ROBUST PID CONTROLLER DESIGN FOR ACTIVE VEHICLE SUSPENSION BASED ON PARTICLE SWARM OPTIMIZATION +

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Abstract :

This paper presents a robust PID neural controller based on particle swarm optimization for a four degree of freedom of half-car active vehicle suspension system .The scheme of the discrete-time PID control structure is based on neural network and tuned the parameters of the robust PID neural controller by using a particle swarm optimization PSO technique as a simple and fast training algorithm.
The robust PID controller is tested at two road profiles, bump and ramp. Simulation results show that the present controller can reduce the peak overshoot and transient period of the displacement, pitch angle acceleration of the vehicle body under different road conditions and vehicle speeds compared to passive suspension system. So the ride comfort and road holding ability will improve during the drive.

تصميم مسيطر عصبي تناسبي تكاملي تفاضلي نشيط لنظام تعليق مركبة أساسه أمثلية حشد الجسيمات

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المستخلص :

أن هذا البحث يقدم مسيطر عصبي (PID) نشيط لمنظومة تعليق لنموذج نصف مركبة ذو اربعة درجات حرية. أن هيكلية المسيطر العصبي (PID) مبني على أساس الشبكة العصبية و تنغيم عناصر المسيطر (PID) تتم من خلال تقنية خوارزمية أمثلية حشد الجسيمات لأنها خوارزمية سهله و سريعة التعلم. المسيطر تناسبي تكاملي تفاضلي النشيط اختبر عند نوعين من مطبات الطريق، الضربة الفجائية والصعود المحدد. اظهرت نتائج المحاكاة ان المسيطر الحالي استطاع تقليل قيمة تجاوز الهدف والفترة الزمنية الانتقالية لكل من الازاحة و التأرجح والتعجيل لجسم المركبة تحت مختلف ظروف الطريق وعند مختلف السرع المركبة بالمقارنة مع نظام التعليق الاعتيادية (بدون سيطرة). وبذلك فان راحة الركاب و التماسك بالارض سوف تتحسن اثناء القيادة.

1-Introduction :

Automotive designers are seeking to provide maximum comfort for the passenger through reducing vibrations of a vehicle body, which may be induced by variety of sources, including road irregularities, aerodynamic forces, vibration of the engine and drive line[1]. The main source of vibration in vehicle comes from road disturbances; therefore, the

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suspension system is used to isolate the vehicle body from road disturbances for comfortable ride. Conventional suspension system consists of a spring and damper, also known as passive suspension. It does not give better compromise between ride comfort and vehicle handling. So, to provide the vehicle with improved ride quality, handling, and performance under various operating conditions, the concept of an active suspension has emerged, and various active systems have been proposed or developed. The force actuator in active system is installed in parallel with a passive suspension (damper-spring system). Practically, the operating conditions of the vehicle are consciously monitored by sensors. Based on the signals obtained by sensors and the prescribe control strategy, the force in the actuator is modulated to achieve improved ride, handling and performance. The force actuator may be come from hydraulic, pneumatic or electric systems.
In recent years, a great number of studies have been engaged in the research about the control of suspension. Optimal control has been used in active suspension system since 1960s [2]. Most design methods for automotive active suspension systems are based on optimal control [3]. The fuzzy logical and neural network control have emerged other method for design of automotive active suspension system [4,5].
PID is the most widely used control method in industry and have been applied to active vehicle suspension system [6,7]. Its popularity is due to its simplicity and its relative ease of tuning either intuitively or with several tuning methods available. It is also popular because it is effective in the adjustment of system parameters of controllers like overshoot, rise and settling time. It however lacks robustness to parameter variation and requires high loop gains [8].
Several methods have been used in the literature to enhance the performance of the proportional-integral-derivative (PID) controllers; for example, [9,10,11] demonstrated the improved performance of active vehicle suspension system control based on the combination of PID and fuzzy logic. In [12], the PID controller was overlaid with a neural network feedforward controller to enhance system reference tracking; this was possible through the reduction of the system sensitivity to noise by the feedforward control overlay. Back propagation multi-layer neural network was employed in [13] to adjust the gains of the PID controller in the position control of a servo-hydraulic system.
In this paper an attempt is made to improve the performance of an active suspension using robust PID controller. The present controller is tested against different types of road profile and different values of the speed. In the most of the published works, the controllers are tested at certain road profile and vehicle speed.
The main advantage of the presented approach is not necessary to use a combined structure of identification and decision, common in a standard self-tuning controller because it is used a PSO as a simple steps algorithm and fast tuning the parameters of the PID controller.

