertical displacements at 0.12 m amplitude for 60 and 120 km/h speeds

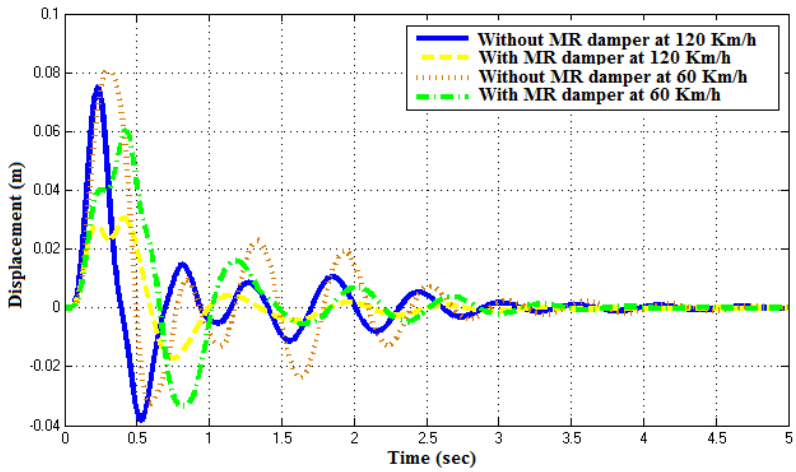

Figure 13. Driver seat vertical displacements at 0.1m amplitude for 60 and 120 km/h speeds

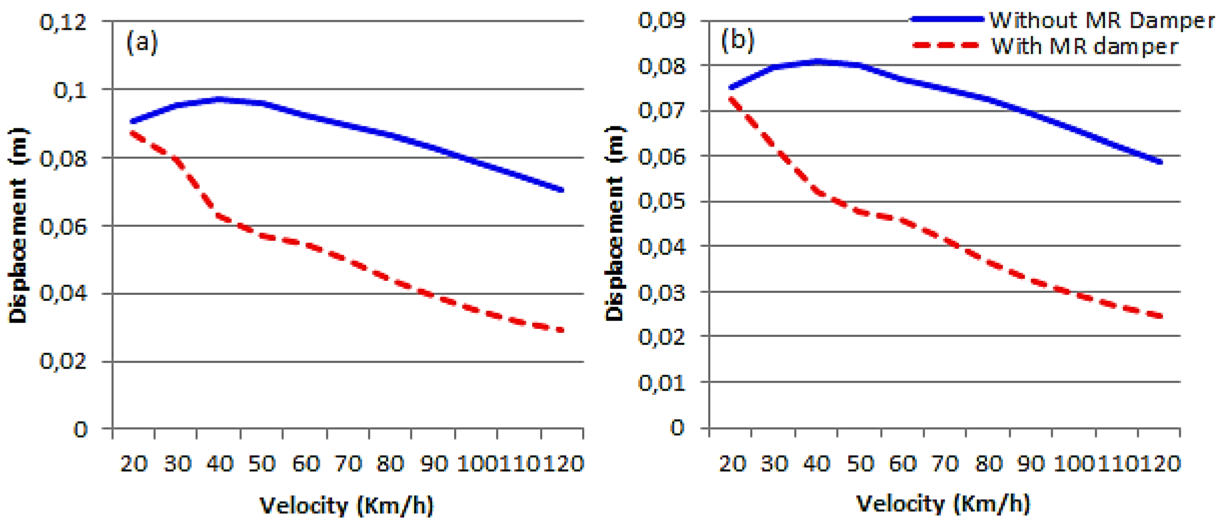

Figure 14. Sprung mass vertical displacements' peak for different speeds: (a) at 0.12 m amplitude and (b) at 0.1 m amplitude

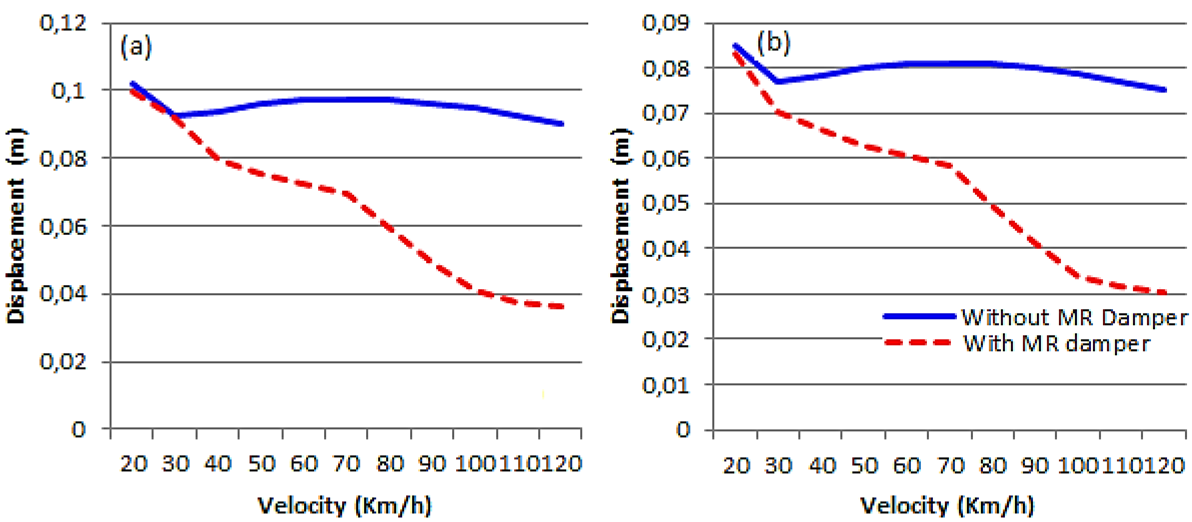

Figure 15. Driver seat vertical displacements' peak for different speeds: (a) at 0.12 m amplitude and (b) at 0.1 m amplitude

As shown in the above diagrams (Figures 14 and 15):

Sprung mass vertical displacement

The improvement is 58.72% at 120 km/h while it is decreased to 40.71% at 60 km/h in the case of 0.12 m amplitude. At 0.1 m amplitude, the response is improved by 58.26% at 120 km/h and by 40.73% at 60 km/h.

Driver seat vertical displacement

At 120 km/h and 0.12 m amplitude, the improvement is 59.67% and at 60 km/h this value decreased to be 24.95%. The response is improved by 59.2% in the case of 0.1 m amplitude and 120 km/h speed while the value of improvements is decreased to 25.37% at 60 km/h with the same amplitude.

CONCLUSION

Providing ride comfort was the objective of this paper, to achieve this goal, an eight DOF full car model was developed using Matlab Simulink. The model was assumed to travel on a speed hump has an amplitude that varies from 0.01 to 0.2 m with different speeds from 20 to 120 km/h. MR damper was implanted into the model to study its effect on ride comfort. ANN was used to find the optimum voltage value applied to the damper. Results show that the MR damper improves the vehicle ride comfort over the passive suspension system. The improvement is in the form of, approximately, 60% reduction in the response peak of the seat and sprung mass vertical displacements at 120 km/h speed, while its level gradually reduced with low speed.

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