2-Dynamic model of vehicle suspension system :

The half-car suspension model consists of a rigid sprung mass supported at either end by the front and rear suspension components (springs, dampers and force actuators), which rest on the front and rear unsprung masses. Thus, it is a 4-DOF system. Figure (1) illustrates the half-car model. Using the Newton's second law of motion and free-body diagram concept, the following equations of motion of 4-DOF vehicle suspension system are derived.

$$m_1 \ddot{x}_1 + c_1(\dot{x}_1 - \dot{x}) + (k_1 + k_{t1})x_1 - k_1 x - ak_1\theta - ac_1\dot{\theta} - k_{t1}w_f + F_1 = 0 \quad \ldots\ldots\ldots\ldots\ldots(1)$$

$$m_2 \ddot{x}_2 + c_2(\dot{x}_2 - \dot{x}) + (k_2 + k_{t2})x_2 - k_2 x + bk_2\theta + bc_2\dot{\theta} - k_{t2}w_r + F_2 = 0 \quad \ldots\ldots\ldots(2)$$

$$\begin{aligned} &M\ddot{x} + (k_1 + k_2)x + (c_1 + c_2)\dot{x} - c_2\dot{x}_2 - c_1\dot{x}_1 - k_2x_2 - k_1x_1 + (ak_1 - bk_2)\theta + \\ &(ac_1 - bc_2)\dot{\theta} - F_1 - F_2 = 0 \end{aligned} \quad \ldots\ldots\ldots(3)$$

$$\begin{aligned} &\ddot{\theta} I - ak_1x_1 - ac_1\dot{x}_1 + bk_2x_2 + bc_2\dot{x}_2 + (ak_1 - bk_2)x + (ac_1 - bc_2)\dot{x} + \\ &(a^2k_1 + b^2k_2)\theta + (a^2c_1 + b^2c_2)\dot{\theta} - aF_1 + bF_2 = 0 \end{aligned} \quad \ldots\ldots\ldots(4)$$

The states that must be controlled are front and rear suspension travel (y_1 &y_2) and determine as

$$\begin{aligned} y_1 &= x_1 - x_a \\ y_2 &= x_2 - x_b \end{aligned} \quad \ldots\ldots\ldots(5)$$

Where

$$\begin{aligned} x_a &= x + a\theta \\ x_b &= x - b\theta \end{aligned} \quad \ldots\ldots\ldots(6)$$

When the road conditions are bump road input , can be formulated as

$$w = \begin{cases} \frac{r}{2}(1 - \cos(6.667\pi V t)) & t_i \le t \le t_f \\ 0 & \text{otherwise} \end{cases} \quad \ldots\ldots\ldots(7)$$

where w is the wheel input disturbances, r is the bump amplitude, t is the time in seconds, t_i is the start time of the bump , t_f is the end time of the pump and V is the vehicle forward speed. Another type of road conditions that is taken in this paper is the road input with limited ramp which is formulated as below where 0.1m is the final road surface elevation:

$$w = \begin{cases} 0 & 0 \le t < t_i \\ 0.1(t - t_i) & t_i \le t \le t_f \\ 0.1 & t > t_f \end{cases} \quad \ldots\ldots\ldots(8)$$

It is clear the behavior of bumps and effect of them on the vehicle motion depend on in vehicle speed, wavelength of bump, number of wheel axels and length between these axels. The two last terms are related to design of the vehicle, But the speed and wavelength of bump in addition to vehicle mass are changing during operation of vehicle ,So these changing must be taken into consideration in any design of active suspension controller. The state variables and the parameters are defined in Appendix (A).

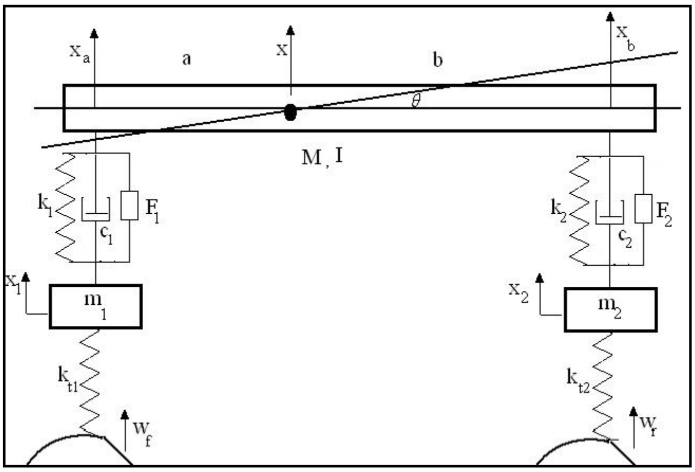

Figure (1): Half –vehicle model with active and passive suspension components

3- Robust PID Neural Controller :

The control of linear Multi-Input Multi-Output (MIMO) dynamics system is considered in this section. The approach used to control on the front and rear suspension travel (y_1 &y_2) of the vehicle that depends on the information available about the system model and the control objectives. The feedback robust PID neural controller is necessary to stabilize the tracking error dynamics of the system when the output variable states of the system are drifted from the desired inputs by using two control signals front and rear force actuators.

The general structure of the robust PID neural controller type can be given in the form of the block diagram shown in figure (2). Two types of road profile (bump road input and road input with limited ramp) with different values of the speed and vehicle mass are used to learn the controller.

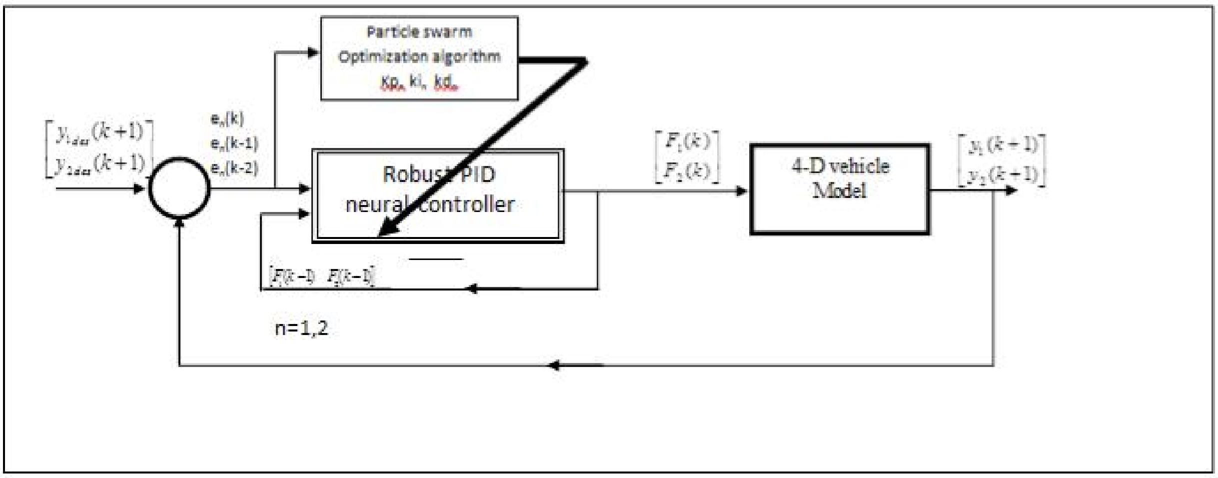

Figure (2): The general proposed structure of robust PID neural feedback controller for 4-DOF vehicle model

The robust PID neural controller for MIMO system can be shown in figure (3). It has the characteristics of control agility, strong adaptability, good dynamic characteristic and robustness because it is based on that of a conventional PID controller that consists of three terms: proportional, integral and derivative. The standard form of a PID controller is given in the s-domain as equation (9) [14].

$$Gc(s) = P + I + D = K_p + \frac{K_i}{s} + K_d s \quad \ldots\ldots(9)$$

where K_p, K_i and K_d are called the proportional gain, the integral gain and the derivative gain respectively.

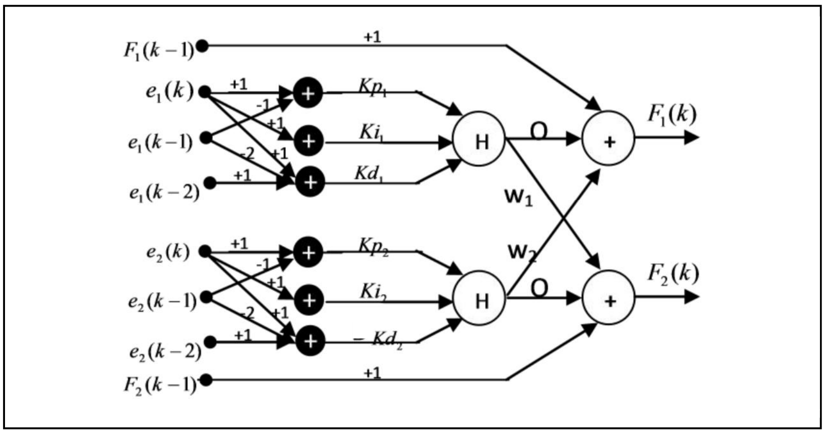

Figure (3): The robust PID neural feedback controller structure

The proposed robust PID neural controller scheme is like neural network PID controller structure as the discrete-time equation (10) [15].

$$F_n(k) = F_n(k-1) + Kp_n[e_n(k) - e_n(k-1)] + Ki_n e_n(k) + Kd_n[e_n(k) - 2e_n(k-1) + e_n(k-2)] \quad \ldots\ldots(10)$$

where n=1,2

Therefore, the tuning PID input vector consists of $e_n(k)$, $e_n(k-1)$, $e_n(k-2)$ and $F_n(k-1)$, where $e_n(k)$ and $F_n(k-1)$ denote the input error signals and the PID output respectively. Particle swarm optimization algorithm technique is used to adjust the parameters of the robust PID neural controller.

The proposed control law of the feedback Front and rear actuator force (F_1 and F_2) respectively can be proposed as follows:

$$F_1(k) = F_1(k-1) + o_1 + o_2 w_2 \quad \ldots\ldots(11)$$

$$F_2(k) = F_2(k-1) + o_2 + o_1 w_1 \quad \ldots\ldots(12)$$

Assume w_1 and w_2 are constant positive weights and there are equal to o.1, o_1 and o_2 are the outputs of the neural networks that can be obtained from sigmoid function has nonlinear relationship as presented in the following function:

$$o_1 = \frac{2}{1 + e^{-net_1}} - 1 \quad \ldots\ldots(13)$$

$$o_2 = \frac{2}{1 + e^{-net_2}} - 1 \quad \ldots\ldots(14)$$

net_1 and net_2 are calculated from these equations

$$net_1(k) = Kp_1[e_1(k) - e_1(k-1)] + Ki_1 e_1(k) + Kd_1[e_1(k) - 2e_1(k-1) + e_1(k-2)] \quad \ldots\ldots(15)$$

$$net_2(k) = Kp_2[e_2(k) - e_2(k-1)] + Ki_2 e_2(k) + Kd_2[e_2(k) - 2e_2(k-1) + e_2(k-2)] \quad \ldots\ldots(16)$$

The control parameters $Kp_{1,2}, Ki_{1,2}$ and $Kd_{1,2}$ of the robust PID neural controller are adjusted using the particle swarm optimization techniques.

3-1 Learning Algorithm :

Particle Swarm optimization (PSO) is a kind of algorithm to search for the best solution by simulating the movement and flocking of birds. PSO algorithms use a population of individual (called particles) “flies” over the solution space in search for the optimal solution.

Each particle has its own position and velocity to move around the search space. The particles are evaluated using a fitness function to see how close they are to the optimal solution [16].

The previous best value is called as *pbest*. Thus, *pbest* is related only to a particular particle. It also has another value called *gbest*, which is the best value of all the particles *pbest* in the swarm.

The robust PID neural controller with six weights parameters and the matrix is rewritten as an array to form a particle. Particles are then initialized randomly and updated afterwards according to equations (17, 18, 19, 20, 21 and 22) in order to tune the proposed robust PID parameters:

$$\Delta Kp_{n,m}^{k+1} = \Delta Kp_{n,m}^{k} + c_1 r_1 (pbest_{n,m}^{k} - Kp_{n,m}^{k}) + c_2 r_2 (gbest^{k} - Kp_{n,m}^{k}) \quad \ldots\ldots(17)$$

$$Kp_{n,m}^{k+1} = Kp_{n,m}^{k} + \Delta Kp_{n,m}^{k+1} \quad \ldots\ldots(18)$$

$$\Delta Ki_{n,m}^{k+1} = \Delta Ki_{n,m}^{k} + c_1 r_1 (pbest_{n,m}^{k} - Ki_{n,m}^{k}) + c_2 r_2 (gbest^{k} - Ki_{n,m}^{k}) \quad \ldots\ldots(19)$$

$$Ki_{n,m}^{k+1} = Ki_{n,m}^{k} + \Delta Ki_{n,m}^{k+1} \quad \ldots\ldots(20)$$

$$\Delta Kd_{n,m}^{k+1} = \Delta Kd_{n,m}^{k} + c_1 r_1 (pbest_{n,m}^{k} - Kd_{n,m}^{k}) + c_2 r_2 (gbest^{k} - Kd_{n,m}^{k}) \quad \ldots\ldots(21)$$

$$Kd_{n,m}^{k+1} = Kd_{n,m}^{k} + \Delta Kd_{n,m}^{k+1} \quad \ldots\ldots(22)$$

$$m = 1,2,3,.....pop$$

where

pop is number of particles.

$K_{n,m}^{k}$ is the weight of particle *m* at *k* iteration.

c_1 and c_2 are the acceleration constants with positive values equal to 1.75.

r_1 and r_2 are random numbers between 0 and 1.

$pbest_{n,m}$ is best previous weight of m^{th} particle.

$gbest$ is best particle among all the particle in the population.

The number of dimension in particle swarm optimization is equal to six because there are two robust PID and each one has three parameters.
The mean square error function is chosen as criterion for estimating the model performance as equation (23) [16]:

$$E=\frac{1}{2}\sum_{j=1}^{pop}(y_{1des}(k+1)^{j}-y_{1}(k+1)^{j})^{2}+(y_{2des}(k+1)^{j}-y_{2}(k+1)^{j})^{2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(23)$$

4- Simulation Results :

The performance of the proposed controller is evaluated using the closed-loop step the front and rear suspension travel (y_1 & y_2) of the 4-D vehicle model. The desired suspension travel must be zero to reduce the vibration in the vehicle body.
The proposed control scheme is applied to the vehicle model and it is used the proposed learning algorithm steps of PSO for tuning robust PID neural controller's parameters. The PSO algorithm is set to the following parameters:
Population of particle is equal to 40. Number of weight in each particle is 6 because there are two robust PID neural controllers. The number of iteration is equal to 300 with sampling time is equal to 0.01 sec. Scaling functions have to be added at the neural network terminals to convert the scaled values to actual values and vice versa.
Time-domain analyses are using to show the performance of passive (without controller) and active suspension system using robust PID controller. The simulations of the present controller are tested against two types of road profile using Matlab program.

a- The road profile type bump road input :

The height of the bump road input is taken 0.05m and the input for the rear wheels are the same as the front ones but delayed by a certain time equal to (a+b)/V.
Figure (4) shows the suspension travel time histories for the front wheel for both active and passive suspensions at three vehicle speeds 10, 20 and 30 m/sec respectively. The maximum suspension travel for the wheels occurred at the maximum heights of the road disturbance input; however the values were below the specified suspension travel limits. At vehicle speed of 10 m/sec, the effect of the disturbance was completely suppressed after about 0.5sec and 2.5 sec in the active suspension and passive suspension respectively for the front wheel. When the vehicle speed is increasing to 20 and 30 m/sec the amplitude of the suspension travel will reduce and the effect of vibration that effect on the body vehicle is less than that vibration at low speed as shown in figures. The same behavior was occurred for the rear wheel. It can be easily seen that active suspension significantly reduces suspension travel (the car body displacement and tire deflection) and settling time more than passive suspension.
In spite of the heave and pitch motion are not taken as controlled variables, time responses the heave and pitch motions with and without controller for the bump road input and at vehicle speed of 10, 20 and 30 m/sec respectively are given in Figure(5). It is seen from this figure that the magnitudes for the heave and pitch are significantly decreased. For the controlled active suspensions vanish faster than the passive suspensions for all vehicle speeds. These results confirm the efficiency of the present controller. In order to fulfill the objective of designing an active suspension system, i.e. to increase the ride comfort and road handling, vehicle body acceleration is important parameters to be observed in the simulations for both two types of road disturbance. Acceleration time history of the sprung mass at different vehicle speeds for bump road input is shown in figure (6). It is clear that the active system is

able to significantly reduce the body acceleration to acceptable range as compared with the passive system.

b- The road profile type road input with limited ramp :

A road input with limited ramp as seen in figure (7) is applied to the suspension vehicle model. This type of road irregularity tests the performance of the controller when there is a sudden change in the road surface elevation. In this case the values of vehicle speeds are not effect on the suspension model therefore the value of speed become meaningless here.
Time histories for the vehicle body heave, and pitch motion for the road input with limited ramp are presented in figure (8). It is seen from this figure that the vehicle smoothly settles to the final height value of the road input and the magnitudes of the displacements are reduced.

5-Conclusions :

The paper presents a robust strategy in designing a controller for an active suspension system which is based on PID neural network controller with particle swarm optimization algorithm technique. A 4-DOF model of a half model for passive and active suspension system considering heave and pitch motions have been used to evaluate the performance of the suspension.
The front and rear actuators in active suspension system are generated from the proposed controller with PSO algorithm that is used to tune the robust PID neural controller with minimum time and more stability of the controller and no oscillation with best parameters of the controller have been found.
From the simulation results, it can be seen that the present controller shows significant improvement in reducing both magnitude and settling time of the displacement and pitch angle the vehicle body. Also, reduce the body acceleration to acceptable comfort level for the passengers.

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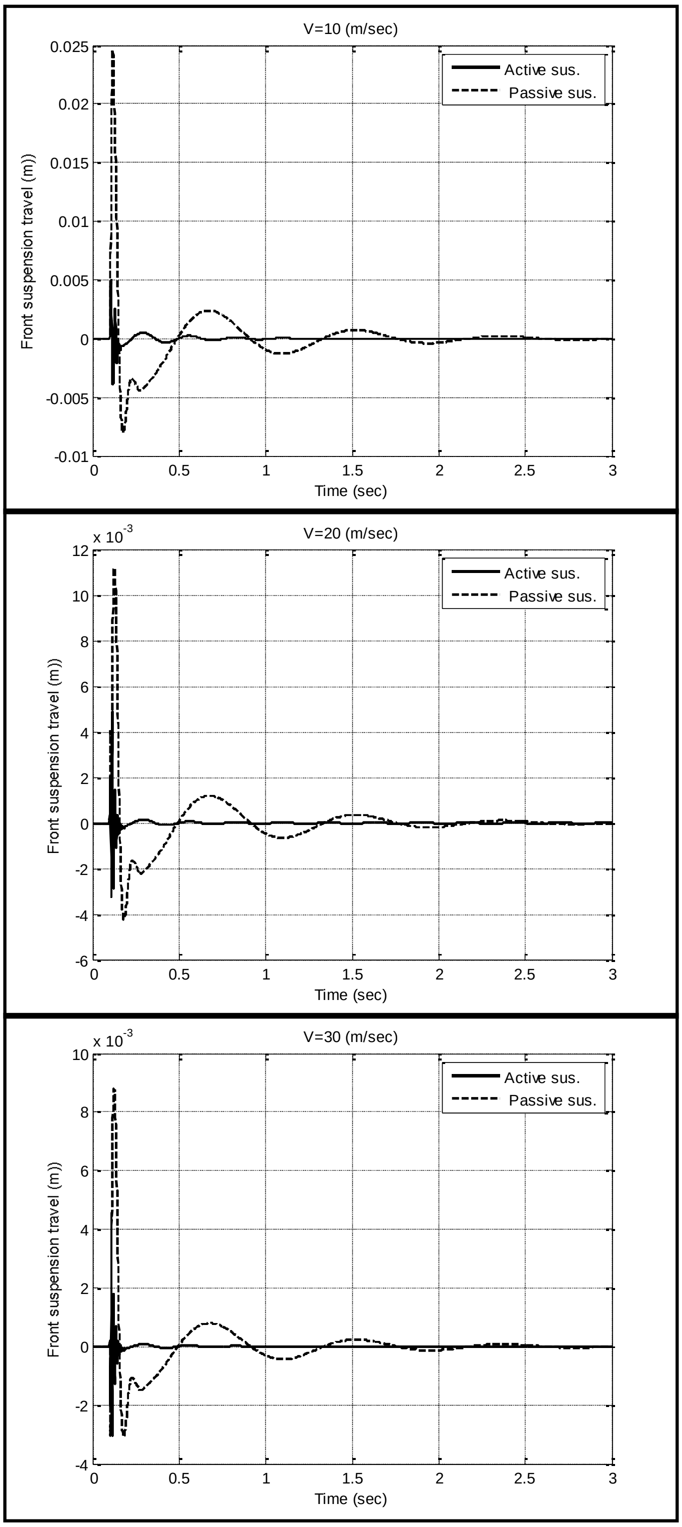


Figure (4): Front suspension travel time history at different vehicle speeds for bump road input

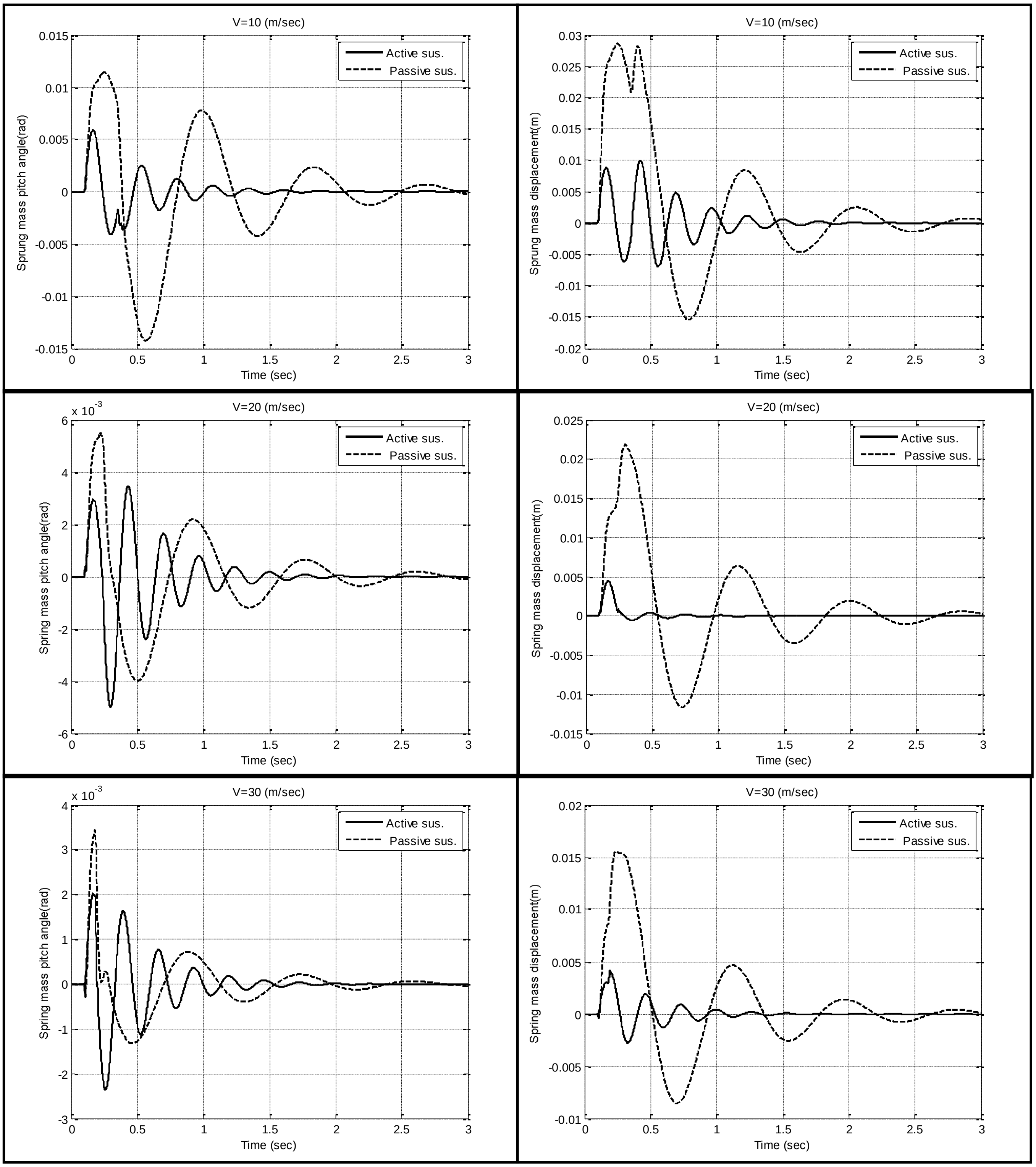


Figure (5): Heave and pitch motion time history of the sprung mass at different vehicle speeds for bump road input

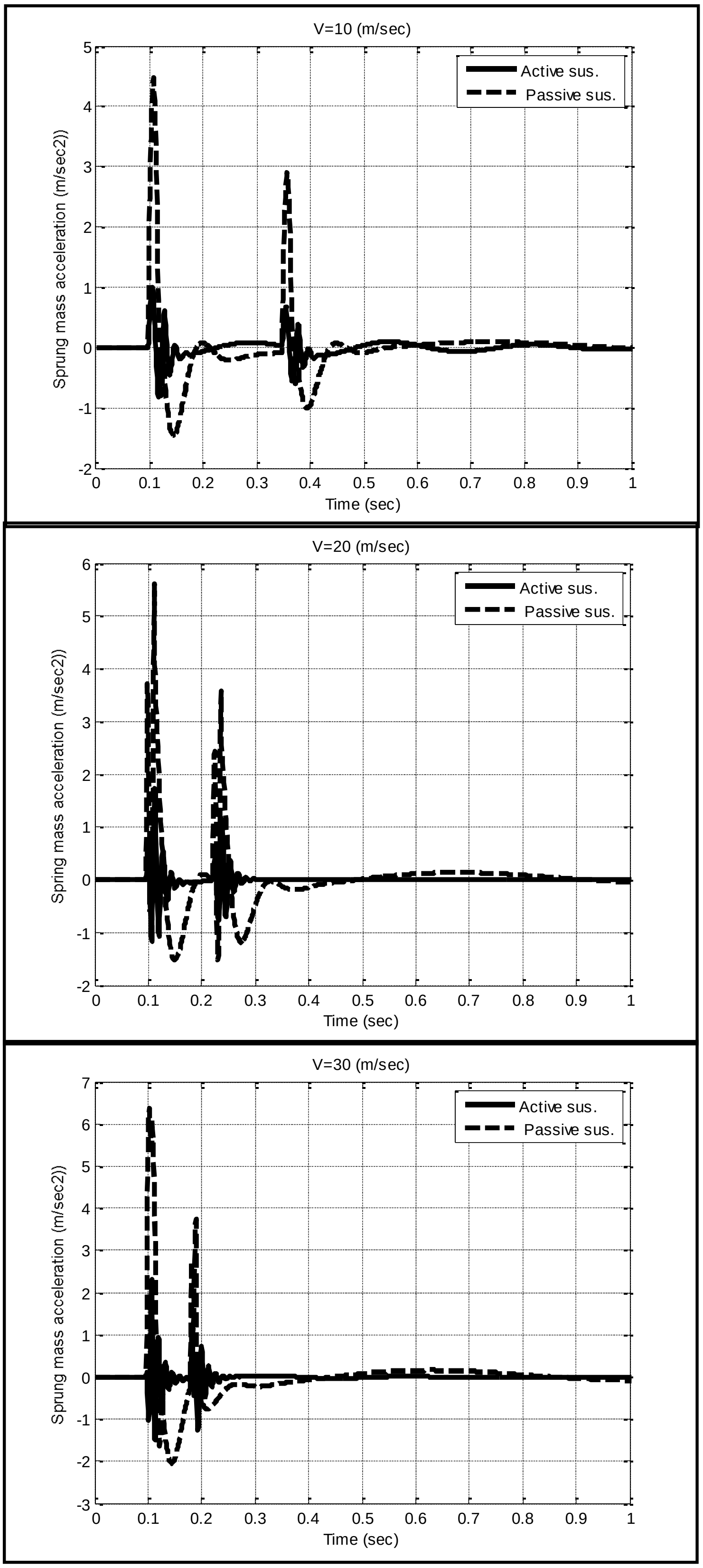


Figure (6): Acceleration time history of the sprung mass at different vehicle speeds for bump road input

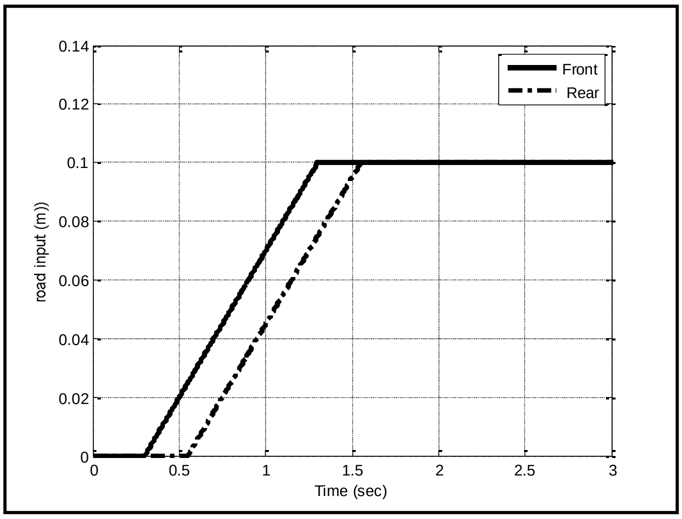
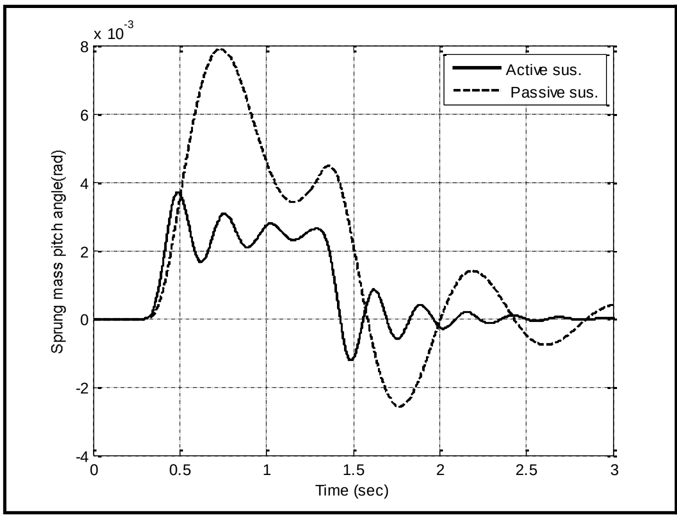
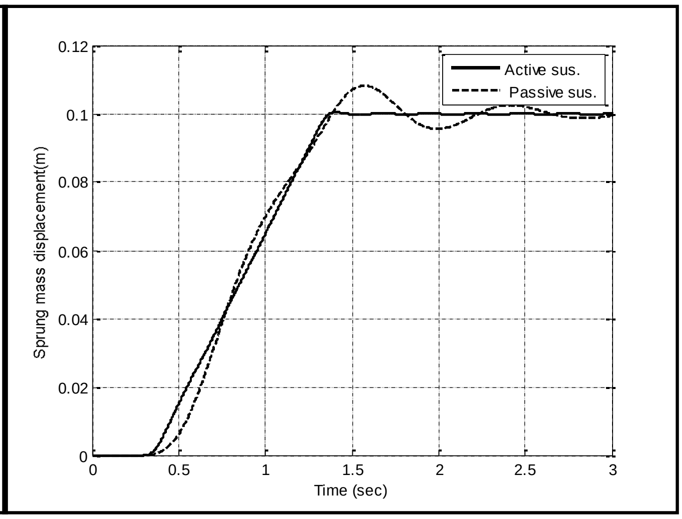


Figure (7): Road input with limit ramp





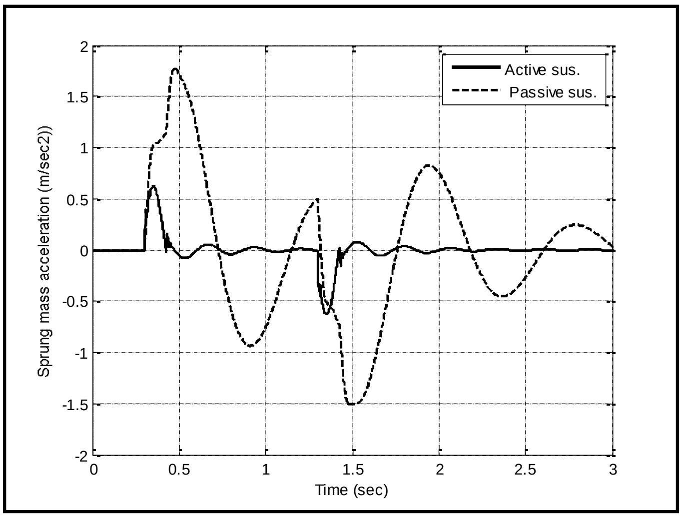


Figure (8): Heave and pitch motion time history of the sprung mass and related acceleration at different vehicle speeds for the road input with limited ramp

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Appendix (A)

Vehicle variables and parameters

Symbol	Description	Value	Unit
A	distance from the center of mass to front axle	1	m
B	distance from the center of mass to rear axle	1.5	m
$c_{1,2}$	Front and rear Suspension damper coefficient	1000	Ns/m
$F_{1,2}$	Front and rear actuator force	-	N
$k_{1,2}$	Front and rear spring stiffness	18600	N/m
$K_{t1,2}$	Front and rear tire spring stiffness	196000	N/m
K_D	Differential time constant.	-	
K_I	Integral time constant	-	
K_p	Proportional coefficient	-	
M	Half vehicle sprung mass	250-350	kg
MIMO	Multi-Input Multi-Output		
$m_{1,2}$	Front and rear unsprung mass	50	kg
PID	Proportional-integral-derivative controllers		
PSO	Particle swarm optimization		
V	Vehicle speed	10-40	m/s
$W_{f,r}$	Front and rear Road profile		m
x	Vertical displacement of the center of the body vehicle		m
$x_{a,b}$	Front and rear sprung mass vertical displacement	-	m
$x_{1,2}$	Front and rear unsprung mass vertical displacement	-	m
$y_{1,2}$	Front and rear suspension travel		m
θ	Pitch angle of the center of the body vehicle		rad